Modeling the energy limits to business-as-usual scenarios : confronting peak oil to the energy transition

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THÈSE

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Modélisation des limites énergétiques aux scénarios business-as-usual : confronter le pic pétrolier à la transition énergétique

Modeling the energy limits to business-as-usual scenarios: confronting peak oil to the energy transition

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Modeling the energy limits to business-as-usual scenarios: confronting peak oil to the energy transition

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Résumé

Le développement des sociétés industrielles a été permis par l'explosion de la consommation énergétique, de laquelle elles sont devenues dépendantes. Les énergies fossiles représentent aujourd'hui 80% du mix énergétique et sont la principale cause du changement climatique.

La transition énergétique est alors souvent invoquée comme solution au problème climatique, se substituant aux énergies fossiles, sans impacts sur la consommation énergétique utile. Néanmoins, le déploiement de l'éolien et du photovoltaïque aussi bien que l'électrification des usages ne sont pas aussi rapide qu'espérés. En effet, de nombreuses barrières notamment techniques et économiques à la transition énergétique sont identifiées et discutées au chapitre 1.

Il faudrait donc réduire la consommation énergétique, ce qui réduirait tout types d'impacts environnementaux. Néanmoins, cela impliquerait également une réduction de l'activité économique. Celle-ci peut être sans conséquences sociales, voire apporter des bénéfices si elle est anticipée et pensée pour le bien commun. Néanmoins la décroissance choisie n'est quasiment jamais politiquement et institutionnellement envisagée.

En fait, les sociétés industrialisées préfèrent suivre un scénario tendanciel ou "business-as-usual" (BAU). Il est ainsi commun d'observer que de nombreux modèles et institutions considèrent ce scénario comme scénario de référence. Néanmoins, l'approvisionnement en pétrole et en gaz devraient atteindre un pic et décroître dès la prochaine décennie (2030—2040). Le chapitre 2 de la thèse étudie de façon critique l'approvisionnement énergétique brut futur et ses incertitudes. Le déclin des taux de retour énergétique (TRE ou EROI) du pétrole et du gaz implique néanmoins un déclin plus prononcé de l'énergie nette extraite du pétrole et du gaz. Cela est modélisé dans le chapitre 3, qui réexamine l'évolution de l'investissement énergétique requis, par sources, dans la chaîne d'approvisionnement du pétrole et du gaz jusqu'au point d'utilisation.

L'approvisionnement de pétrole est alors particulièrement critique. En effet, son pic intervient très tôt, dès 2030 ou au plus tard 2035. De plus, une partie importante de ses usages n'est pas facilement substituable. Enfin, la consommation énergétique du transport repose à 95% sur le pétrole, alors que ce secteur est critique pour les chaînes d'approvisionnement, et donc pour l'économie. Le pic pétrolier est donc à même de mener à des crises économiques structurelles.

Ainsi, le chapitre 5 prend une approche contrefactuelle pour étudier les éventuelles impossibilités d'un scénario BAU: on cherche à déterminer si et quand l'approvisionnement en pétrole pourrait ne plus satisfaire la demande d'un scénario BAU. L'évolution de la demande en pétrole à l'horizon 2050 est d'abord modélisée au chapitre 4. Le secteur du transport routier est étudié par pays puisqu'il est relativement incertain alors qu'il constitue le principal usage du pétrole. Les résultats permettent de conclure qu'il est alors très probable que l'approvisionnement en pétrole cesse de satisfaire la demande d'un scénario BAU autour de 2030—2035, même avec des niveaux importants de déploiement de véhicules électriques.

L'incertitude principale de cette modélisation réside dans la projection du déploiement des véhicules électriques (VE ou EV). Partant du constat du surcoût des EVs par rapport à leur équivalent thermique, les chapitres 6 et 7 développent alors des modèles permettant de déterminer la distribution du stock de voitures en fonction du revenu des foyers au sein d'un pays, ainsi que de déterminer le déploiement d'EV maximum réalisable par pays lorsque seule la barrière de leur accessibilité économique est prise en compte.

Cette thèse apporte donc des éléments de cadrage importants sur les futurs possibles de l'approvisionnement et de la consommation énergétique, en montrant notamment l'impossibilité

de scénarios BAU dès la prochaine décennie à cause du déclin de l'approvisionnement en pétrole.

Summary

The surge in energy consumption has been a crucial factor in the ongoing development of industrialized societies. Fossil fuels currently represent 80% of the energy mix and are the main cause of climate change.

The energy transition is therefore often seen as a solution to the climate issue, allowing fossil fuels to be substituted without impacting the useful energy consumption. However, the deployment of wind turbines and photovoltaic panels as well as the electrification of energy uses are not deployed as quickly as expected. Indeed, several major technical and economic barriers to their deployment are identified and studied in chapter 1.

Reducing the energy demand is therefore required, and would reduce all environmental impacts. Nevertheless, this would entail a reduction in economic activity. This might possibly be achieved without negative social consequences — or even bring social benefits — if anticipated and pursued for the common good. Still, political bodies and institutions never invoke degrowth.

Therefore, the industrialized societies are very likely to seek business-as-usual (BAU) policies. Many models and institutions assume these to be the reference scenario. However, oil and gas supply are expected to peak and decline within the next decade (2030—2040). Chapter 2 critically assesses future gross energy supply and discusses associated uncertainties. The decline of the energy return on investment (EROI) however entail a decline of the net energy retrieved from oil and gas gross supply. This is modelled in Chapter 3, which reinvestigates the evolution of the energy investment required in the oil and gas supply chains up to the point of use, disaggregated between energy sources.

Oil supply is particularly critical. Indeed, it is expected to peak as early as 2030 and no later than 2035. Furthermore, oil cannot be substituted in a large fraction of its applications. Finally, 95% of the energy consumption of the transport sector relies on oil, while this sector is critical to supply chains and thus to the economy. Peak oil may thus potentially induce structural economic crises in the future.

Therefore, Chapter 5 takes a counterfactual approach in order to analyse potential inconsistencies of a BAU scenario: it seeks to find if and when oil supply would be unable to match a BAU demand. Oil demand up to 2050 is first modeled in Chapter 4. The road transport sector is studied by countries as it constitutes the largest sectoral demand for oil as well as the most uncertain one. This leads to the conclusion that the oil supply will most likely be unable to match a BAU oil demand by around 2030—2035, even with high electric vehicles deployment levels.

The main uncertainty in this model lies in the deployment of electric vehicles (EVs). Given that the purchasing prices are higher for EVs than for conventionnal thermal vehicles, chapters 6 and 7 builds models that allow the computation of the distribution of vehicles stock as a function of households income, as well as the maximum possible EV deployment by country, when only the purchasing overcost barrier is taken into account.

This thesis therefore brings crucial elements on possible future energy supply and demand scenarios, particularly showing the inconsistency of BAU scenarios as early as the next decade due to the decline of oil supply.

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General acronyms

2W Two wheeled vehicles

4W Four wheeled vehicles

BAU
Business-as-usual

CTL Coal to liquids

CV Commercial vehicles

EROI
Energy return on investment

EJ Exajoules (10^{18} joules).

EV Electric vehicles

GDP
Gross domestic product

GTL Gas to liquids

IAM Integrated assessment model

ICV Internal combustion engine vehicles

IEA International Energy Agency

IPCC
International panel on climate change

LCOE
Levelized cost of electricity

NGL
Natural gas liquids

PV Photovoltaic panels (in chapters 1, 2 and 3)

PV Private vehicles (in chapters 4, 5, 6 and 7)

URR
Ultimate recoverable resources

Introduction

Fossil fuels: a blessing and a curse

In 2022, 622 exajoules (EJ) of primary energy were consumed worldwide, 81% of which were fossil fuels (IEA, 2024b). This is 30 times larger than the annual energy consumption in 1800 (Smil, 2017), which was mostly biomass energy.

The modern industrialized societies we live in are based and reliant on this energy consumption. Each product consumed has undergone multiple fabrication and transformations steps, most of which some are carried out by machines and involve transportation to several locations. The energy invested in a product's supply chain is called "embodied" energy. Conversely, all activities realized in these societies involve an energy consumption, either directly (e.g. oil in cars) or through the use of products for which the embodied energy is accounted for.

Current industrialized societies have been developed since 1850, based on the co-development of technologies and energy extraction. Coal extraction first enabled the development of the first industries and modern technologies, based on steel production and steam engines. Later, oil extraction enabled the development of vehicles (primarily cars and trucks), which are crucial for supply chains. Note that energy extraction and technological development are interconnected. Energy extraction fed technologies, which in turn fostered the development of other technologies, enabling the extraction of more energy. This allowed the decrease of labor intensity in the production sector, including agriculture, and raised demand for new products. These processes form the basis of industrialized societies (Carrey, 2020; Fressoz, 2024; Smil, 2018).

Not surprisingly, the growth of GDP (gross domestic product) — a metric commonly used to measure the economic activity — has been found to be very strongly correlated with energy consumption (Haberl et al., 2020).

Due to this interdependence between energy extraction and the economy, a decrease in energy consumption [1] — voluntary or not — would most probably result in a decrease in GDP per capita and economic decline.

Energy is therefore pivotal to the way industrialized societies operate. However, the energy system faces multiple challenges: fossil fuels should be phased out very quickly in order to contain the impacts of climate change, oil and gas supply are expected to peak in the next decade, and their energy return on investment (EROI) are expected to decrease. On top of that, increasing systemic risks of all kinds threaten modern societies.

[1] The relevant correlation is in fact between GDP and useful energy, as Haberl et al. (2020) pointed out. This is particularly important in the context of the energy transition, as wind and photovoltaic (PV) energy sources have better primary to useful energy conversion efficiencies than fossil fuels.

Global systemic risks and planetary boundaries

Environmental pressures

The development of industrialized societies goes along with the increase of environmental pressures. The "Great Acceleration", an expression used by Steffen et al. (2015b, 2004) depicts this correlation between the exponential industrial and socio-economic development with some environmental pressures, e.g. carbon dioxide emissions, ocean acidification and terrestrial biosphere degradation. Concurrently, land clearing and deforestation, overfishing, pollution and climate change result in massive biodiversity loss, leading to the 6th mass extinction (Ceballos et al., 2015). Meanwhile, topsoil erosion, combined with pollution, overexploitation of resources and climate change directly are directly eroding the capacities of our societies to grow food and access freshwater in an irreversible manner (IPBES, 2019; Pereira et al., 2024; Dirzo et al., 2014; Scheffer et al., 2001; Lenton et al., 2008; Morgan, 2005; Wang-Erlandsson et al., 2022). This has led Rockström et al. (2009) to define "planetary boundaries", some of which are already exceeded(Steffen et al., 2015a).

When efficiency brings vulnerability

Industrialized societies have reached a high level of efficiency primarily through the optimization of supply chains, which in turn creates vulnerabilities. Indeed, the price of this optimisation is a low robustness against perturbations or shocks. These vulnerabilities were revealed, for example, by the widespread economic impacts of the Covid-19 pandemic and the subsequent rise in prices of many products and raw materials, the supply chain disruptions caused by the 2021 Suez Canal obstruction, or the semiconductor shortage that began in 2020 which was fostered by the concentration of semiconductor production in south-east asia, with 92% of advanced semiconductors being produced in Taiwan in 2021 (Varas et al., 2021). Outside of supply chains, electrical blackouts lasting for extended period of times would have major socio-economic impacts in Western countries (Petermann et al., 2011). The economy has also proven to be very sensitive to surges in oil prices (Hamilton, 1983, 2009). Finally, specialization has led the economies of some countries to rely on the production of limited number of commodities, which has already resulted in major country-specific economic crises[2].

The combination of environmental pressures, vulnerabilities and interdependences

Global networks are complex and interconnected, making them interdependent, vulnerable and sensitive to the possibility of cascading failures (Helbing, 2013; Homer-Dixon et al., 2015; Mignan and Wang, 2020). The term "global systemic risk" has therefore been used to describe the risks arising from these characteristics (Centeno et al., 2015). The combination of environmental pressures, vulnerabilities and interdependences therefore results in high risks for industrialized societies. Some of these were as well as development and growth issues have been recognized early on by the Club of Rome, which eventually led Meadows et al. (1972) to model some of these risks and conclude that society would collapse in all growth scenarios. The global Risk Report of the World Economic Forum (2025) also attempts to illustrate the main risks and their interconnection based on surveys of stakeholders and experts. The term "polycrisis" has recently been defined by Lawrence et al. (2024), who calls for research on the subject.

Another lens used by Tainter (1988) relies on the concept of complexity to study societal collapses. He argues that societies tend to increase their complexity in order to solve issues,

[2] A few examples are presented in the Supplementary Materials of Chapter 4

resulting in societal collapse due to the diminishing marginal returns of complexity.

While global systemic risks are often studied conceptually, they are difficult to model. This is due to the multitude of factors to model, the difficulty of modeling social phenomenons quantitatively, but also to the fact that the occurrence of shocks involves a degree of randomness and that some phenomenons are non-linear or even subjects to threshold effects that trigger tipping points. Such models are by nature interdisciplinary.

Conclusion on global systemic risks

Global systemic risks arise from the development of industrialized societies, which would not have been possible without new major sources of energy. However, these risks do not directly result from energy consumption (except in a few cases, such as climate change), but rather from the impacts of the ever-increasing rate of activity of these societies. This means that the energy transition alone will not affect most of these risks, except for climate change.

Nevertheless, due to the correlation between energy consumption and the development of industrialized societies, a long-term major reduction in energy consumption would ultimately lead to a reduction in complexity and environmental pressures. Note that this is likely to occur quite rapidly if systemic risks lead to a global collapse. Even in the absence of collapse, the irreversible phenomena that have been unfolding for decades imply that the Earth system will never return to its pre-industrial revolution state.

First issue related to the energy mix: climate change

Climate change is caused by the emission of greenhouse gases (GHGs), of which three-quarters are CO2 emitted by fossil fuels[3] (IPCC, 2023). According to the data from HadCRUT5 (Morice et al., 2021)[4], this average rise in the global land and ocean temperatures reached 1.5°C in 2024 compared to pre-industrial (1850—1900 average) temperatures (but one needs to wait another number of years for the 1.5°C threshold to be permanently crossed). Climate change is a well-known major threat to societies in the 21st century as it degrades the habitability of some regions (due to floods or heat waves), accelerates biodiversity loss, disrupts water systems including access to freshwater and the water cycle, as well as agricultural systems (mostly due to the previous impacts). This is well documented in the IPCC reports (IPCC, 2023).

Note that fossil fuels have a direct major responsibility in climate change. Containing global warming is most often the main argument used to advocate for energy transitions toward low-carbon sources.

Second issue: peak oil and gas

Oil supply is expected to peak around 2030—2035 (Laherrère et al., 2022; Delannoy et al., 2021a), when it will reach a plateau and then decline. The historical evolution of oil supply would then have followed a bell-shaped curve. Following this peak, gas supply is also anticipated to peak around 2040 (Delannoy et al., 2021b; GGR, 2024). This is discussed in more details in chapter 2.

[3] See https://www.wri.org/insights/4-charts-explain-greenhouse-gas-emissions-countries-and-sectors

[4] Updated data were found at https://www.eea.europa.eu/en/analysis/indicators/global-and-european-temperatures/global-and-european-annual-average.

While this can be viewed positively in terms of climate change, oil and gas currently represent 53% of the energy mix. Moreover, oil is crucial for transport thus for supply chains and thus on the global economy, and its substitution remains difficult, as discussed in more details in chapter 5. These anticipated supply peaks therefore threaten the global economy.

Third issue: metabolic concerns

The energy return on investment (EROI) of an energy production system is defined as the ratio of total gross energy produced to the amount of energy invested in the process. Due to the high EROI values of coal, oil and gas, investments in the energy production sectors represented only a small proportion (Delannoy et al., 2021a,b) of global activities. However, the EROI of oil and gas is expected to decrease significantly in the coming years due to their decreasing accessibility and lesser quality (especially for oil). This has two main effects.

Firstly, additional energy investments will be required in energy production sectors, thereby increasing energy demand. Secondly, from a metabolic point of view, the decline may affect society through the size of its economy and its level of complexity Tainter (1988); Hall et al. (2009); Brandt (2017); Fizaine and Court (2016).

The EROI of wind and PV is uncertain, however Aramendia et al. (2024) state that it is likely to be higher than that of oil and gas. Nevertheless, this could be at least partially offset by investments in electrical storage and electric grid balancing required for high levels of renewable energy penetration in the electricity mix. Furthermore, the temporary energy investments required for constructing wind and PV infrastructures could temporarily reduce the global EROI of the energy production system (Capellán-Pérez et al., 2019; Slameršak et al., 2022).

Geographic disparities

There are also significant geopolitical stakes regarding energy supply. The United States, Russia and the Middle East concentrate an important proportion of the oil and gas production. Europe, for example, only produced about 5% of oil and gas in 2024, despite consuming 10—15% of the global production (Energy Institute, 2025). More importantly, China, despite consuming 27% of the global energy supply, only produced respectively 4% (a quarter of its consumption) of the oil and 6% (half of its consumption) of the gas global production in 2024. This partially explains why China has chosen to rely on coal rather than on oil and gas for activities wherever possible: coal represented 58% of its energy mix in 2024, compared to 28% globally. In fact, China produced half (52%) and consumed 56% of the global coal supply in 2024. Interestingly, this Chinese reliance on oil imports also partially explains why China has invested in the development of electric vehicles (EVs) since before 2010[5].

In a context in which the global supply of oil and gas is likely to come under tension in the future, geographic disparities in production will play an increasingly important role in geopolitics.

[5]There were at least two other main reasons for this investment. Firstly, China aimed to become a leader in the EV market at a time when the Chinese thermal automobile industry was lagging behind Western countries. Secondly, air pollution was an issue in big cities.

Possible pathways regarding these issues

When faced with these issues, a few responses are often invoked. Firstly, it is possible to reduce the energy consumption, however this would entail economic degrowth. Secondly, some argue that efficiency gains would induce a reduction of energy consumption without reducing GDP, but they ignore rebound effects and historical evidence. Thirdly, the energy transition is expected to reduce fossil fuel consumption without reducing the total energy supply, but the desired extent of the process suffers from many barriers.

These three points are addressed in the following subsections.

The difficult choice of Degrowth

Decreasing the supply of fossil fuels would be an easy and efficient way to address climate change, as well as to avoid future tensions between declining supply and increasing demand.

Millward-Hopkins et al. (2020) computed the minimum final energy required in order to provide "decent material conditions and basic services for all", estimated to be around 15—20 GJ/yr/cap. This would result in a final energy consumption of 160 EJ for a population of 8 billion people, which is nearly three times lower than the current final energy consumption at a time at which billions of people worldwide currently still lack access to basic material necessities.

However, there is no historical example of a country that has met social well-being indicators as well as ecological ones at the same time (Fanning et al., 2022). Ranjan and Kanitkar (2025) indeed indicates that about 70 GJ/cap/yr of energy consumption was historically needed in order for individuals to reach sufficient levels of life expectancy, schooling, access to freshwater and unpolluted air. Finally, Tamberg et al. (2024) indicates that a level of income of around 10 000 $/cap/yr would be a sufficient level of income in order to ensure high levels of need satisfaction. While all of these energy and income levels are lower than the current global average, it should be noted that these rely on historical examples and do not necessarily reflect future degrowth pathways. Indeed, reorganizing societal activities to focus on global well-being and reducing inequality while decreasing energy consumption may allow the emergence of societies with lower energy consumption levels than for industrialized societies in the 21st century.

Nevertheless, due to the GDP/energy coupling (Haberl et al., 2020), a reduction in energy consumption would result in a decrease in GDP. While degrowth and post-growth futures are increasingly being studied in the scientific literature, as described in Kallis et al. (2025), they are ignored in political institutions and parties[6].

Energy efficiency: chasing phantoms

Gains in energy efficiency consist in reducing the energy consumption of an activity while maintaining the same output. They are sometimes viewed as an important solution for reducing CO2 emissions (IEA, 2024d; BP, 2024). However, this ignores rebound effects. Indeed, Brockway et al. (2021) state that energy efficiency gains are always partially or completely offset by economy-wide rebound effects, whereby the energy saved in one process is reinvested elsewhere through various mechanisms. In fact, the robustness of the GDP/energy coupling

[6] This neglect can be explained by several factors. Among these, I think of: States policies aiming to concentrate the maximum power which results in the pursuit of GDP growth, institutional lock-ins (particularly ideological and regulatory), and social tensions due to the struggle of the capitalist class to maximize their wealth while poorer people struggle to achieve and maintain a decent living standard. The barriers should however be studied more carefully.

suggests that efficiency gains have always been offset on a global, economy-wide, scale.

Consequently, relying on energy efficiency to reduce energy consumption while pursuing pro-growth policies is illusory, particularly given the immense reduction in CO2 emissions required in order to contain climate change.

The energy transition and its limits

The energy transition is the most widely discussed solution to climate change. Low carbon energy sources, primarily wind turbines and photovoltaic panels (PV), are expected to replace fossil fuels so that energy system can maintain steady energy supply levels while reducing CO_2 emissions. Indeed, wind and PV energy production are being deployed quickly, with PV production increasing exponentially. These energy sources are currently cheaper than fossil fuels (IRENA, 2025; NEA and IEA, 2020).

However, wind and PV energy production currently only represent 3—4% of the primary energy supply (Energy Institute, 2025). Several barriers to their large-scale deployment are expected. For example, the high capital costs of projects, social opposition, and grid connection currently hinder wind deployment. The electrical network also needs to expand in order to connect these distributed energy sources. Moreover, in the long term, the intermittency of wind and PV will require the deployment of storage and balancing systems, which add non-linear costs to the electricity when a certain threshold is reached (around 30—40% of wind and PV grid penetration). Additionally, fossil fuel production infrastructures as well as consumer infrastructures must be phased out, which induces economic costs and faces technical barriers.

However, these barriers can be overcome to some extent through, for example, taxes on fossil fuels combined with subsidies towards low-carbon energy sources and electric consumption equipment. However, taxing fossil fuels requires significant political will as this would impair the economy due to taxes transmitting to overall prices.

Business-as-usual (BAU) scenarios, or the default option

Opting for voluntary degrowth or accelerating the energy transition while phasing out fossil fuels requires strong political will and long-term commitment. It is possible that neither of these options will be chosen. This is referred to as the "business as usual" scenario.

In this scenario, industrialized societies will continue to seek maximum energy consumption and will face oil and gas supply peaks with no anticipation, leading to destabilization and tensions within and between countries. Furthermore, they will also then face the long-lasting disastrous effects of climate change.

Research questions

To this point, decreasing the energy consumption of our societies is physically possible. However, it is highly probable that societies will tend to follow business as usual (BAU) scenarios rather than degrowth/post-growth, or energy transition ones, as explained earlier. Due to the anticipated oil and gas supply peaks and barriers to the energy transition (discussed in previous sections), the energy supply may be limited. This thesis is therefore dedicated to answering the following question:

Leading research question: **Will the energy supply be able to meet the energy demand of a business-as-usual (BAU) scenario by 2050?**

A negative answer to this question will indicate that BAU scenarios — which represent the most probable future trends — will lead to disruptions, rendering BAU impossible thereafter.

To address this leading research question, it is useful to expand it into a number of subtopics and related questions.

The energy system and the barriers to the energy transition

The pace at which an energy transition may occur is quite uncertain. Indeed, much is expected of such a transition (see IEA 2024d; BP 2024 for example) while many barriers ignored. While many of these barriers are identified in the literature, few estimations have been made, and they remain uncertain. Chapter 1 studies the expected barriers to the energy transition and their significance. This will provide information on the pace of the energy transition in a BAU growth scenario, and on what would be required to overcome these barriers — either partially or completely. This will therefore constrain possible futures regarding the substitution of fossil fuels by low-carbon energy sources.

Research question 1: What are the biophysical barriers to the energy transition ? How do these barriers limit the maximum pace of the energy transition?

Gross energy supply VS demand up to 2050. Will post-2035 oil and gas declines be eased by the energy transition?

While oil and gas supply peaks are identified, their projected supply projections are somewhat uncertain. This is also the case for coal. As these three energy sources currently represent 80% of the energy mix, it is important to discuss their possible supply projections as well as the uncertainties surrounding them. Using the insights from Chapter 1 to produce scenarios on the deployment of wind and photovoltaic panels (PV) as well as projections of the other energy sources, this leads to analyze the conditions under which the gross energy supply could meet the global energy demand of a BAU scenario. Chapter 2 is thus dedicated to the following question:

Research question 2: What is the likely gross energy supply in a BAU scenario ? What are the conditions required for the gross energy supply to meet a BAU total energy demand?

Escalating energy investments in the oil and gas supply chains call for choosing a rapid oil phase out over a race for fueling oil supply

The EROIs of oil and gas are also already declining. This implies that the remaining energy yielded from oil and gas extraction after self-consumption declines sooner and faster than their gross supply. This is studied in chapter 3, which disaggregates energy investment in the oil and gas supply chains by energy sources, extending classical analyses to auxiliary boundary and the

point of use.

Research question 3: How will net oil and gas energy supplies decline up to 2050? How will the required oil, gas and other energy investments in their supply chains increase? How will this translate into EROI values?

Peak oil vs energy transition: which will win the race?

The previous step however neglects the barriers to the deployment of energy consumption technologies. In particular, oil consumption technologies are difficult to substitute, due to techno-economic challenges (see section 1.4.4). Moreover, the peak in oil supply is the earliest of all fossil fuels, around 2030—2035. Oil is therefore critical when assessing the possibility of meeting a BAU energy demand. The remainder of the thesis therefore focuses on whether the oil supply will be able to meet a BAU oil demand.

Research question 4: Will oil supply be able to match the oil demand of a BAU scenario up to 2050? What are the required conditions for this to occur?

Indeed, oil demand is expected to increase in some sectors. In addition to oil investments in the oil and gas supply chains, vehicle ownership is expected to rise in China and India resulting in increased energy demand for road transport, of which 90% is currently met by oil. Anticipated rises in demand for petrochemicals, aviation and shipping are also expected to increase oil demand. On the other side, the deployment of electric vehicles (EVs) will displace some of this oil demand, but their deployment remains highly uncertain. This issue is studied in Chapter 4, with a focus on modeling the evolution of the vehicle fleets over time across countries, allowing the comparison of a BAU oil demand with supply in a BAU scenario in Chapter 5.

Research question 4.1: What would the oil demand be in a BAU scenario ? Particularly, what would the evolution of the energy demand for road transport be in a BAU scenario?

Modeling the affordability barrier to the adoption of electric vehicles among worldwide households

The main uncertainties of this model are concentrated in the deployment of EVs. Indeed, the purchasing prices of electric cars are still higher than for conventional petrol or diesel ones. This is a major barrier to their widespread deployment and raises the question of whether households would invest in an EV (new or second-hand) given this purchasing price overcost.

Research question 5: How would households in different income categories behave with regard to purchasing electric private vehicles, considering the purchasing price overcosts? How would these behaviors influence the global deployment of private electric vehicles?

Chapter 6 first develops modeling tools that allow the distribution of the current vehicle

fleet in countries to be computed as a function of buyer's income. Chapter 7 then models the distribution of new and secondhand private vehicles as a function of households income, and paves the way towards a model of EV diffusion under their affordability barrier.

Chapters 2, 3, 4, 5, 6 are articles that are or will be submitted to journals.

Contributions to articles

This thesis has been mostly supervised by Pierre-Yves Longaretti. The analyses performed in the articles of this thesis have been carried out jointly with Pierre-Yves.

In particular, he estimated fossil fuels supplies of Chapter 2, formalized the initial models of Chapter 3, the main mathematics of Chapter 6 and assisted in formalizing the model of Chapter 7. I developed most of the remainder, I implemented and computed all the data, the models and the results of this thesis.

CHAPTER 1 | THE ENERGY SYSTEM AND THE BARRIERS TO THE ENERGY TRANSITION

1.1. INTRODUCTION

The energy transition is envisioned as a path towards the reduction of CO_2 emissions without reducing the energy supply on which industrialized societies rely. Still, fossil fuels represented 81% of the energy mix in 2024 while wind and PV accounted for only 3—4% (Energy Institute, 2025). A common characteristics of net-zero emissions scenario is their significant level of penetration of renewable energies in the energy mix by 2050, at which point they would produce more energy than fossil fuels.

However, with only 25 years until 2050, assuming a complete transformation of the energy system within this timeframe seems radical, particularly when considering historical evidence of the evolution of the energy system. Some articles have already highlighted barriers to the energy transition.

This chapter therefore discusses these barriers. This is primarily studied in the context of a business as usual (BAU) scenario, though the barriers should also be studied in cases where there is strong political and economic commitment to the energy transition.

This chapter first presents fundamentals of the current energy system in section 1.2, section 1.3 discusses the expected future of energy production technologies, section 1.4 reviews the anticipated barriers to the energy transition and section 1.6 concludes this first chapter.

In this manuscript, the term "energy transition" will refer to the set of processes involved in transforming the current energy system into an energy system in which non-fossil energies represent more than 90% of the energy supply. This set of processes will reflect major structural changes in supply and demand. The time horizon taken in this manuscript is generally 2050. Due to the expected global systemic risks and forthcoming energy issues, models would be too uncertain beyond this limit. The 90% objective reflects an ambitious energy transition scenario, which still allows the use of fossil fuels in applications for which substitution by other energy sources is the most difficult.

Indeed, while definitions of the "energy transition" can be vague, people are generally interested in phasing out fossil fuels, primarily for climate change purposes, but also sometimes to

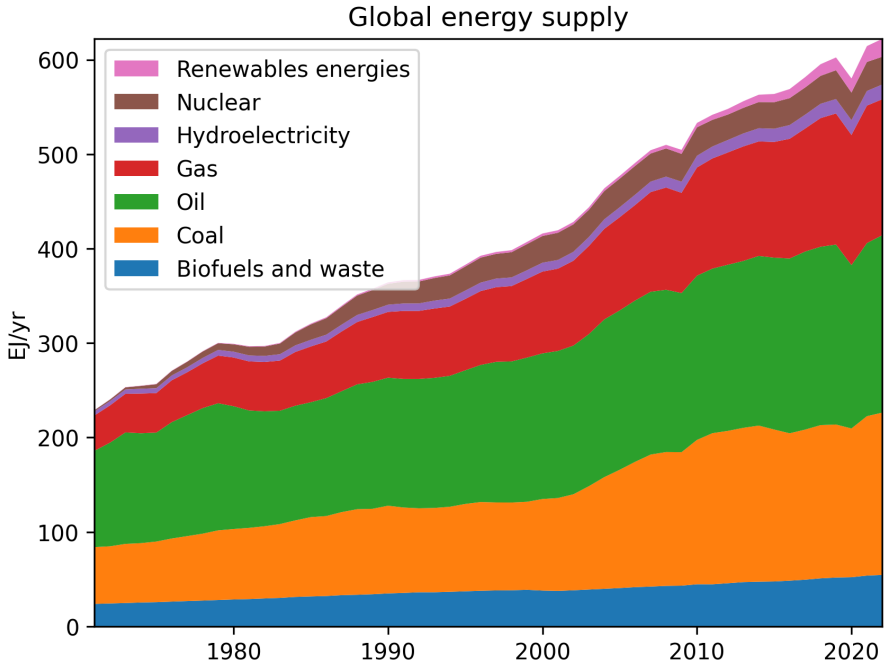


FIGURE 1.1: Global primary energy supply, disaggregated by energy source, since 1971. Data come from the IEA's World Energy Balances (IEA, 2024b).

anticipate supply limits.

As wind and photovoltaic solar (PV) power only represented 3—4% combined in 2024 (Energy Institute, 2025), no major substitution or structural change is currently occurring. Moreover, no energy transition — here simply defined as a major shift in the energy system — has ever occurred. Historically, energy sources have always been added to one another, but never substituted in absolute terms, although this is not true in relative terms. Therefore, nothing proves *a priori* that an energy transition is possible.

In this first chapter, I am thus interested in exploring whether an energy transition would be possible and, if so, under what conditions. Firstly, I will study each energy production technology and its potential role in an energy transition. Secondly, I will study the barriers than can be anticipated to an energy transition. Finally, I will also discuss several aspects regarding energy dynamics.

1.2. THE CURRENT ENERGY SYSTEM

It is important to lay some basics regarding the current global energy mix. The current energy supply is shown in Figure 1.1. Biofuel and wastes, Fissile nuclear and hydroelectricity account for 9%, 5% and 2.5% of energy production, respectively.

This production continues to grow. The average annual growth rate of energy production was +1.8% per year between 2000 and 2020.

The electricity vector captures 30% of primary energy production in 2022.

However, there are a few points to note regarding energy accounting.

Firstly, this is primary energy. The "primary" energy of an energy source corresponds to

the energy available before any transformation. This is, for example, the energy contained in a barrel of oil. Conversely, the energy accounted for in the desired physical process is called "useful" energy. This is, for example, the energy used to move a car. Thus, since the efficiency of a car's combustion engine is around 30%, this means (ignoring other losses in the transmission chain) that the useful energy required is three times lower than the required primary energy of oil. On the other hand, in the case of electric cars, the efficiency is around 95%. If the energy is produced by a renewable energy source, the conversion results in few losses, so the useful energy output of the electric car will be very close ($\approx$85%) to the initial primary energy. While accounting for primary energy is useful because it provides an idea of the quantities initially extracted, this accounting becomes limited when considering the substitution of fossil fuels with renewables. Indeed, the amount of primary energy from a renewable source used to power an electric car could replace a larger amount of primary fossil energy used to power a combustion engine car for the same purpose. Data provided by various institutions often quantify primary energy, and this is particularly the case with the data of the International Energy Agency (IEA) World Energy Balances database, used routinely in this thesis. Quantifying useful energy would require a bottom-up approach, as the total amount of useful energy would then depend on uses rather than sources, a much more complex task. In the research work presented in this manuscript, the energy will be quantified as primary energy, using data from the IEA's World Energy Balances.

Finally, it is important to note that the energy accounted for here is only the energy of the energy system. This therefore excludes all solar energy that is not captured by energy technologies, which is however central to life on Earth through the maintenance of biogeochemical cycles and the production of heat. This excludes, for example, solar energy that heats buildings or the energy contained in food. Moreover, wind and hydraulic energy are forms of energy that are indirectly derived from solar energy[1]. The solar energy reaching the Earth each year is approximately 6,000 times greater (4 million exajoules) than the energy system's production.

One might now ask how all this energy production is consumed. Figure 1.2 displays the total energy consumption over time and its disaggregation by sector.

In 2022, approximately 100 EJ were consumed in transport, 200 EJ were consumed in the industry either as energy products or consumed as non energy products (feedstocks), and an another 100 EJ in private, commercial or public buildings ("Residential, Commercial/public services"). The "Transformations" sector represents the losses occurring during the conversion of an energy source into another energy product, typically when gas or coal is burnt in a thermal plant to generate electricity; and it also includes the losses occurring during the transport and distribution of energy products.

The energy consumption is currently still increasing in every sector (see Fig. 1.2).

1.3. Energy production technologies overview

This section presents and discusses salient points regarding the future of each main energy production technology. Numbers used generally come from the IEA's World Energy Balances (IEA, 2024b). Note that some of these data can be viewed freely on the IEA's "Energy Statistics

[1] If wind and the water cycle are generated by the interaction of solar energy with the Earth's environment, it could also be argued that fossil fuels are indirectly derived from solar energy. Indeed, they come in part from the transformation of living organisms, whose lives were largely fuelled by solar energy and the transformations that result from it. Nevertheless, the geological action that enabled their transformation is fuelled less by the sun than by the planet's internal geological activity.

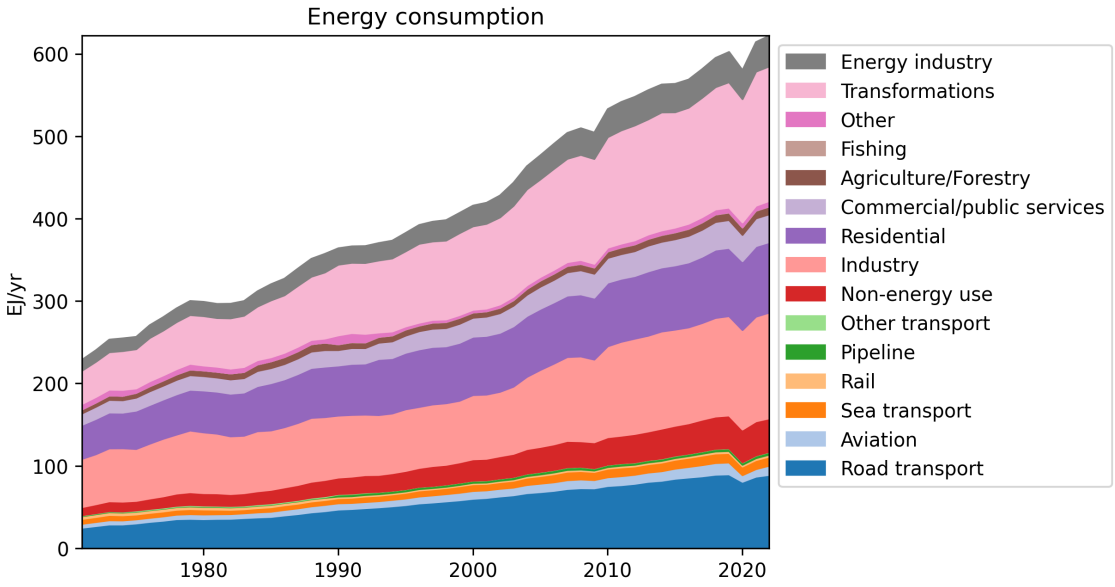


FIGURE 1.2: Global energy consumption, disaggregated by sector. The evolution of the cumulative consumption is logically the same as this of the supply of Fig. 1.1. Data come from (IEA, 2024b).

Data Browser" webpage[2]

1.3.1. OIL, GAS AND COAL

First, let me discuss the fossil energies, which have historically formed the backbone of industrialised societies.

Oil is currently crucial for transport. Its liquid form at normal temperatures is really convenient. 99% of aviation and maritime transport are fueled by oil. In 2022, road transport was fueled by oil at 93%. Conversely, Figure 1.3 shows that transport represented at least 56% of oil uses (IEA, 2024b) in terms of energy. It should be noted that oil is also used in petrochemicals or as a feedstock, accounting for 16% of oil usage in 2022. However, oil supply is expected to peak around 2035 (Laherrère et al., 2022; Delannoy et al., 2021a; Rabas, 2024), mostly due to the depletion of giant old oil fields. Moreover, the energy return on investment of oil (EROI, presented in section 1.5) is already decreasing (Delannoy et al., 2021a; Brockway et al., 2019; Aramendia et al., 2024; Feng et al., 2018a; Slameršak et al., 2022) meaning that extraction will require a greater amount of energy investment.

A shortage in oil supply may therefore occur quite soon, which would affect transport and, consequently, supply chains and the economy. Due to the significance and plausibility of this risk, it is studied in more detail in the chapters of this thesis.

Gas is mostly used for heating and in thermal power plants to generate electricity. Its gaseous form allows it to be easily transported via pipelines and it is easy to ignite. The good efficiency of its combustion in power plants also makes it economically interesting. Figure 1.4 shows gas consumption by sector. In 2022, 28% was consumed in the generation of electricity, with a further 10% being used in power plant for co-generation of electricity and heat. Note that the consumption in the "Residential" and "Commercial/public services" sectors is assumed to be primarily for heating purposes. Similarly, it can be assumed that a great share of gas uses in the

[2] Accessible at `https://www.iea.org/data-and-statistics/data-tools/energy-statistics-data-browser`. Last accessed at 2025/10/02.

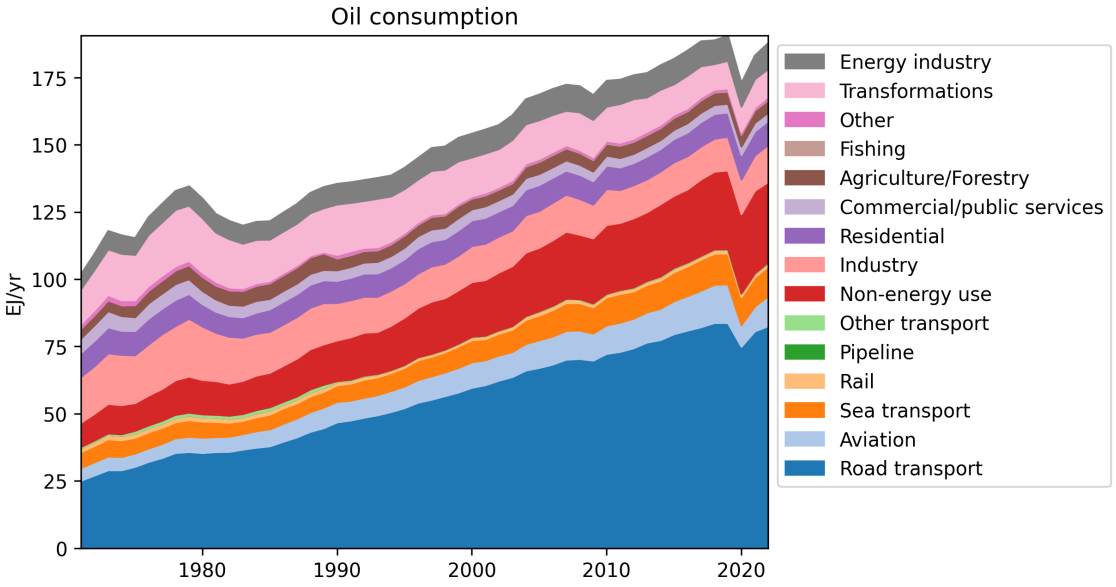


FIGURE 1.3: Disaggregation of the oil consumption by sector, following the IEA World Energy Balances (IEA, 2024b)

"industry" is due to heating in industrial processes. Finally, the non-energy uses of gas (as a feedstock) do not represent a large share of its final use, although they are crucial in the production of fertilisers.

A peak in gas supply is also anticipated around 2040 (Delannoy et al., 2021b) and the EROI of gas is also already decreasing, albeit to a lesser extent than for oil. Gas supply will be discussed in chapter 2.

Finally, coal consumption by sector is displayed in Figure 1.5. It is mostly used in thermal power plants to generate electricity (accounting for around 60% of coal consumption), but also in some industrial processes requiring energy and carbon inputs, such as steel and clinker (used in concrete) production. Coal is relatively inexpensive, but transporting it is costly.

Nowadays, coal production and consumption are mostly concentrated in China (IEA, 2024a). It is indeed a regional energy source, as the consumption regionally matches production. In 2022, China's coal consumption represented 55% of the global coal consumption. India was then the second consumer with only 11%. In terms of production, China represented again 53% of the production in 2022. China relies heavily on coal, which represented 60% of its energy mix, which is a uniquely high figure among countries. While western countries are phasing out coal, China is still increasing its coal power plant capacity[3].

The USA and Russia account for 40% of the reserves (Energy Institute, 2025), with China only being third with 14%. A Hubbert's fit performed on the historical coal production data with a well-chosen ultimate recoverable resources (URR) value discussed in chapter 2 indicates a peak in coal production around 2065.

As carbon emissions from fossil energies are their major issue compared to the other energy sources, it is useful to discuss the differences between the three fossil fuels. Dividing the CO_2 emissions of each source by their energy supply (from the data found in IEA 2024d), one finds that the average CO2 emission per unit of primary energy is 91 MtCO2/EJ for coal, 59 MtCO2/EJ for oil and 55 MtCO2/EJ for gas. As coal, oil and gas are not directly interchangeable, it is not possible to deduce from these figures the amount of CO2 that would be saved by

[3] See `https://globalenergymonitor.org/projects/global-coal-plant-tracker/dashboard/`

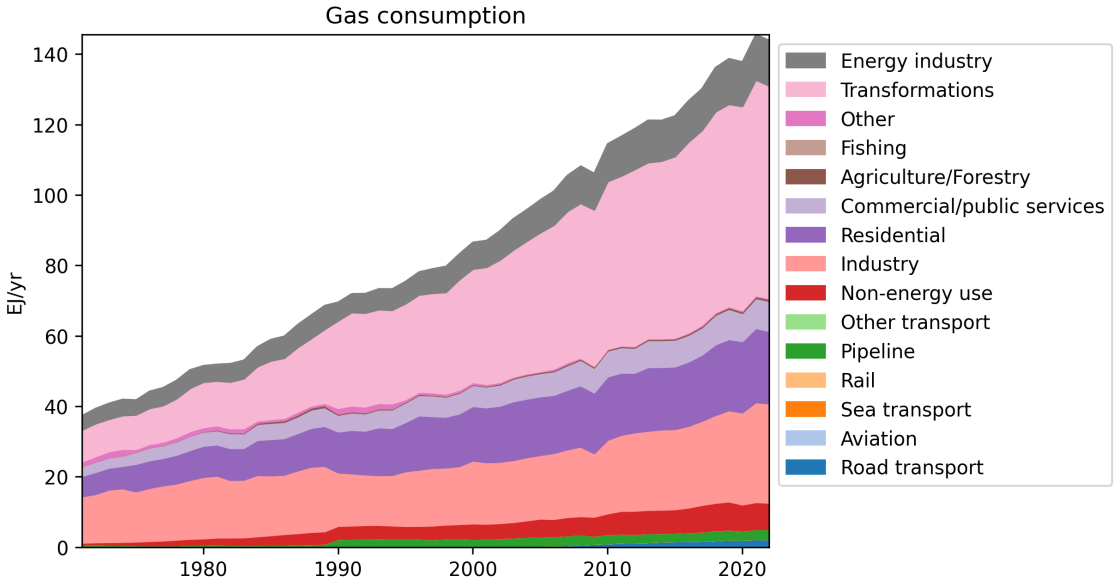


FIGURE 1.4: Disaggregation of the gas consumption by sector, following the IEA World Energy Balances (IEA, 2024b)

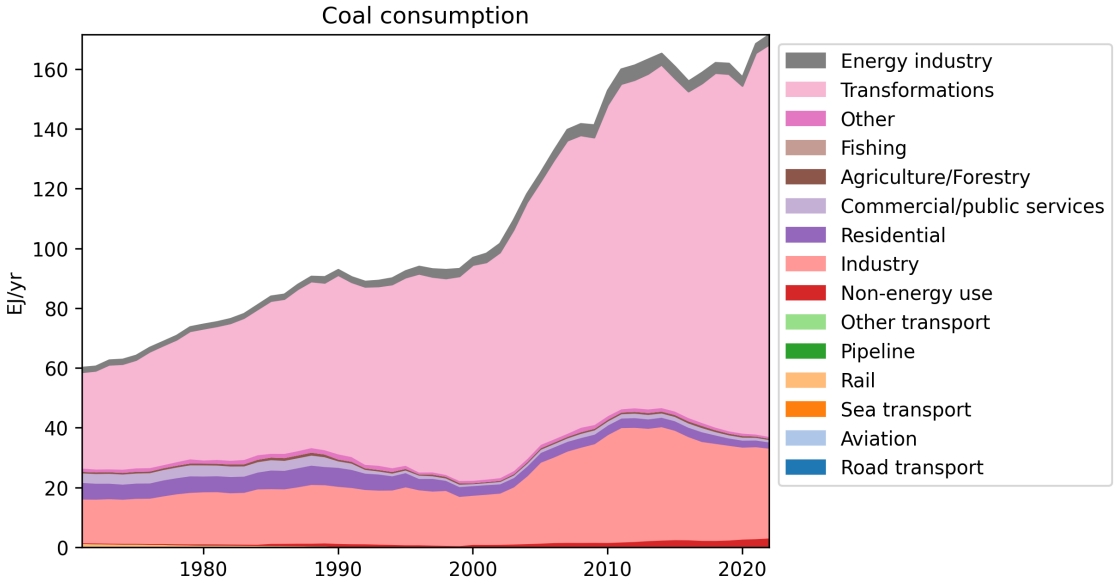


FIGURE 1.5: Disaggregation of the coal consumption by sector, following the IEA World Energy Balances (IEA, 2024b)

replacing one energy source by another. However, coal emits much more CO_2 than gas and oil. Indeed, all three energy sources are burned and used in machines with similar energy efficiency. Moreover, coal could be largely replaced by gas in the electricity production and some other processes. Replacing coal with gas would benefit the climate. Conversely, replacing gas by coal would be detrimental to CO_2 emissions, although the anticipated peak in oil and gas production suggests that this may actually be the case past 2040.

Pursuing growth in fossil extraction will in any case lead to exceeding the CO2 emissions limit set by the Paris Agreement (IPCC, 2023).

1.3.2. Nuclear Energy

1.3.2.1. Characteristics of nuclear projections

Nuclear fission energy production represented in 2022 5% of the global energy supply, a figure stable since 1990. Nuclear fission grossly consists in retrieving energy from the split of uranium-235 atoms. This process is used to create heat, which is in turn boils water (or other fluids) to create high-pressure steam that rotates a turbine to generate electricity[4]. This implies that nuclear power plants must be located next to water sources for cooling, like rivers or seas.

The nuclear industry is the most complex energy industry, requiring highly skilled workers and a close connection with heavy industries. It is also highly capital-intensive (IPCC, 2023). Indeed, the initial investments represent the larger share of the total costs of a projects (about 90% according to Weißbach et al. 2013). Moreover, nuclear plants have a lifetime of around 40—60 years, although some of them see their lifetimes extended by 20 years so that we can expect this trend to become more common. Their construction takes around 10 years (5—20 years, see for example Shykinov et al. 2016).

90% of nuclear power plant projects are therefore primarily State-led (IPCC, 2023). Indeed, the investments in nuclear projects are not only highly capital-intensive but also risky: States can decide to suspend or cancel projects, and costs overruns are common. Nuclear projects are political choices that can be controversial within society, so that governments may choose to cancel a previously approved commissioning. These risks make financial loans more expensive.

Moreover, nuclear projects imply industrial capacities for uranium enrichment, which are to be controlled and regulated by the United Nations. It should also be remembered that nuclear power programs were initially linked to nuclear weapon development precisely in relation to uranium enrichment.

Nuclear energy production is controversial in civil society. Concerns focus on the safety of plants, nuclear waste, and the link with military purposes. Firstly, nuclear fission energy production uses a chain reaction that amplifies by itself, bringing the risk of a catastrophe if the operators lose control on the reaction (which is not supposed to happen in any scenario). Secondly, there are concerns about the emission of radioactive particles in the environment (water, air and ground) near the plants. Thirdly, managing nuclear waste — often radioactive for hundreds of thousands of year — requires planning for decades and solutions that will last far beyond the century of plant lifetime. While these risks necessitate careful management, it is observed that fossil energies, particularly coal, pose greater health risks than nuclear energy[5] accoding to IPCC (2023).

[4] Nuclear power plant can also co-generate heat for processes at temperatures below 300°C. However, this currently represents a negligible amount of the total energy production.

[5] When quantities are divided by the total energy production

1.3.2.2. Projections on nuclear energy supply

Deployment of nuclear energy mostly occurred between 1970 and 2000 in the United States, Western Europe and Japan; and has stagnated since then. However, China has strongly developed its nuclear energy since 2010. Reports from the International Atomic Energy Agency (IAEA), IEA, the US Energy Information Administration (EIA), British Petroleum (BP) and the Organization of Petroleum Exporting Countries (OPEC) (IAEA, 2023; IEA, 2024d; US EIA, 2023; BP, 2024; OPEC, 2025) forecast growth in nuclear energy production of +25% to +195% between 2023 and 2050. IAEA's projections in its report "Energy, Electricity and Nuclear Power Estimates for the Period up to 2050" are the most optimistic, with growth ranging from +60% in the "low" scenario, to +195% in the "high" scenario. This growth is expected to be distributed among different regions of the world, with each region anticipated to experience growth. These projections are more optimistic than in other reports and than expected from the barriers mentioned in the next paragraphs. This is not much surprising given that IAEA has a direct interest in promoting nuclear energy. IEA's World Energy Outlook (WEO) assumes a +60% growth in nuclear energy production in 2050 compared to 2023 in its business-as-usual (BAU) scenario ("STEPS" scenario) and +120% in its "Announced Pledges Scenario" which reflects the climate commitments taken by the states, which may not necessarily be met). The 2023 International Energy Outlook (IEO) from EIA is less optimistic. Indeed, it forecasts a +24% global growth between 2022 and 2050 in the reference scenario, and only +54% in their "Low zero-carbon technology cost" scenario, which is less than the lower bound of IAEA's scenarios. In the scenarios from IEA and EIA, China is the main contributor to this growth. The projections from the "Current trajectory" of BP forecasts +50% and OPEC forecasts a +70% increase. Finally, most scenario projections from EPRI (2022) forecast a stable nuclear capacity value. Some of the aforementioned reports also provide normative scenarios, designed to achieve a specific objective (e.g. limiting global warming to +1.5°C). I did not quote these as they do not address the plausibility of the energy mix evolution, but rather provide the necessary energy mix to meet the objective.

It should be noted that nuclear energy production was 30EJ in 2023. Even an increase of +195% would result in nuclear energy production of 90 EJ only. While this is significant, this is still little compared to the 600 EJ of energy demand in 2022, anticipated to increase in BAU scenarios.

From IAEA (2023) IEA (2024d) and US EIA (2023) it can be deduced that the uncertainties surrounding nuclear energy mostly stem from its deployment in China. This country has 118GW of prospective capacity until 2030, which would double its nuclear energy production capacity (Bernardi and Huang, 2024). As China only accounts for 16% of the global nuclear energy production in 2024 (Energy Institute, 2025), this would only increase the global total nuclear energy production by +16% by 2030. The deployment after 2030 is unknown.

1.3.2.3. Barriers to the deployment of nuclear energy

However, some barriers to the deployment of nuclear energy are anticipated (Moriarty and Honnery, 2022; Moriarty, 2021). Firstly, Yu et al. (2020) highlights an economic barrier in China, limited by the growth in electricity demand. Indeed, Chinese coal power plants are rather young :70% of the annual energy production have been deployed in the last 20 years (IEA, 2024b) while the lifetime of coal power plants is historically around 60 years. Furthermore, China is still deploying coal power. Slow growth in electricity demand therefore results in a competition between coal and nuclear production, reducing both capacity factors and their economic profitability. In turn, this reduces the economic attractiveness of new energy projects.

Furthermore, the costs of nuclear power plants are assumed to be higher than those of coal power plants (NEA and IEA, 2020). This causes the economic optimisation algorithm performed by Yu et al. (2020) in the GCAM model to forecast only a +120—180% increase in Chinese nuclear power production.

Secondly, in the case of a significant growth in nuclear power production as in IAEA's scenarios, one could anticipate that the extraction and supply of uranium may not follow demand. Indeed, the current uranium's supply is lower than the demand and has been stable for 2 decades. Muellner et al. (2021) and IAEA itself (NEA and IAEA, 2024) state that there will be challenges in the uranium supply chain. The long-term availability of uranium resources (stock) is not a major concern as outlined by Monnet (2016). It should be noted that an increase in the price of uranium is not an immediate issue as its costs only represents a small proportion of the costs of nuclear projects.

Thirdly, nuclear projects require many dedicated specific and heavy industries. While the US and nuclear western Europe countries had these industries when they first developed their nuclear industries between 1970 and 2000, this is not necessarily the case today. This leads to difficulties in achieving projects on time and within budgets.

Fourthly, the aforementioned barriers discussed earlier are still valid for future projects, including the state's long-term implication, high capital and financial costs, social controversy, safety and waste issues.

Fifthly, the nuclear plants built between 1970 and 1990 are anticipated to reach their end-of-life in the next decades. Maintaining the same production of nuclear energy in these countries will then require the replacement of 20 EJ of nuclear power plants.

Finally, the anticipated decline in oil and gas supply will probably lead to economic shocks and downturns if unanticipated, and could lead to loss of power from the States. This could be a risk given that nuclear power plants are a century-lasting project and require investments, highly skilled workers and specific industries to operate effectively, avoiding failures and nuclear contamination. Furthermore, global warming will decrease the water levels of many rivers around the world in summer, when the need of plant cooling is highest, which directly affects nuclear power plants that are cooled by river water.

A few nuclear technologies may be invoqued as future ones, however they are confronted to their own limits. Small modular reactors (SMR) consist of nuclear power plants with a reduced power and size making them easier to install. However, SMRs lose the economies of scale that conventional nuclear plants benefit from. They are consequently expected to be even less profitable than conventional nuclear power plants (Ramana, 2021; Thomas and Ramana, 2022; Mignacca et al., 2020). IAEA assumes that SMRs will account for 6—24% of the additional nuclear energy between 2023 and 2050. Fast breeder reactors have also been studied for decades. These use uranium-238 (the dominant isotope of uranium in nature and even in the enriched uranium used in power plants) instead of the 235 isotope. Consequently, they can be fueled by uranium that has been used in nuclear power plants. This has two advantages: it uses uranium that would otherwise be considered as nuclear waste, and it runs on a fuel that is far more abundant than uranium-235. However, no commercial reactor has yet been built and operated, only experimental ones. Moreover, fast breeder reactors are not mentioned in any previous nuclear reports.

Let me end this section on nuclear energy by talking about nuclear fusion. This grossly consists in the combination of deuterium and tritium, producing energy. This process is appealing because deuterium and tritium may be widely available, and because the reaction does not produce nuclear waste. However, temperatures of millions of degrees have to be reached in a confined space for this reaction to occur. Creating the necessary conditions to produce energy

raises many technical issues, which scientists have been working on for decades. No commercial nuclear fusion reactor is therefore expected before the end of the century (Moriarty and Honnery, 2022; Ripani, 2024), if one will ever exist.

1.3.2.4. Conclusion on nuclear energy

To conclude, nuclear fission energy production is likely to increase at the 2050 horizon but it is subject to several limitations and still raises societal issues. In any case, it will not represent an energy source at the scale of current energy fossil sources.

1.3.3. Hydroelectricity

Hydroelectricity is produced by using the energy of water to rotate a turbine, primarily through a controlled flow in dams, but also in run-of-river systems. In hydroelectric dams, the output flow can be controlled, leading to production control. Pumped-storage systems also allow electric overproduction to be converted into gravitational potential energy. This enables long-term — seasonal — storage. This is currently the only widespread electricity storage technology.

Construction mostly consists in building massive concrete structures and flooding vast areas. This leads to lots of social — mostly due to the land requirements, and in some cases to dam failures — and environmental impacts — due to induced changes in ecosystems, and CO2 emissions due to the decomposition of drown organic material as outlined by IPCC (2023) (of which section 6.6.2 provides valuable information on each energy technology). Hydroelectric energy is still cheaper than fossil energies and far less carbon-intensive.

The hydroelectric energy production in 2022 was 16 EJ. The economically viable energy potential is assumed to be between 29—54EJ/yr (IPCC, 2023). Most of the remaining potential is in non-OECD countries. In line with this limited potential, IEA (2024d) forecasts a growth between 23 and 28 EJ/yr in 2050 among their different scenarios.

Hydroelectricity may also raise tension in some regions. Indeed, the construction of a dam on a river allows control of its flow, which can give upstream countries a geopolitical instrument of power when a river crosses other countries. Tensions arise due to water supply issues, which are amplified by future water issues resulting from climate change.

1.3.4. Bio-energies

The production of bio-energies reaches 54EJ in 2022, as depicted in figure 1.6, which also shows that solid biofuels dominate bioenergy production (46 EJ over 54EJ), while liquid biofuels (mostly biodiesel and biogasoline) only produced 4EJ in 2022.

The main issue regarding biofuels is their pressure on land-use. Indeed, land used to grow energy crops or trees competes with forests, meadows and agricultural lands, which is a major issue and barrier to their deployment (IPCC, 2023; de Castro et al., 2014; Searchinger et al., 2017; Moriarty, 2022). They may also raise tensions regarding water and fertiliser use. Searchinger et al. (2017) and de Castro et al. (2014) also mention that the generation of energy by solar PV has a far higher surface energy density than biofuels. Moreover, from an energy perspective, biofuels have a quite low energy profitability (Papagianni et al., 2024; de Castro et al., 2014) (measured by the energy return on investment, discussed in section 1.5), and carbon emissions of biofuels are controversial Moriarty (2022).

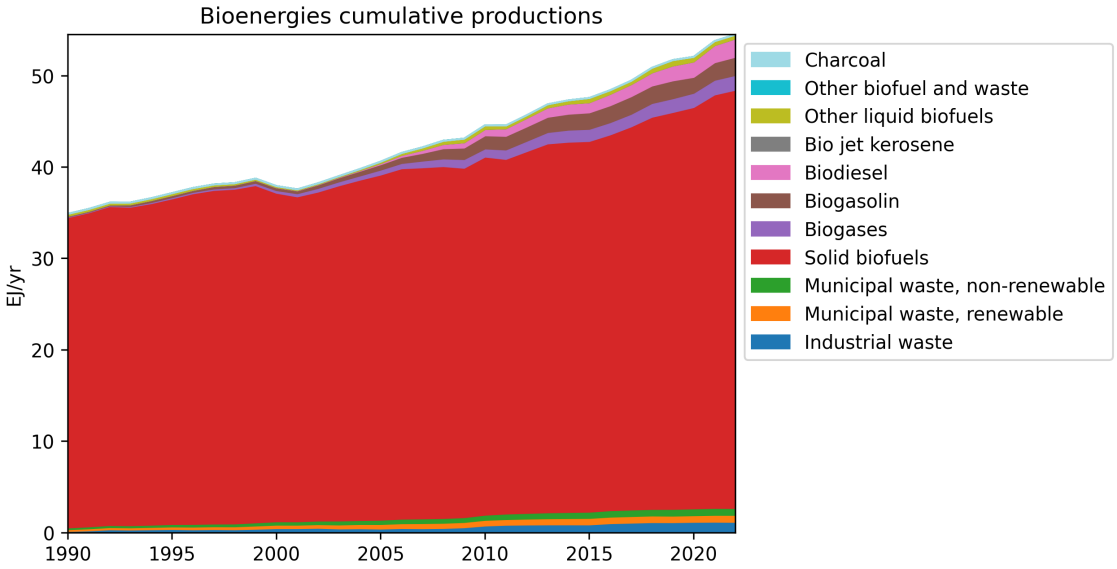


FIGURE 1.6: Evolution of the production of biofuels. Data come from IEA (2024b)

IEA (2024d) forecasts an increase of bioenergy production to 82EJ and 101 EJ in 2050 in the STEPS and APS scenario respectively. BP (2024) and OPEC (2025) only quantify the evolution of the modern use of biomass, which is expected to increase by +70% (from 31 EJ/yr to 52EJ/yr) and 25% (from 29 EJ/yr to 37 EJ/yr) respectively in the "current trajectory" from BP (2024) and the scenario from OPEC (2025).

1.3.5. WIND AND PV

Wind turbine and solar photovoltaic (PV) energy production technologies occupy a central place in the debates on the energy transition, as it is often assumed that they could be the main energy sources in a decarbonised world at the 2050 horizon (Moriarty and Honnery, 2020; IEA, 2024d). In 2024, their deployment were still growing fast, representing 9EJ of wind and 8EJ of PV production, which sums up to 3% of total energy supply. The main barriers to their deployment will be discussed in section 1.4. Wind power capacity is often disaggregated between onshore and offshore (in the seas) farms. It should be noted that onshore wind dominates wind energy production, with offshore wind capacity representing only 7% of total wind capacity in 2023 (IEA, 2024).

The installation of a wind farm mainly consists of building massive concrete foundations[6], raising a mast up to ≈200m at the top of which blades up to ≈ 80m will rotate an electrical generator, and laying electric cables to connect to the electric grid.

Installing solar PV requires building photovoltaic cells, constructing the support on which they will be installed, and connecting to the electric grid. About 99% of the photovoltaic panels produced in 2024 were monocrystalline. Most of the PV potential is assumed to be in PV farms rather than on roofs, more costly (IPCC, 2023; Dupont et al., 2020).

[6]These can weight 2000 tons in the case of wind turbines with current power. `https://www.freeingenergy.com/math/wind-turbine-weight-pound-mwh-gwh-m148/` provides estimations based on elements of the literature.

1.3.5.1. Low costs of wind and PV

The main driver behind the deployment of wind and PV plants is currently their low cost. Indeed, the levelized costs of electricity (LCOE)[7] of onshore wind was 34 $/MWh, 43 $/MWh for PV (and 79$/MWh for offshore wind) according to IRENA (2025). The IRENA also indicates that this makes onshore wind 50% and PV 40% cheaper than the least-cost fossil fuel generation alternative. It should be noted that this computation relies on assumptions about the lifetime of the projects, which are in fact still uncertain. The lifetimes of wind and PV are generally supposed to be around 20—30 years, however these technologies are close to maturity and widely developed since less than 10 years. This makes real lifetime numbers impossible to assess. Nevertheless, these figures confirm that these renewable technologies are cheaper than fossil fuel-based electricity generation.

The evolution of the costs is also interesting. Indeed, the LCOE of these technologies has historically decreased following learning curves (looking like exponential decreases). This is the consequence of technological progress and economies of scales in the production and installation of PV cells and wind turbines. For example, the size of wind turbines has increased steadily. However, it has been observed that their LCOE have been stagnated since 2021. This suggests that these technologies are reaching maturity. For example, the rate at which wind turbine size increases is expected to slow down[8]. Consequently, one can now expect the costs of projects to be subject to two different factors. First, the evolution of the price of raw materials would drive the input costs of the projects, particularly for PV. Second, the evolution of the quality of the locations of these plants will be crucial. Indeed, one can expect that locations with the best weather conditions (wind or sun coverage) and easiest to exploit (either because it is easy for construction machines to access, because of regulatory perspectives or because of the easy connection to the existing electric grid) would have been exploited first. This suggests that the profitability of wind and PV plants could then decrease over time. While Dupont et al. (2018, 2020) quantified the evolution of the energy profitability of world regions, the quantification of the increases in costs due to the decrease in the location quality has not been modeled yet to my knowledge — which is not surprising given that it requires the modeling of multiple aspects, just aforementioned.

1.3.5.2. Barriers to the deployment of wind and PV

The energy and economic energy investments in wind and PV farms are concentrated in the construction phase of the project (capital investments) rather than in their operation (see for example Dupont et al. 2018, 2020). In other words, they are highly capital-intensive. Indeed, their operation only requires little maintenance over their lifetime. This is important for two reasons. First, this means that the financial costs represents a significant proportion of the costs of the project. Moreover, the profitability of the projects will depend on the discount-rates[9] used.

Wind and PV production cannot be piloted to meet demand. Their production relies solely on the weather. Consequently, significant penetration of wind and PV in electric grids would require either flexibility measures on demand, and/or by electric storage capacities. However, demand flexibility is currently very limited, and increasing electric storage capacity would imply

[7] LCOE is defined as the division between the integrated costs over the lifetime by the integrated earnings over the lifetime and the total energy generated. This is the common metric used for comparing electricity generation costs.

[8] As the wind blades bend when rotating, increasing their size requires adapting the wind turbine to avoid the blades hitting the mast. This can be seen as a threshold effect.

[9] When project owners calculate the profitability of a project, they use a coefficient to account for the fact that delayed profits are considered less valuable than present ones, called discount rate.

significant additional economic costs. The issues raised by the deployment of wind and PV on electric grids are discussed in section 1.4.3.

Finally, there are obviously social and environmental considerations. The life-cycle CO2 emissions of PV are controversial and can be quite high (although still lower than those of fossil fuel generation), since a large part of the supply chain is located in China, where the energy mix is based on coal (see section 1.3.1). This is less the case for wind energy. PV has also a high land requirement (conversely, its power density in kW/m^2 is quite low) which can create tensions surrounding projects due to the competition with other land uses, mainly agriculture and forestry. Agrivoltaics, which involves placing PV panels above crops, could solve this issue. However, this only works with shade-tolerant crops and limited covering factors, and the need for tractors to circulate under the panels in intensive agriculture raises constraints on the structure and may make it impossible or unprofitable. In any case, agrivoltaics is still not widely developed. Finally, wind projects alter the landscape and are often opposed by communities, that are rarely consulted during the elaboration of the projects.

1.3.5.3. Conclusion on wind and PV energy

In conclusion, wind and PV farms are seen as crucial energy sources for the energy transition, however their deployment faces multiple barriers, making it quite uncertain. This will be studied in section 1.4.

1.3.6. Other minor energy sources

There are some other energy production technologies, but they have a limited interest or potential compared to the previous ones.

Concentrated solar power (CSP) consists of installing hundreds of square meters of mirrors that concentrate the sun onto a receiver, which heats water to rotate a turbine. Unlike PV, CSP requires constant power from the sun, making it mostly suitable for desert regions where connection to electric grids would be highly expensive (Moriarty and Honnery, 2020). Dupont et al. (2020) found that the potential for this technology was low, and that PV would be more profitable in most locations.

Geothermal energy consists of exploiting the heat from the crust to generate electricity[10]. Its potential has been considered low (Moriarty and Honnery, 2020), less than 20 EJ/yr, and localized to a few regions of the world. However recent technologies are foreseen to extend this potential according to IEA (2024). Nevertheless, this technology is still experimental, and the potential is only estimated to extend to approximately 20 EJ/yr worldwide by 2050.

Some marine renewable energies exist such as wave power, tidal power and ocean thermal energy conversion (OTEC), but their potential is quite low (Samsó et al., 2023; Moriarty and Honnery, 2020).

Finally, it should be noted that solar energy is not accounted for in the energy mix when it is exploited without an "energy production technology", i.e. when directly heating buildings. This means that increasing the surface area of buildings exposed to the sun could reduce the energy demand in the summer. However, 1) the reduction in the energy demand is assumed to be low, 2) every construction choice incurs an energy cost during construction, which could result in an increase in energy demand when assessed over the entire life-cycle, 3) there may be some rebound effects (Brockway et al., 2021). Consequently, not accounting for direct solar

[10] Again, the heat creates steam which rotates an electric generator

energy in the energy mix has a negligible influence on this thesis.

1.3.7. Hydrogen storage

Di-hydrogen, often referred to as "hydrogen" for simplicity, is sometimes cited as an important technology for the energy transition. While this is not an energy production technology but an energy vector, it has a place in the debates on the future of energy systems.

Water electrolysis allows dihydrogen (H_2) to be produced from water using electricity, thus from wind or PV. The chemical reaction writes: $2H_2O(l) \rightarrow 2H_2(g) + O_2(g)$. The hydrogen produced in this way is called "green hydrogen". It can be stored for months and transported. Finally, fuel cells reverse this chemical reaction, generating electricity from hydrogen: $H_2(g) + O_2(g) \rightarrow 2H_2O(l)$. The hydrogen obtained in this way could then be useful for long-term electricity storage, as well as for some direct applications. Applications of hydrogen in energy use (in transport or electricity generation) always involve a fuel cell to convert hydrogen into electricity. However, the use of hydrogen for energy purposes may not be that relevant (Moriarty et al., 2022), due to reasons specified thereafter.

1.3.7.1. Barriers to the deployment of hydrogen

Firstly, hydrogen is currently not produced using electricity, and is not used for energy purposes. In 2022, 63% of the hydrogen was produced from natural gas (using the steam methane reforming method), 20% from coal (using the coal gasification process) and the remainder was obtained as a by-products (IEA, 2024d). Production by water electrolysis was negligible, as it is still in the experimental stage. Hydrogen produced from gas is referred to as grey hydrogen, and as black or brown H_2 from coal. 60% of the hydrogen is used in the industry: for the production of ammonia (which represent 60% of the uses of the industry, of which 90% is used for the production of fertilisers), methanol (30%) and in the production of direct reduced iron (10%). The remaining 40% of hydrogen is used in refining oil and gas products (IEA, 2024).

Secondly, the electricity-to-electricity conversion efficiency of the hydrogen chain is poor. The efficiency of the electrolysis is expected to be around 60% and that of the fuel cell around 50%. This yields an overall efficiency of 30%. The compression of hydrogen for its storage also consumes about 10% of its energy content (Elberry et al., 2021). Consequently, using hydrogen is not profitable in applications where electricity can also be a substitute.

Moreover, the use of hydrogen as a substitute for fossil fuels is not straightforward. In transport, section 1.4.4.2 states that using hydrogen in aviation is impossible and would be too expensive for maritime transport. In road transport, fuel cell vehicles are far more expensive than electric vehicles due to the fabrication costs of the fuel cells and tanks[11]. Hydrogen trucks may be interesting in some applications as electric trucks suffer from a moderate autonomy and higher purchasing costs than conventional oil trucks, but they may still be more expensive than oil ones. In nearly all other applications, such as in the industrial and residential sectors, substitution from fossil fuels to electricity is more relevant than substitution to hydrogen, as presented in section 1.4.4.

Thirdly, the storage and transport of hydrogen is subject to important costs. In the case in which the penetration of wind and PV in electric grids reaches a high level, storage solutions would be needed to match the permanent instant balance between electricity supply and demand, as presented in 1.4.3. One issue with electric storage is that electric batteries presently

[11] Due to the volatility and small size of dihydrogen molecules, the tank must be made of special materials such as platinum, which makes it expensive.

only allow day-to-day storage, and not inter-seasonal storage. Water storage in dams allows inter-seasonal storage, but its storage capacity is limited. In this context, hydrogen storage appears to be a promising solution, as it would enable inter-seasonal storage. However, this method of storage may be very costly. Indeed, tanks are expensive (see footnote 11), and underground storage is only considered feasible in specific locations.

This perspective on the limited potential of hydrogen is confirmed by IEA's projections which forecast no hydrogen production in the STEPS (business as usual) scenario in 2050, 2EJ in the announced pledge scenario and at maximum 5 EJ in the net-zero emissions scenario. In all three cases, this represents less than 3% of the energy production by wind and PV.

Natural hydrogen, which is essentially the extraction of hydrogen from underground sources, has attracted interest in recent years. However, IEA indicates that: "as of August 2024, there are no natural hydrogen wells that have demonstrated commercial feasibility" (IEA, 2024). This directly limits the importance of natural hydrogen extraction by 2050.

1.3.7.2. Conclusion on hydrogen

To conclude, the deployment of green hydrogen is not environmentally beneficial as long as the penetration of wind and PV in electric grids does not reach the threshold at which energy storage is needed. Indeed, due to the low efficiency of the hydrogen conversion chain, it is more relevant to substitute fossil fuels with wind and PV than to substitute fossil-based hydrogen production with green hydrogen production. The relevance of green hydrogen in the case the aforementioned threshold is reached is however unclear due to storage difficulties and low efficiency, as evidenced by IEA's low hydrogen projections in all of their scenarios.

1.4. Barriers to the energy transition

The previous section revealed that wind and PV technologies are crucial to the energy transition. However, their deployment is uncertain and would require significant modifications to the energy system. Consequently, several barriers to their deployment are anticipated.

This section identifies several barriers to the energy transition and discusses some of the literature. However, the aim of the section is not to provide an exhaustive list of barriers or of literature discussing them. Further work would be needed in order to implement these barriers into models up to 2050.

1.4.1. Energy potentials of wind and PV

First, the global potentials for wind and PV energy production have to be estimated.

Dupont et al. (2018) and Dupont et al. (2020) are fundamental in the estimation of these potentials. Firstly, these articles quantify the land surface that would be suitable for wind and PV production. Secondly, they model the weather (wind and sun coverage) in each location. Thirdly, they quantify the capacity factor of each technology in each location, based on technical coefficients and weather data. In the case of wind energy, they also quantify the maximum exploitable kinetic energy from wind. This enables the energy potentials of each region to be computed, along with the evolution of the energy return on investment (EROI) with the potential. The WILIAM model from the project LOCOMOTION adapted these models with

some modifications in the parameters (Papagianni et al., 2020).

Both Dupont et al. (2018, 2020) and Papagianni et al. (2020) found similar results. The wind energy potentials with EROI>5 is assumed to be around 900 EJ/yr for onshore and offshore wind while the PV energy potential with EROI>5 around 1400 EJ/yr for monocrystalline panels. Other solar technologies are ignored as they compete for the same surface area and as monocrystalline panels have quite systematically a better efficiency than other technologies. The absolute potentials without EROI considerations is slightly superior in both cases: 20% higher for wind and less than 5% higher for monocrystalline PV.

The results from Papagianni et al. (2020) also show that the combined wind and PV regional potentials are higher than the current primary energy production in these regions. This suggests that the wind and PV potentials are sufficient to power a 100% wind+PV energy mix. Additionally, it should be noted that the useful energy obtained from 1 EJ of wind or PV production is expected to be higher than from 1 EJ of fossil fuels primary energy (see Appendix "Energy substitution between wind/PV and fossil fuels" of Chapter 2).

However, the regional combined wind and PV energy potentials are often of the order of magnitude of the current primary energy production. This is important as this model does not consider other geographical barriers to wind and PV potentials. Consequently, some other regional barriers or constraints such as proximity to the electric grid may cut down these potentials. For example, this can be anticipated in China where remote areas would not be equipped with wind turbines and PV panels due to the cost of transport at the building stage and the cost of connecting them to the electric grid.

1.4.2. Maximum growth rates in the industrial deployment of wind and PV

Figure 1.7 shows the evolution of the energy production of wind turbines and PV panels. It should be reminded that onshore wind energy accounts for approximately 90% of all wind energy production, leaving only 10% to offshore wind (as mentioned in section 1.3.5).

This figure shows that wind and PV are still experimenting high year-to-year growth rates. The growth of PV is still exponential. Wind deployment trend seems to be between an exponential growth and a linear one. It is therefore rational to question how long such trends could be maintained in the future.

1.4.2.1. Logistic deployment of wind and PV

Indeed, it is relevant to expect an S-shaped deployment of wind an PV, that begins with an exponential-like growth, reaches an inflection point and then slows down before saturation. It has historically been observed that the deployment of some technologies may experience an S-shaped deployment over time, often modeled by a "logistic" function (Verhulst function) as described by Grübler (1990). This function writes:

$$f(t) = \frac{L}{1 + \exp\left(-k\left(t - t_0\right)\right)}, \tag{1.1}$$

with L being the saturation, k the steepness of the curve and t_0 the x-axis value of the inflection point.

In energy production technologies, this logistic trend has also been observed for example for hydroelectricity or nuclear deployment (Hansen et al., 2017). This S-shaped curve is indeed mostly observed in cases in which demand is not limited, as for the substitution of horses by

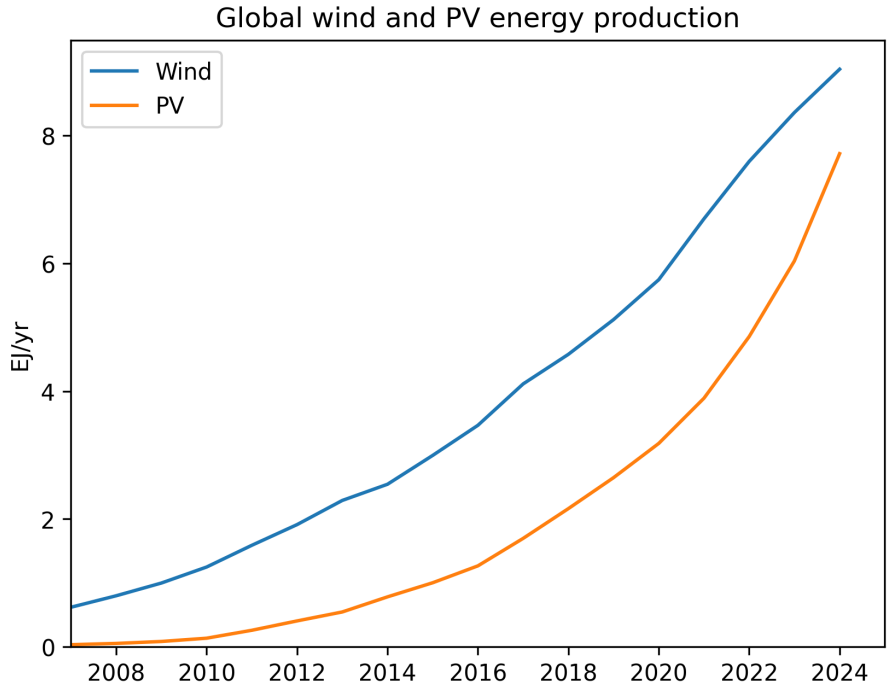


FIGURE 1.7: Historical evolution of the energy production from wind and PV. Data are from the Statistical Review of World Energy from the Energy Institute (Energy Institute, 2025).

car in the USA between 1900 and 1930, discussed in Grübler (1990) with the data from Nakicenovic (1986). It can be expected that wind and PV deployment would also experience this logistic shape Cherp et al. (2021). However, this is valid as long as their deployment are not limited by electricity demand, by competition with fossil fuels in the electricity mix or by other limits and barriers. Indeed, this logistic is mostly the result of industrial dynamics.

This is why the deployment of fossil energies has historically not been logistical. Indeed, industrial societies have been developed with the extraction of fossils fuels, which means that the consumption infrastructures (physical, social or institutional) has a crucial role in demand — thus in the development — of fossil energies.

Consequently, ignoring in a first instance the barriers to the deployment of wind and PV besides industrial ones, one could logically question when their deployment would reach an inflection point and the level at which they will saturate.

Nevertheless, before arguing about the possible growth of wind and PV, it is useful to make a summary on their current deployment.

The annual PV energy production growth is currently around 25% per year, and about 10% for wind. This means that PV energy production doubles every 3 years with this exponential growth. In the case of wind energy production, the deployment seems to be linear rather than exponential in the very last years. This suggests that the growth of the wind energy production is already dampened by some barriers, that still do not apply to PV production.

1.4.2.2. BARRIERS IN THE INDUSTRIAL DEPLOYMENT OF WIND AND PV

Indeed, some barriers currently seen in the industrial deployment of wind energy do not apply to PV energy. This is always linked to the difference in the scale of the wind and PV projects as well as the complexity of building the related infrastructures (GWEC, 2025; IRENA, 2025). It should be reminded that, as mentioned in section 1.3.5, wind turbines are heavier,

larger and more constraining infrastructures than PV. In turn, the modularity of PV makes it more adaptable to the constraints of a particular project. Firstly, land-surface constraints are stricter for wind farms that must be located where the wind does not interfere with upstream or downstream relief than for PV. Moreover, regulatory constraints often prevent wind farms to be located near cities. Secondly, wind projects lead times are often higher as they require more steps in the construction, particularly with the need of road access to the building site. Moreover, regulatory and permitting delays can be longer for wind than for PV projects. Thirdly, wind farms are often located in remote areas. This implies that connection to the electric grid is more difficult and more expensive than for PV. Fourthly, there is more social opposition to wind projects than to PV ones. Greig et al. (2025) actually report that costs and schedule overruns are lower in PV than in wind projects. Consequently, the latter are more risky and incur larger financial costs than the former. This is exacerbated for offshore wind projects compared to onshore ones.

IRENA (2025) reports that the levelised cost of electricity (LCOE) for onshore wind and PV projects are similar (respectively 34$/MWh compared to 43$/MWh), offshore wind is quite higher at 79$/MWh. However, the figure for wind may be underestimated by IRENA. Indeed, the capacity factor assumed does not match the average capacity factor deduced from Energy Institute (2025) and IEA (2024b). The average capacity factor deduced from the data of the Energy Institute is around 25% for all wind production, compared to IRENA's 34% and 42%. This implies that onshore wind LCOE is underestimated. The correction would make it comparable to (actually slightly higher than) PV. The cost is therefore not an argument in favor of wind in comparison to PV.

Continuing the discussion, Wilson et al. (2020) presents the advantage of the more "granular" technologies, which are defined as "[having] smaller and more variable unit sizes (MW/unit), lower unit investment costs in absolute terms ($/unit), and are more modular or divisible so are more likely to scale through replication". It is argued that the granularity has many advantages, and particularly that it facilitates diffusion speeds. This helps to explain the faster growth of PV compared to wind.

1.4.2.3. Maximum growth rates at the point of inflection

This leads to question the diffusion speed of wind and PV. Wind deployment experienced growth rates of 10—20%/yr between 2010 and 2020 while PV experienced 20—40%/yr growth rates between 2015 and 2024. It is possible to question whether these growth rates are only valid in an early stage of the deployment of these technologies. In this case, the growth rates would decline soon significantly. Nonetheless, it is also possible to consider that these technologies are not at all in an early stage. Indeed, their learning curves are stagnating since 2020 (IRENA, 2025), and their combined energy production reached 17 EJ in 2024. In this case, these high growth rates would be representative of the deployment caracteristics of these technologies, and would not decline very fast.

Nemet et al. (2023) provides insights on this question. The authors assume that the deployment of technologies follow a logistic function, and they report their growth rates. Particularly, they note that the median growth rate is around 6%/yr at the inflection point and the median logistical steepness coefficient around 0.13. It should be noted that the growth rate at the inflection point is half of the steepness of the curve[12]. Fitting logistic functions to the current deployment of wind and PV results in steepness values of 0.19 and 0.25 respectively. This means that the growth rates at the inflection point would be of 10%/yr and 13%/yr. This can be considered

[12] This is shown in an Appendix of Chapter 2

high as the highest historical value observed in energy production technologies was 12%/yr, and as the digitalisation technologies experienced 12%/yr. It is therefore likely that the deployment of wind and PV will slow down toward a slower logistic.

However, saturation values limit the duration over which these growth rates could be maintained.

1.4.2.4. Possible saturation of the deployment of wind and PV

The other great uncertainty regarding the logistical deployment of wind and PV is their saturation value. Indeed, it is not possible to deduce their saturation based on their historical deployment. The growth of wind have been slowed down in the last two years (in 2023 and 2024), however this does not allow to deduce the future form of the logistic (or non-logistic) deployment as this could be due to temporary setbacks. PV energy is still in an exponential stage, which does not provide insights on future possible saturation. It is clear that saturation will be — at least — limited by the regional potentials. However the potentials discussed in section 1.4.1 are maximum potentials and ignore other geographical barriers such as the electric grid configuration and urbanism or access constraints. Moreover, other barriers discussed in the following sections will also constrain the deployment of wind and PV.

While logistical fit of wind and PV deployment at the global level is currently not relevant, Cherp et al. (2021) fitted regional logistic curve on their deployment. With the data from the Energy Institute (2025) it is possible to update these fits and then to aggregate them at the global level. However, this may not be conclusive for several reasons. Firstly, the study of the trends observed in each country show that PV is still in an exponential stage which prevents from extrapolating relevant saturation levels. Secondly, in the case of wind energy, multiple countries depict a saturating trends; however China represent a growing 40% of the global wind energy production and does not show signs of saturation but a slight inflection. Thirdly, most fits would have to be performed mainly on early stages. There are — in individual countries — often heavily influenced by local subsidies and policies, the influence of which fades over time in favor of other drivers (industrial and market logics). Studying regularities in the deployment and saturation of these technologies may be more relevant in some years.

1.4.2.5. Conclusion on the industrial deployment of wind and PV

To conclude, it is difficult to extrapolate the future deployment of wind and PV by studying current trends and past historical comparable example. The only thing that is quite certain is that they may still deploy fast until the end of the decade. In the end, their deployment are very likely to be constrained, limited or driven by the other barriers presented in this chapter.

1.4.3. Barriers linked to the electric grid

The integration of wind and PV — which are variable renewable energy sources (VRE) — into electric grids faces several barriers.

1.4.3.1. Competition between energy sources in a saturated electricity market

In some countries, the deployment of wind and PV competes with other existing energy sources — primarily gas and coal. For economic reasons, gas and coal power plants are not decommissioned early simply because renewables are deployed. Consequently, if electricity de-

mand does not increase in parallel with new generation capacities, all energy sources compete to sell their output.

This competition backfires on the economic profitability of new energy sources, particularly wind and PV. Indeed, in several markets, electricity prices fall during periods of overcapacity — for instance when both wind and PV generate simultaneously at high levels. This is known as price cannibalism. This, in turn, reduces the profitability of wind and PV. However, this effect is less pronounced in electricity markets that rely on alternative price-setting mechanisms.

1.4.3.2. Delays in the deployment of the electric grid

The electric grid of many countries — especially western countries — were not designed for the integration of decentralized and distributed energy production sources, but rather for a small number of large centralized power plants. This implies that the grid — primarily transmission lines and small substations — must be expanded to connect new renewable sources (Guo et al., 2023). This lag in grid deployment currently slows down wind and PV, as presented in IEA (2023) and Grimault (2021). The expansion of wind and PV therefore requires to modify grid design grid design. Nevertheless, IEA (2023) also points out that the timescale for building new grid infrastructure structure — about 15 years — is much longer than the timescales for deploying renewable energy projects — about 5 years. This suggests that grid limitations will remain a significant barrier to wind and PV deployment in the coming years in Western countries. By contrast, countries where the grid is still in its development stage may be less exposed to this barrier, since they can integrate variable renewable energies considerations into their planning.

Western countries also face issues linked to the age of their grid infrastructures. In these countries, infrastructures are slowly reaching the end of their lifetime and must be replaced. This adds to the scale of required investments. If not anticipated, this could further delay wind and PV projects due to bottlenecks in grid connection (Gorman et al., 2025).

1.4.3.3. Technico-economic barriers linked to grid balancing

Electric grids must ensure a continuous real-time balance between production and consumption. High penetration of wind and PV raises issues for grid balancing (Obuseh et al., 2025; Pithwa et al., 2024).

First, wind and PV production depend on weather conditions (wind speed and solar irradiation) which means that operators cannot choose when this energy is generated, although curtailment is possible. By contrast, all conventional energy sources used so far are dispatchable: fuel supply to thermal plants (gas or coal, and sometimes biomass or oil) can be adjusted rapidly and precisely; nuclear production can also be modulated to some extent; and most hydropower capacities are fully controllable. Wind and PV must therefore be complemented by dispatchable energy sources or storage solutions. However, once penetration reaches some level, the variability of VRE would require very large amounts of dispatchable or storage capacity. Indeed, it must be possible to supply 100% of electricy demand by other means when ther is neither wind nor sun. This implies that either: 1) dispatchable capacity will remain under-utilised (reducing profitability and increasing costs), or 2) additional storage capacity must be built (also raising costs). Thus, high penetration of wind and PV in the grid, at levels around 30—40% of the annual electricity production — entails significant grid costs. Attributing these costs to wind and PV would increase their effective costs (often quantified by LCOE: levelised cost of electricity).

High VRE penetration also brings other technical challenges for grid balancing. Thermal, nuclear, and hydropower plants all generate electricity through synchronous machines (a ro-

tor spinning inside a stator). By contrast, PV requires power electronics to transform the raw DC signal into a three-phase AC signal of the appropriate frequency and voltage. Rotating machines also provide mechanical inertia, which stabilises the grid by compensating for rapid frequency variations. PV panels, however, do not. As a result, PV plants require reactive power compensation and virtual inertia. This is also true, though to a lesser degree, for wind power — depending on turbine design. These additional infrastructure requirements translate into additional costs for wind and PV.

In short, a high penetration of wind and PV induces a non-linear increase in grid costs. While the generation cost of wind and PV is currently lower than forfossil fuels, once grid adaptation costs are included, their effective costs may converge with fossil alternatives at moderate penetration levels, and become prohibitive at very high penetration levels.

Instead of deploying only production-side technologies, demand-side flexibility can also be envisioned: shifting consumption to match the time profile of wind and PV production. This could for example involve delaying the charging of electric vehicles, shifting heating or cooling of buildings, or operating industry utilities during periods of maximum electric generation. Such strategies require rethinking both consumption behavior (of households and of industries) and electricity market design. While possible, this would have economic consequences and require voluntary collective decisions. This has historically been the exception rather than the rule. Therefore, demand-side flexibility may remain limited.

Although models increasingly account for integration costs (energy or economic ones) associated with the deployment of wind and PV as in Way et al. (2022), Sahin et al. (2024), Capellán-Pérez et al. (2019) and Capellán-Pérez et al. (2020), the evolution of the costs as a function of penetration levels has not yet been thoroughly quantified. IEA and RTE (2021) concluded that the technical challenges raised by high penetration of wind and PV are manageable, but they did not quantify the costs associated with these technologies, nor the challenges associated with their deployment.

1.4.3.4. Conclusion

It should be reminded that electric grids often span multiple countries or entire regions. Balancing the grid is therefore a collective task. This explains why some countries (e.g. Denmark) achieve high wind and PV penetration levels without facing all of the aforementioned issues: their neighbors with lower VRE penetration compensate for supply-demand gaps. To date, no entire grid has reached high levels of wind and PV penetration[13].

To conclude, the deployment of the electric grid is a current barrier to the deployment of wind and PV; it is anticipated that energy storage and balancing technologies will remain major barriers to the high-penetration of wind and PV, primarily due to their costs.

1.4.4. Barriers to the decarbonization of consumption technologies

For now, I have only focused on supply-side barriers. However, the energy transition also implies transforming consumption-side technologies, such as cars, residential heating and industrial machinery.

Fossil fuels represented 81% of the energy supply in 2022. Substituting fossil fuels used to produce electricity with renewable energies will not require a transformation of consumption technologies that use electricity anyway. Around 20—25% (IEA, 2024b) of fossil fuels are con-

[13] Heptonstall and Gross (2021) studied historical examples of the electric grid adaptations, but this study is therefore limited by the historically low grid-level wind and PV penetration.

sumed in order to produce electricity. Still, in 2022, fossil fuels constituted 65% of the total final consumption, i.e. of the all the energy consumption excluding energy industry own uses and investments and losses in the transformation processes of energy products.

Substituting these 65% energy investments would require a complete technology shift in many sectors. However, most of these substitution technologies have not yet proven to be either technologically mature or economically competitive with the established fossil fuel technologies.

Economic costs are not (and should not be) the only consideration when choosing between technologies. However, increasing technology costs in sectors where they represent a high proportion of total costs results in higher prices, leading to higher prices in all downstream sectors.

1.4.4.1. Examples in some sectors

Electric vehicles (EVs) are the best known example. Road transport consumed 89 EJ of energy in 2022, 82EJ of which was oil. The EV technology is now mature, but suffers from higher purchasing prices compared to conventional internal combustion engine vehicles (ICVs) because of battery prices. This still remains the main barrier to the deployment of EVs, except in China (IEA, 2025b). Moreover, due to the lower energy density of batteries compared to oil, EVs are also confronted to autonomy issues[14].

The industry sectors consumed 128 EJ of energy in 2022. Gailani et al. (2024) quantified the technological readiness level of substitution technologies, concluding that low-temperature heat processes technologies are mature whereas high-temperature technologies are not. They also discuss the costs additions in these technology changes.

For example, in concrete production, non-fossil production technologies are not yet considered as relevant candidates to the substitution of conventional high-temperature fossil-based processes (Pisciotta et al., 2022). Concrete production consumed approximately 15 EJ of energy in 2022. Busch et al. (2022) also highlights that the barriers to their deployment have not been studied enough. Around 60% of CO2 emissions arise from the carbonate calcination chemical process. This means that reducing the CO2 emissions of concrete also requires studying possible changes to concrete composition or, more straightforwardly, changing the materials used in construction (Cao et al., 2020).

Steel production is shared between primary production which represent 70% of the production, and secondary production (i.e. recycling) which constitutes the remaining 30% (Holappa, 2020). Its production consumed 22 EJ in 2022. The recycling process uses an electric arc furnace (EAF) that is already fueled by electricity. Primary production first uses a blast furnace (BF) to reduce iron oxides (direct iron reduction, or DRI), and then a basic oxygen furnace (BOF) to transform iron into steel (Pisciotta et al., 2022; Vogl, 2023). This primary process mainly uses coal, which provides the carbon inputs required in the process, and natural gas. These two furnaces could be replaced by the combination of hydrogen direct iron reduction (H-DRI) with an EAF. These technologies are currently under development (Holappa, 2020; Wang et al., 2021; Pisciotta et al., 2022), meaning there is little chance of them replacing conventional fossil fuels on a significant scale before 2050. Moreover, they require a hydrogen supply, which faces its own deployment issues (section 1.3.7).

Fertilizers are made from ammonia, which is produced through di-hydrogen using the Haber-Bosch process. They are currently essential to agriculture. They account for around 5—10EJ of energy consumption[15]. Di-hydrogen is currently produced from natural gas. Green fertil-

[14] Increasing the autonomy mostly implies increasing the capacity of the battery, which increase the price of the vehicle as well as its weight.

[15] These figures are estimated from Ramírez and Worrell (2006) and data fertilizer demand found at `https://ourworldindata.org/`

izers would use green ammonia, which is ammonia produced using hydrogen from electrolysis (from renewable energies) rather than from natural gas (or even coal). Again, its deployment is contingent upon the deployment of green hydrogen, discussed in section 1.3.7. Green ammonia is therefore currently more expensive than conventional ammonia (Olabi et al., 2023), and its decarbonisation potential depends on the development of green hydrogen.

The military sector is also unlikely to be decarbonized at the 2050 horizon. Indeed, it mostly relies on operational and economic considerations. Due to the lower energy density of low-carbon technologies compared to conventional fossil ones as well as their current higher prices, it is highly unlikely that they will be deployed before civil applications. Particularly, aircraft and naval ships have quite no chance of being transformed in the coming decades[16]. The energy consumption of the military sector is not accounted for in the IEA's World Energy Balances (IEA, 2024b), however the oil consumption is estimated to be around 1.5EJ/yr in Transform Defence (2020) while oil constitutes the main energy source of the military sector.

1.4.4.2. Non-substitutability of oil in aviation and shipping

This section delves in more details in the potential for decarbonization in aviation and shipping. This question is of more interest as these sectors currently rely on oil, which is expected to be under tension at the 2035 horizon, as shown in Chapter 5. The energy consumption of the aviation sector was 14 EJ of oil in 2019, and 12 EJ for shipping.

Aviation and shipping (maritime transport) currently rely on oil: in 2022, oil represented 100.0% and 99.5% of the energy consumed in aviation and in shipping respectively (IEA, 2024b). Indeed, these sectors require dense energy sources. Moreover, the type of oil used — jet kerosene and fuel oil — are among the cheapest. Due to their operational constraints, the potential for oil substitution in these sectors are very low. The analysis in this section is based on the study of the following articles: Bergero et al. (2023); Detsios et al. (2023); Balcombe et al. (2019); Ansell (2023); Bauen et al. (2020); Cabrera and de Sousa (2022); Afonso et al. (2023); Islam Rony et al. (2023); Prussi et al. (2021); Foretich et al. (2021). In this section, we focus on medium- to long-haul transport (more than 100km), which represents the vast majority of energy consumption. This neglects marginal small-scale uses.

Firstly, "drop-in" biofuels are seen as the most technically feasible option to substitute part of the oil used in aviation and shipping. These biofuels can be incorporated directly into jet and marine fuels without the need for major modifications to engines or carrier. However, they face multiple challenges. Their prices are still higher than those of oil fuels. According to Detsios et al. (2023) and Ansell (2023), the prices per litre of these biofuels was two to four times higher than those of the average price of jet kerosene between 2015 and 2022, and the price of biofuels per ton was at least twice as large as marine fuel oil in Balcombe et al. (2019), although their volumetric and mass energy density is lower than for jet kerosene and fuel oil, making the price difference higher (Bergero et al., 2023; Balcombe et al., 2019). Then, competition for land-use is the main issue regarding biofuels (and is discussed in all studied articles). Considering that the liquid biofuel production was only 4EJ in 2022 while the cumulative energy demand of aviation and shipping represented a growing 22 EJ in 2022, there is little chance that biofuel production could expand quickly. Moreover, road transport would compete for biofuels too. Finally, none of the specific jet-biofuels are currently ready to be produced at large scales. To conclude, in agreement with Balcombe et al. (2019); Bergero et al. (2023), biofuels are unlikely to expand at a significant scale in aviation and shipping.

grapher/fertilizer-total-use.

[16]Some ships use nuclear propulsion. However, this is for operational reasons it can not be replicated in the general military fleet.

Secondly, di-hydrogen and derived products such as ammonia and methanol are being studied as a potential energy vectors for aviation and shipping. The use of these fuels would require airplanes and ships to be redesigned with changes to engines and increased storage capacity for the energy vector. The lifetime of aircrafts is around 20 years and 30 years for ships, which limits the speed at which these energy vectors can be deployed. The main barrier to the deployment of these energy sources is their costs, which are higher than for jet kerosene and fuel oil. Additionally, these energy vectors first need to be produced using an energy source. As discussed in section 1.3.7, 63% of di-hydrogen is produced by gas, 20% by coal and the reminder is a by-product. The production of di-hydrogen by water electrolysis (using electricity) is negligible. Ammonia and methanol are produced from di-hydrogen. Consequently, using these energy vectors in aviation and shipping would result in a substitution of oil by gas and coal, with poorer energy efficiency due to losses in the process. Producing these energy vectors using renewable energy would require developing the production of di-hydrogen with electrolysis. However, this would compete with other uses of electricity, and the electricity-hydrogen-electricity conversion process has a ≈30% efficiency (the efficiency of the electricity-hydrogen-combustion conversion is of the same order of magnitude). Therefore, from a systemic point of view, using it rather than oil would not be environmentally beneficial unless the deployment of renewable energies is limited by electricity demand. Otherwise, this substitution with 40% losses would replace a more efficient substitution of fossils by electricity. More than these considerations of cost and energy efficiency, di-hydrogen (whether in fuel cells or in internal combustion engines) and its derivatives are not at all technologically mature solutions for aviation and shipping. This also prevents significant deployment in the short and medium term. To conclude, di-hydrogen and its derivatives would not be able to represent a significant portion of the energy consumption of the aviation and shipping sectors before 2050.

Thirdly, liquefied natural gas (LNG) could be used as a substitute for fuel oil in shipping. However, its energy density is lower, which is why it cannot be used in aviation. Moreover, it provides low or no CO2 emission reductions compared to fuel oil according to Balcombe et al. (2019). It also requires ships to be retrofitted. Ultimately, the cost increases of LNG solutions compared to oil may be much more limited than for biofuels and di-hydrogen-based solutions.

Finally, the low energy density of batteries limits their use to very specific, small-scale applications in maritime transport and tourism aviation. This represent only a tiny proportion of all energy use.

To conclude this section, it is highly unlikely that oil use in aviation and shipping will be substituted by other solutions before 2050. The costs of biofuels and di-hydrogen-based solutions are expected to remain higher than those of conventional jet fuel and fuel oil, the scalability of biofuel solutions is limited and the di-hydrogen based solutions are not yet technologically mature. Finally, LNG could be used in shipping, however this solution is of little interest regarding climate issues, and it is anticipated that gross gas supply will peak around 2040 (see Chapter 2).

1.4.4.3. Inertia and lock-ins due to the lifetimes of infrastructures

The lifetime of infrastructures and the inertia in system changes are also an important barrier to the energy transition at the 2050 horizon and to limit climate change to the 1.5—2°C target. Indeed, fossil infrastructures are expected to reach their end of life before being replaced, in order to maximize return on capital investments. This is a first barrier to phasing out fossils.

For example, kilns used in the production of cement have a 40—80 year lifetime, steel basic oxygen furnaces have a 100 year lifetime (Pisciotta et al., 2022) while both of these technologies currently rely on coal and natural gas. It can be expected that other heavy industry technologies

also have high lifetime. This creates a lock-in.

Most importantly, China and India (as well as some other Asian countries) recently developed their coal production infrastructures: 70 EJ/yr of the annual coal energy production of China have been deployed in the last 20 years, and 10 EJ/yr in the case of India. Moreover, their coal energy production are still increasing. Due to the typical 60 years lifetime of coal power plants, these 80 EJ/yr of coal production are not expected to be phased-out before 2050. This represents 50% of the coal consumed in 2022.

Consequently, this coal lock-in is estimated to be a major barrier to the decarbonization of the energy mix. Vinichenko et al. (2021), Vinichenko et al. (2023) and Muttitt et al. (2023) estimate that the required coal phase-out paces in order to respect the Paris' agreements are higher than ever observed in history.

Nacke et al. (2022), Nacke et al. (2024) and Muttitt et al. (2023) also mention other types of lock-ins in the coal industry, due to the interdependence between energy systems, but also to other economic, political and geopolitical reasons.

Conversely, an early coal phase-out would require to finance compensation for the affected countries (Hauenstein, 2023). Nacke et al. (2024) estimate this compensation could be of the order of magnitude of the 100 billion dollars committed in climate agreements.

1.4.5. Raw material flows required in the energy transition

The demand for several raw materials is expected to grow strongly in a scenario of fat energy transition, due to the deployment of electric vehicles (EVs) and their batteries, of wind and PV energy sources, and of electric grid networks (IEA, 2025a). For example, lithium extraction has grown threefold between 2020 and 2024 mostly due to the demand for EV batteries which currently constitute over 85% of lithium demand (Energy Institute, 2025; IEA, 2024d). Many institutions and researchers have therefore investigated whether supply could meet demand. This section briefly introduces the discussion, without delving into the literature.

Firstly, absolute resources (stocks) are rarely a concern, but production flows are. Indeed, reserve estimates rely on economic conditions and increase with the market price of raw materials.

Secondly, some raw materials can be substituted with others. For instance, manganese and cobalt of NMC (Nickel-Manganese-Cobalt) EV batteries are replaced by iron and phosphate in LFP (Lithium iron phosphate) batteries. Rare earth materials are substituted by copper when a wound-field rotor replaces the permanent magnet in wind turbine motors. However, the substitution of materials can be costly. This is one of the criteria for a material to be considered as critical.

Thirdly, the main issue is whether growth in extraction rates could meet demand. Indeed, a surge in demand for certain materials can put strong pressure on supply chains. This issue therefore relies heavily on political, geopolitical and economic considerations.

1.4.6. Other barriers

This section presents several anticipated barriers to the energy transition. Further studies would be needed in order to evaluate the extent to which these barriers would limit the pace of the energy transition.

A rapid energy transition implies a rapid increase in financial flows, for wind turbines ond PV plants deployment but also industrial (mostly electric) equipment. Wind and PV are known

to be particularly capital-intensive (see Section 1.3.5). The increase in money flows and debt would thus be tremendous (Jacques et al., 2023). Such a debt growth could have adverse effects on the economy (Gonzalez-Redin et al., 2018), which suggests that several mechanisms would tend to limit its growth. Capital flows could therefore be limited.

A rapid energy transition would also imply an increase in the demand for specialized workers in the related economic sectors. This flow of new workers towards these new activities may be limited, mostly due to skill suitability and training times, at each required skill level. Some job shortages are already being observed today (IEA, 2024c; Černý et al., 2024; Lucas et al., 2018; IPCC, 2023; Xie et al., 2023), raising concerns about the feasibility of rapid energy transition scenarios. This barrier should be studied more carefully.

Social barriers have been mentioned in section 1.4.2.2. Wind projects (and PV projects to a lesser extent) face social opposition. This raises questions about the desirability of these projects, and more broadly, of the energy transition. Ideally, from a democratic point of view, plans for the energy transition should be the result of a collective decision and have collective legitimacy.

Finally, institutional and regulatory barriers may arise (Palle, 2021; Brutschin et al., 2021; Stammer et al., 2021). Consequently, the institutional conditions under which the energy transition could be fostered should be explored.

1.5. Energy dynamics and EROI

1.5.1. EROI issues

The energy return on investment (EROI) of an energy production technology is defined as the ratio of the gross energy produced to energy investments required for production (Hall et al., 2009). In other words, the higher the EROI, the lower the energy production energy costs. Net energy is defined as gross energy minus energy investments and reflects the energy available to the society after the consumption in the energy sector.

This EROI can also be computed for an entire energy system. In this case, EROI can be viewed as an indication of the energy metabolism of society. Some authors (Hall et al., 2009; Fizaine and Court, 2016; Brandt, 2017; Tainter, 1988) have argued that a decline in EROI directly impact economic activities, such as a decline in GDP. This can be seen from two different perspectives. Firstly, a reduction in EROI implies an increase in the energy costs of energy production, which translates into higher prices. Since services and commodities require energy consumption (embodied energy) in industrialized societies, their prices would increase accordingly. Secondly, linking energy consumption to economic activities implies that the energy sector's share of economic activities increases. This increase may replace some other economic activities. The link between energy consumption and economic activities can reasonably be established by considering the GDP/energy correlation (Haberl et al., 2020), taking into account that the energy intensities of economic sectors are of similar order of magnitudes (Andrieu et al., 2022).

Beyond a certain level, a reduction in economic activities would impact the satisfaction of basic needs, although the extent of these effects is a matter for political and social science rather than a mechanical consequence of the energy metabolism. Moreover, Brandt (2017) concluded that there would be non-linear and even thresholds effects in the impacts of EROI decline on

societal metabolism. This is due to the cliff effect of net energy with EROI decline, and to metabolic impacts on all sectors.

1.5.2. The impact of the energy transition on the EROI of the energy system

The impact of the energy transition on the EROI of the energy system is therefore a key issue. Firstly, the energy transition may temporarily reduce the dynamic EROI of society (Capellán-Pérez et al., 2019; Sgouridis et al., 2016; Dale et al., 2012; Sers and Victor, 2018; Slameršak et al., 2022). This is primarily due to the capital intensity of wind and PV. These articles systematically discuss the implications of this decline in EROI, with Dale et al. (2012) particularly modeling the retroaction on energy systems.

Secondly, the EROI value of an energy system (primarily) based on wind and PV has to be studied. It is important to compare this with the EROI value of the current energy system. This would indicate whether the energy transition would ultimately increase or decrease the EROI of the energy system, after the initial transitory stage. Some articles have studied this issue (Aramendia et al., 2024; Slameršak et al., 2022; Capellán-Pérez et al., 2020). Aramendia et al. (2024) suggests that the EROI of wind and PV technologies are currently higher than that of fossil fuels. However, comparing the EROI of the current energy system with that of post-energy transition system (mostly based on wind and PV) is difficult from a methodological point of view:

- The perimeter of the supply chain and the boundary (direct, indirect, auxiliary, etc.) of the energy investments must be clearly defined. This is discussed in Chapter 3, and summarized in Table 3.1 and Fig. 3.1. The perimeter and boundary in EROI estimations often differ among articles, when they are specified.
- Estimations of EROI values are often quite uncertain, due to a lack of robust data on the embodied energy of the energy sector, at the point of use and the cumulative boundary (as specified in Chapter 3).
- EROI values for wind and PV will evolve over time due to two competing phenomenons: technological progress slowly increases EROI, to a certain extent; but the energy production potential of the unused sites decreases over time because sites[17] with the best potential are first exploited. The models of Dupont et al. (2018, 2020) are valuable regarding this last issue.
- High levels of wind and PV penetration in electric grids require investments to balance the grids and to adapt to these distributed energy sources (see Section 1.4.3). These additional energy investments decrease the EROI of the overall energy system. This has been partially studied in Capellán-Pérez et al. (2019).
- Many consumption technologies (e.g. transport, heating and industrial machines) would need to be replaced in order to use electricity instead. This new equipment will have different primary to useful conversion coefficients. This first implies that the relevant stage of energy in the EROI calculation would have to be useful energy. Data on energy supply and consumption are usually expressed in terms of primary energy. Converting gross energy supply and energy investments from primary energy to useful energy would require significant work, as this would necessitate modeling in-use consumption technologies. Significant work in this area has been carried out by Brockway et al. (2024).

[17] On which it is possible to install wind and PV, due to land and regulatory limits

Long-term phenomena such as climate evolution could cause EROI values for wind and PV to change over time. A decline in the quality of raw materials (because the highest quality materials are extracted first) would imply an increase in the energy intensity of raw materials. However, the DyMEMDS model[18] (Vidal et al., 2022) suggests that this is not the case for most structural materials up to 2050[19]. These phenomena would in any case be negligible compared to the effects of political and social choices on the energy system and on the energy metabolism.

1.5.3. Conclusion on EROI issues

Chapter 3 confirms that the EROI values of oil and gas are declining and shows there are lower than the results found in most analyses. Although this is not surprising, it would increase the comparative interest of a post-energy transition (mostly based on wind and PV) energy system. This however leads to a paradoxical situation: the deployment of wind and PV technologies with higher EROI values in order to compensate for the decline of the EROI values of oil and gas would temporarily decrease the dynamic EROI of the energy system due to the capital intensity of wind and PV.

In conclusion, an ambitious energy transition to post-energy transition energy systems would temporarily decrease the EROI of the energy system. Current wind and PV EROI values are assumed to be higher than those of fossil fuels, although the EROI of a post-energy transition energy system is unknown. Meanwhile, the EROI values of oil and gas continue to decline, and Chapter 3 shows that the EROI of the energy system in the absence of an energy transition is expected to decrease towards low values. Given the reliance of economic growth in industrialized societies on high EROI values, EROI issues are therefore of significant concern.

1.6. Conclusion

This Chapter examined the barriers to the deployment of the energy transition by 2050. Firstly, wind turbines and photovoltaic panels (PV) — which produced 3% of the energy in 2024 — were identified as the only low-carbon energy sources capable of growing rapidly to significant production levels. However, several barriers are anticipated: the potentials for wind and PV as well as their growth rates could be limited, the deployment of electric grids could limit the penetration levels of wind and PV, some consumption sectors are expected to be technically and economically difficult to decarbonize, there are lock-ins in fossil fuels systems, and financial, labor and institutional barriers may slow down and limit the energy transition. Furthermore, the metabolic implications of the energy transition must be considered in forecasting exercises.

Although some studies have quantitatively addressed some of these barriers (e.g. as in Dupont et al. 2018, 2020 for wind and PV potentials), the literature on the barriers presented in this chapter is generally scarce. This can partially be explained by two reasons: 1/ the deployment of wind, PV and of low-carbon consumption technologies such as electric vehicles (EVs) is quite recent, evolving rapidly, and articles can quickly become obsolete. 2/Modeling these barriers is uncertain due to technological progress, to the evolution of the economic and political context, and to some extent to the lack of data. Nevertheless, the lack of literature on these barriers does not mean that they do not exist.

[18] To which I had access, thanks to Olivier.

[19] In the case of copper, the energy intensity is however expected to stagnate up to 2050, and to increase after.

The limits — mostly technical and economic — discussed in this chapter are mostly valid in a business-as-usual (BAU) scenario. Indeed, strong political commitment, substantial investment in the energy transition, and significant taxation of fossil fuels could eliminate some of the economic barriers to low-carbon technologies and foster their deployment. However, none of these actions are currently being taken. The current deployment of wind and PV electricity production can be explained by their lower costs (LCOE, or levelized cost of electricity) compared to fossil and nuclear production. Conversely, investments in the energy transition are likely to be further limited in a world experiencing crises. Ambitious investments in the energy transition as well as taxing fossil fuels (resulting in higher commodity prices) would be highly unlikely in such contexts.

This chapter does not suggest that the energy transition should be avoided. Rather, it presents biophysical limits to the energy transition by 2050 and states that an ambitious energy transition by this date may not be possible under BAU conditions.

Committing to the energy transition would be an efficient way to reduce CO_2 emissions and reliance on limited fossil reserves while producing energy. Under ambitious energy transition scenarios it may even be possible to maintain the current level of useful energy supply while limiting global warming to +2°C, although this assertion must be studied in light of the aforementioned barriers in the context of an ambitious energy transition scenario.

There are two main messages in this chapter. Firstly, the feasibility of ambitious energy transition scenarios under BAU conditions should be questioned. Any scenario assuming an ambitious energy transition must justify the consistency of its assumptions, in light of the biophysical barriers discussed above. Secondly, these barriers could be significantly reduced with strong political commitment (the required investments and actions should be examined in light of the information in this chapter). The deployment of the energy transition is therefore an economic and political issue.

CHAPTER 2 | Gross Energy Supply vs Demand up to 2050. Will post-2035 oil and gas Declines be Eased by the Energy Transition?

This chapter first critically analyses future gross energy supply from oil, gas and coal. Combined with analyses from Chapter 1, this allows deducing the deployment rate of wind turbines and photovoltaic panels (PV) that is required in order to compensate for the decline in the gross energy supply from the fossil fuels in a business-as-usual scenario.

This material is intended for submission to Energy Policy.

Abstract

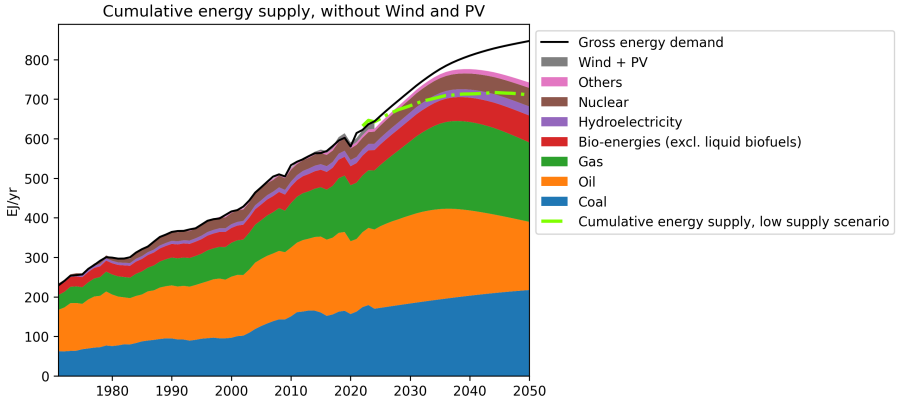
Both optimistic and pessimistic points are often expressed in the literature on the future of primary energy production at the world scale. In particular, the question of fossil fuel energy reserves and annual supply is often viewed as secondary due to the abundance of resources, while, on the other hand, a number of authors insist on the limits to conversion of resources in reserves and on the more or less imminent supply peaks of oil and gas. This dichotomy also underlies a disagreement on whether the upcoming decline of oil and gas are due to a demand or a supply side peak.

The present work aims to revisit this energy supply/demand issue, by critically analyzing data on ultimate recoverable reserves (URRs), and by using realistic estimates of the potentials of wind and solar energy. In particular, we quantify under which conditions these sources of renewable energy may cope with the expected decline in oil and gas while meeting the expected energy growth demand in a moderate business-as-usual (BAU) scenario.

We find that renewable energies may meet fossil fuels decline and rising gross energy demand if their normalized growth rates are 3 – 6%/yr for solar energy and 4 – 5%/yr for wind.

This represents an annual additional capacity of nearly a third of the present world electricity production. Such sustained rates require major long term commitments.

Graphical abstract



2.1. Introduction

The energy transition is a widely debated issue and definitely one of the main challenges of the century. The debate is mostly driven by the need to mitigate climate change (IEA, 2024d; Slameršak et al., 2022; Sgouridis et al., 2016; Nieto et al., 2020; Wang et al., 2023; Bogdanov et al., 2021a; Crownshaw, 2021). In this context, the issue of fossil fuels abundance is often viewed as secondary. Indeed, oil and gas producers on the one hand, and international institutions such as the International Energy Agency (IEA) on the other, implicitly or explicitly indicate that reserves are large enough, based on very large known resources and expected future discoveries (IEA, 2013). This is at odds with parts of the academic literature and oil intelligence companies, which on the contrary point out that ultimate recoverable reserves (URRs) may be less or even much less abundant than expected (e.g., Delannoy et al. 2021a, Delannoy et al. 2021b, Laherrère et al. 2022, Michaux 2020, GlobalShift[1] or Rystad Energy[2]).

Quite interestingly, though, in spite of this huge difference in point of view, where the latter envision a supply peak of oil and gas around 2035 – 2040, the former see a demand peak at roughly the same date (IEA, 2024d; BP, 2024; OPEC, 2025). Obviously, demand and supply in the end must balance one another, but which one drives the other is of critical importance. In particular, voluntarily phasing out oil and enduring sooner than later an unanticipated oil shortage have definitely not the same macroeconomic consequences, as past crises have amply shown (Tverberg, 2012a).

With this background in mind, the main objective of this work is to discuss in a non normative way the issue of gross energy demand vs supply at the 2050 horizon. Indeed, some analyses of the topic define some normative objective (most often, in terms of climate change) and examine how this can be satisfied (IPCC, 2023; IEA, 2024d; Bogdanov et al., 2021b). Although of interest for some questions, such an approach is not very informative on the most crucial

[1] https://globalshift.co.uk/
[2] https://www.rystadenergy.com/news/upstream-breakeven-shale-oil-inflation.

one, namely, the feasibility of such normative objectives. For example, quite a few normative prescriptions on energy efficiency have consistently failed in the past (see, e.g., Brockway et al. 2021). In the present work, while we also start by pinpointing necessary conditions for renewable energies to meet both oil and gas decline and a mild growth in gross energy demand, we critically discuss their feasibility. A similar analysis was performed by Solé et al. (2018), but restricted to oil liquids. To this effect we first establish a moderate world GPD growth scenario and the associated growth in energy demand.

To this effect we first define a moderate world GPD growth scenario and the associated growth in energy demand. Then, on the one hand, we model future gross production of coal, oil and gas, based on URR estimates, and solar photovoltaic and wind renewable energy production projections on the other; for oil and gas, we also rely on existing projections by experts and energy intelligence companies. Finally a comparison of gross energy supply vs demand is performed in the last part of this article, taking into account other renewable sources of energy as well as nuclear energy.

This paper is organized as follows. Section 2.2 introduces our data sources for past production (oil, gas, coal, wind and solar renewable energy) and for oil and gas future gross energy productions. Our results are exposed in section 2.3, starting with coal future gross energy production (section 2.3.2), followed by renewable future energy supply (section 2.3.3). These two analyses rely on logistic fits, whose ins and outs are summarized in Appendix 2.F; we pay particular attention to URRs (for coal) and potentials (for renewables) due to their critical role in projection annual productions. Extensive discussions follow in section 2.4. First, uncertainties in oil and gas URRs are addressed (section 2.3.1 with the most involved and lengthy elements of this discussion collected in Appendix 2.A). Next, a discussion of the issue of gross energy demand vs supply in our adopted mild BAU growth scenario is presented (section 2.4.1). The conclusion (section 2.5) summarizes our most important results and outlines some points of focus for future work.

2.2. Materials and methods

The discussion on the future of energy supply in this work mostly focuses on the three fossil fuels (oil, gas and coal) and on the two major sources of renewable energy, namely wind and solar (photovoltaic panels, PV) energy. This section introduces the sources of data used in our modeling of the future production of these sources of energy as well as the methods used.

2.2.1. Oil and gas past supply data and future supply projections

Following Delannoy et al. (2021a) and Delannoy et al. (2021b), we make use of the GlobalShift oil and gas supply data, as these disaggregated data (by oil and gas type) are already at our disposal[3]. We also use two other sources at the aggregated level for oil: Rystad Energy and Jean Laherrère data and projections (these were also used in Delannoy et al. 2021a), as a point of comparison of oil production projections. Rystad Energy is a highly reputed oil intelligence company, while Jean Laherrère is a well-known expert with decades of experience in and with

[3]One of the present authors coauthored these earlier pieces of work. This reuse is done with the agreement of GlobalShift. Note that GlobalShift follows the common convention of counting NGLs (natural gas liquids), CTL (coal to liquid) and GTL (gas to liquid) as oil liquids. Double counting is avoided by excluding them from gas and coal. Similarly, a fraction of NGLs is obtained as refinery products, but are not included in the NGLs included in oil liquids to avoid double counting.

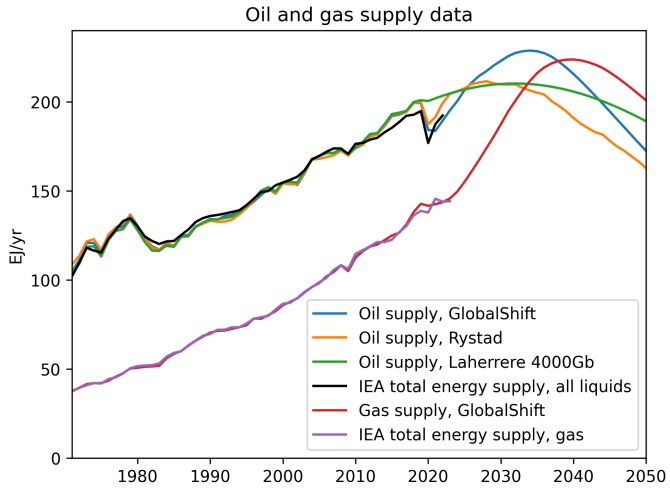


FIGURE 2.1: Gross supply data of all liquids, and of gas, from multiple sources as indicated in the figure legend. The projections data begin at year 2020 or 2021, which explains why the decline in oil consumption in 2020 (due to the COVID pandemics) is not reflected in Laherrere's data. IEA's historical oil and gas supply data are also shown. "Oil" refers to all liquids.

the oil industry. GlobalShift also relies on decades-long expertise in the oil and gas sector. It may be worth noting at this point that data from oil (and gas) producers themselves may be misleading, and in any case may not be reliable due to various (geo)political, economic or technical considerations (see, e.g., Laherrère et al. 2022 for explanations on this point). Furthermore oil producers themselves do rely on projections such as those of Rystad Energy; considering the high price tag of such oil intelligence companies databases, this indicates that producers do consider such data reliable for the part of the industry they have little information on. These three oil supply projections are shown on Fig. 2.1, along with the gas supply ones.

A number of other sources are used in our analysis of the URRs of oil and gas. These are quoted in section 2.3.1 and Appendix 2.A. Finally, we also make Hubbert models of oil and gas, constrained by our URR critical analysis, for purposes of comparison and/or error estimates.

2.2.2. COAL, WIND AND SOLAR PAST GROSS SUPPLY DATA

Data on energy production of solar and wind energy come from the Energy Institute (2025). Wind and solar potentials are taken from various sources, quoted in section 2.3.3. Coal supply data are retrieved from Our World In Data (2024). On top of this, coal URR estimates are taken from a number of sources, quoted in section 2.3.2.

2.2.3. COAL, WIND AND SOLAR ENERGY PROJECTIONS

We make our own models of coal and renewable energy future projections. For coal, we start from a critical analysis of existing proven reserves and URR estimates to pinpoint a most likely URR value/range, and make a Hubbert fit for future annual projections (i.e., a logistic fit of the cumulative production, constrained by our URR value and past production data).

For wind and solar energy, we also extract potential estimates from the literature and make a logistic projection based on past data, and constrained by different scenarios on possible normalized growth rates as well as by our best estimate of the maximum potential. This is presented in section 2.3.3.

2.2.4. GDP growth scenario

In order to compare energy supply and demand, a business-as-usual (BAU) future gross energy demand scenario is produced. This is based on a GDP growth projection at the world level, noticeably more moderate than available projections (OECD, 2023; IEA, 2024c; Cointe and Pottier, 2023), and the projection of the well-known GDP/primary energy use correlation with a slight relative decoupling correction due to the deployment of renewable energies. This is further detailed in Appendix 2.B.

Past GDP data come from the World Bank, and primary world energy data are retrieved from IEA's World Energy Balances (IEA, 2024b).

2.3. Results

We start with an in-depth analysis of uncertainties in oil and gas URRs, as these control the uncertainties in the future supply of these two energy sources.

Furthermore, in order to draw a complete (or at least complete enough) picture of the energy supply/demand balance in the next decades (discussed in the next section), one must have at hand at least some pieces of information about coal and the two most discussed sources of renewable energy, wind and solar radiation. The first subsection provides a simple gross production projection for coal, while renewable sources of energy are discussed in the next subsection.

2.3.1. Uncertainties in oil and gas ultimate recoverable resources (URRs) and implications for annual future productions

2.3.1.1. Oil production projections and ultimate recoverable reserves

The three projections shown on Fig. 2.1 are in reasonable agreement. Among these, Laherrère's, providing the milder decrease.

Another point worth mentioning is that Laherrère's data for past productions come from various sources including intelligence companies, ASPO data[4], and the projections for the future rely on a procedure called Hubbert linearization[5]. This procedure (HL in short) suffers from well-known defects, in particular when exploitation is still preliminary compared to estimated reserves (Sorrell and Speirs, 2010), that will be discussed later on when providing our own critical assessment of various available projections. For the time being, we merely point out that, instead, GlobalShift and Rystad projections come from collecting individual well data, making projections for their future production at the well level, and aggregating them to produce world projections. Still, the results are reasonably consistent. Another noteworthy piece of work proceeding in a similar way (in French) is a very recent report of June 2024 from the French ASPO association[6]. The results are very similar to GlobalShift's (see in particular figure 21 on page 20 of the report), in particular for the shale/tight oil proportion in the overall gross production although GlobalShift peaks about 20% higher than the report's.

Still, and maybe somewhat less immediately obvious, all three projections assign small over-

[4] Association for the Study of Peak Oil and Gas.

[5] This procedure is explained in Appendix 2.F.

[6] *Productions et exportations d'hydrocarbures. Historique et perspective*. `https://aspofrance.org/2024/12/18/productions-et-exportations-dhydrocarbures-historique-et-perspective/`

all production capacities to types of oil liquids sources that are rather abundant in terms of resources (and not reserves), albeit technically challenging and expensive to recover. For example, GlobalShift projects very small contributions from extra-heavy oil sources (tar sands oil). One may question why this is realistic, in light of the gigantic resources often quoted for this type of oil source.

In order to put these projections in perspective, we turn to another useful piece of information, namely ultimate recoverable resources (URRs), in particular for the categories of oil for which rather wide ranges of available estimates can be found, i.e., extra-heavy oil, kerogen (shale) and light tight oil. Such an analysis is often obscured by the fact that URRs are not always distinguished from technically recoverable resources (TRRs). For the present work, we adopt the following definitions of URRs and TRRs[7]: the latter refer only to technically accessible resources (with present day technology) independently of any other consideration, while the former includes (often implicitly) considerations on economically sustainable fossil fuel prices, as well as, when relevant, legislative constraints.

In what follows, we will contrast and critically analyze two main sources of URRs projections:

- One of the most extensive and recently published article providing URRs for different oil categories, i.e., Laherrère et al. (2022). URRs projection estimates in this article rely on Hubbert linearization for four categories of oil sources: conventional and offshore, conventional/offshore + shale/tight oil (LTO + kerogen in the article), conventional/offshore + shale/tight + extra-heavy (XH in the article) and all oil liquids (adding NGL, CTL, GTL, biofuels and so-called refinery gains to the third category). These authors also provide in appendix a number of estimates by other authors and institutions, which offer useful points of comparison. In case of need we may also refer to the most recent projections made by Jean Laherrère and available on the ASPO France website[8].

- IEA "technically recoverable reserves", as given in IEA (2013). This is the last of an annual "Resources to Reserves" series of reports. Discontinuing this series was an unfortunate decision as some of the data that used to be reported in there have become difficult to find elsewhere. This is the case in particular of the estimates of the "technically recoverable estimates" and break-even by category for oil, gas and coal, that can be found in chapter 8 of IEA (2013). Fortunately these data do not change very fast, at least for the categories of oil liquids most critical for the present discussion. In case of need, we also refer to a blog post of Art Berman (an oil expert), which reproduces the most recent (2024) IEA data for technically recoverable reserves[9], and that we have been unable to locate on IEA's website.

We also compare these to some data gathered from one of Rystad Energy web posts[10], and, of course, to GlobalShift's implicit URR behind its projections. Finally, we also refer to the proven resources reported in BGR (2023) and to URRs estimated and quoted in Mohr et al. (2015). It turns out that BGR proven reserves (once completed with past production) provide estimates that closely resemble an actual URR; BGR is widely used for coal, but also gives estimates for all three fossil fuels in its annual reports. Similarly, Mohr et al. (2015) provide estimates for all three fossil fuels.

[7] There are some variations in the literature on the definitions of proven and probable reserves, URRs, TRRs and the many shades of such concepts.

[8] Forecast of world and US energy production, Jean Laherrere, 17 février 2025. `https://aspofrance.org/2025/02/25/forecast-of-world-and-us-energy-production-jean-laherrere-17-fevrier-2025/`.

[9] Lazy Thinking: How Memes Get Oil All Wrong. `https://www.artberman.com/blog/lazy-thinking-how-memes-get-oil-all-wrong/`. We thank Roger Bentley for pointing out this post to us.

[10] See footnote 2.

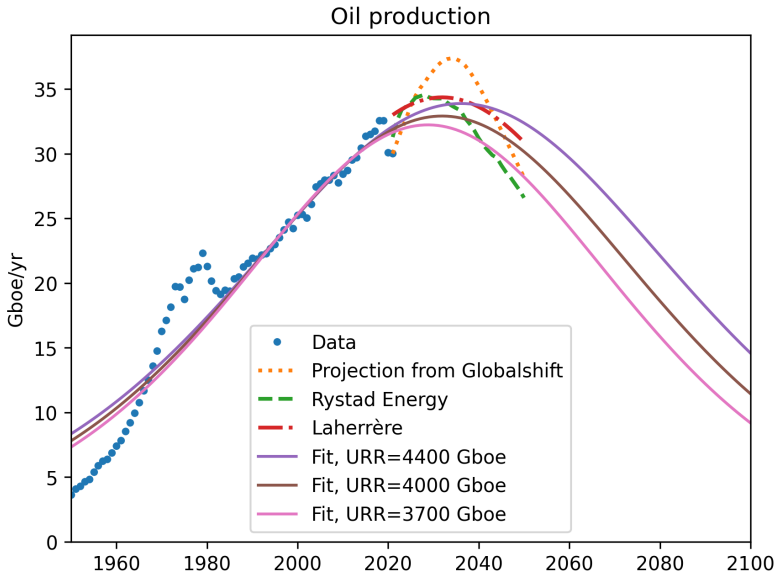


FIGURE 2.2: Hubbert logistic fit to oil production for 3 different URRs: 3700 Gbbl, 4000 Gbbl and 4400 Gbbl. Fit on data begins in 1985. The projections from Globalshift, Rystad Energy and Laherrère are also shown. Oil data are from GlobalShift.

The critical discussion of each category of oil liquids is rather lengthy, and presented in Appendix 2.A. We just summarize here the conclusions drawn from this discussion.

We end up with an all oil liquids URR reliable estimate in the 3750 – 4300 Gbbl range, largely from various projections made by Jean Laherrère, although we looked at a number of other sources in the academic or gray literature, as just mentioned. This is one of the reasons we added the Laherrère 4000 Gbbl projection to figure 2.1. The other reason is that this projection relies on a different approach than Rystad Energy's and GlobalShift's. The overall agreement is in itself a reasonably strong argument in favor of their likeliness.

For comparison, we have estimated that GlobalShift's URR is $\sim$ 3700 Gbbl, similar to Rystad's. Interestingly enough, adding BGR (2023) proven oil reserves to past production leads to a total of $\lesssim$ 3700 Gbbl. This is surprising because proven reserves lead to reserves estimates that are often much tighter than URRs, but this appears not be the case with the way BGR estimates proven reserves. Finally, Mohr et al. (2015) gives three estimates (low, best guess and high) of $\sim$ 3500, $\sim$ 4400 and $\sim$ 7500 Gbbl, respectively. Our range falls in between the low and best guess estimates. The high estimate is more compatible with the IEA's TRR estimate, which largely overestimates oil URRs.

This makes us confident that, at least on this front, our results are robust. Indeed, the sensitivity analysis of Delannoy et al. (2021a) indicates that even for sizable variations of EROI, the date and amplitude of the net oil "peak" (end of a plateau, really) varies by a couple of years with little variations of its amplitude. Our range of URR uncertainty does in fact give similar results. The variations of URR that have been discussed here are quite contained, within $\sim$ 10%; this follows because conventional oil is past its peak and all oil liquids are past the inflection point of their collective annual production curve, leaving little room for large uncertainties. Note that a narrower production period would lead to a higher peak amplitude variation and smaller peak date variation.

From Hubbert fits to past production data[11] where the total URR is constrained, we have

[11] See Appendix 2.F for an explanation of the fit procedure.

checked that a $\pm 10\%$ variation around a mean of 4000 Gbbl while keeping fixed the production in the past leads to a variation of peak amplitude of ± 1 Gbbl/yr around a maximum of 31 Gbbl/yr and $\sim \pm 4$ – 5 yrs around the gross supply peak date, 2029 (see Fig. 2.2). Note that GlobalShift's gross peak date for a 3700 Gbbl URR occurs slightly later than suggested by these simple logistic fits, namely in 2034. However logistic fits are sufficient to provide a reliable amplitude of uncertainty both for peak production and peak year (see Appendix 2.F for a justification of this statement). Note finally that the rather tight constraint on URR used in the fit reflects historical events in the data. The conventional peak oil of the US in the 70s is the cause of the production break seen around 1975, which, due to its lasting effect, is an indication that the annual production inflection point is behind us.

The only potential caveat, as always, is the possibility of an unforeseen technological breakthrough reducing in a substantial way the break-even of one or more unconventional oil sources, thereby significantly increasing the reserves. Short of this, it is unlikely that URR uncertainties affect the expected date and magnitude of oil liquids supply peak in a sensitive way.

2.3.1.2. Gas supply projections and gas URRs

There are very few projections of gas supply and URRs in the literature.

We estimate that GlobalShift's data and projection correspond to a URR of $\sim$500 Tm^3. With a conversion factor of $\sim$ 37 EJ/Tm^3 ($\sim 6\times10^9$ boe/Tm^3), GlobalShift's URR amounts to 18500 EJ. The estimate of IEA (2013) is twice as large. BGR (2023) gives $\sim$ 210 Tm^3 of proven reserves; adding the cumulative production to date, $\sim$ 150 Tm^3, leads to $\sim$360 Tm^3 or $\sim$13320 EJ, substantially smaller than GlobalShift's.

A recent research article gives $\sim$313 Tm^3 or 11600 EJ for the same quantity from the same source (Wang and Bentley, 2020). Mohr et al. (2015) gives a low estimate of $\sim$375 Tm^3 ($\sim$13900 EJ) a best guess of $\sim$750 Tm^3 ($\sim$27800 EJ) and a high value of $\sim$1260 Tm^3 ($\sim$46600 EJ). An earlier publication by the same lead author gave instead a range of $\sim$440 – 870 Tm^3 ($\sim$16300 – 32200 EJ) (Mohr and Evans, 2011). However one must keep in mind that Mohr and Evans (2011) and Mohr et al. (2015) estimates include NGLs from gas, whereas these are excluded from GlobalShift. In Appendix 2.A, this has been estimated at 650 Gbbl, i.e., $\sim$4000 EJ or $\sim$110 Tm^3. This brings these authors best guess or mid-range in GlobalShift's vicinity. Finally, Laherrère's 2025 estimate amounts to 18000 EJ, very close to GlobalShift's[12]

The higher estimate of Mohr et al. (2015) is comparable to or even higher than IEA's, and thus more akin to a TRR than a URR. The large range (and difference between these two estimates at a mere 4 year interval) comes from unconventional sources (shale/tight and hydrates[13]). Shale/tight gas is also a major source of gas in GlobalShift's projection, but to a somewhat lesser extent. At the other end of the spectrum Rystad Energy (as reported in GGR 2024, figure 69) forecasts a supply peak in 2031, 9 years before GlobalShift, at 4.6 Tm^3/yr ($\sim$170 EJ/yr), nearly 25% lower than GlobalShift's 6 Tm^3/yr ($\sim$220 EJ/yr). A URR is not given in this report but is probably close to the low estimate of Mohr et al. (2015) (375 Tm^3), for which these authors give a peak production of $\sim$150 EJ/yr for a peak date in 2041.

Looking at break-even and prices is not very informative. IEA (2013) range of mean break-even is rather limited for conventional and unconventional sources of natural gas, 4.5 to 8 USD/MBtu for an 5-yr average price of $\sim$4 USD/MBtu and a maximum of $\sim$9 USD/MBtu in the past few years. Because 10 MBtu $\approx$ 1.8 boe, IEA's range corresponds to 25 to 45$/bbl. The highest break-even (12 $/MBtu) reaches only an equivalency of 60 or 65 $/bbl. This indi-

[12] See reference in footnote 8.

[13] The economic viability of methane hydrates exploitation is not yet ascertained, especially with current natural gas prices.

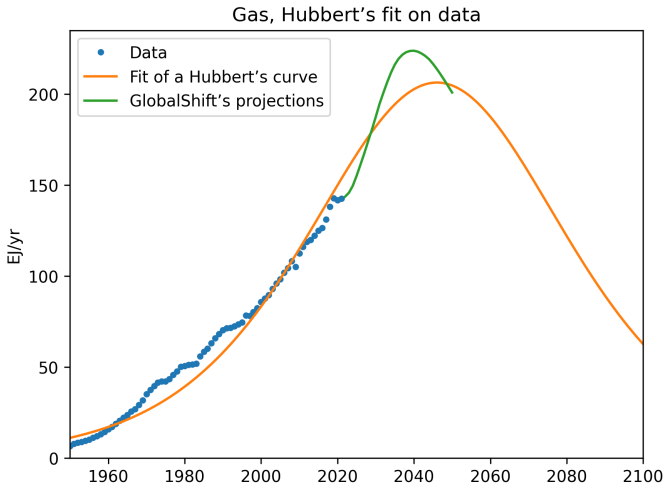


FIGURE 2.3: Hubbert logistic fit to gas production for a 18500 EJ URR. Gas supply data from GlobalShift. GlobalShift's projection also shown for comparison.

cates that gas prices will probably never be a constraint on natural gas URRs, except possibly for methane hydrates.

In the end, we retain GlobalShift's 500 Tm^3, i.e. 18500 EJ, a reasonable compromise between Rystad Energy low estimate (GGR, 2024), probably at ∼370 Tm^3 (∼13700 EJ) from the above discussion, and Mohr et al. (2015) best guess at 640 Tm^3 or 23700 EJ (NGLs excluded), probably largely overestimated in light of the most likely more reliable Rystad Energy's one. In this choice, we lean on overestimating gas reserves (due precisely to the reliability of Rystad Energy estimates), in line with our slight and reasoned bias towards optimistic fossil fuel reserves.

For illustrative purposes, logistic and Hubbert fits to the gas cumulative and annual production have been explained in Appendix 2.F. Fig. 2.3 shows the resulting gaz supply fit and related projection (compared to GlobalShift's) and Fig. 2.F1 shows the fit on the cumulative projection. The remarks made for oil about the effect of a ±10% variation in URR apply in the same way here. The amplitude of the other estimates (∼ ±30% around GlobalShift's) leads to ∼ ±10 – 15% of maximum production and a ∼ ±5 – 10 years of peak date. The bottom line is that the constraint on gas URR imposed on the fit is essential to obtain meaningful estimates of the peak date and amplitude.

2.3.2. COAL FUTURE GROSS ENERGY PRODUCTION

Coal reserves are uncertain because the most quoted source, the German Federal Institute for Geoscience and Natural Resources (BGR), gives proven reserves (nearly 800 Gt for hard coal and 320 Gt for lignite) and resources (∼16 600 Gt for hard coal, and ∼3700 Gt for lignite), but no explicit URR estimate (BGR, 2023). If one adds the already produced[14] coal (∼325 Gt or ∼9750 EJ) and lignite (∼160 Gt or ∼1600 EJ) to proven reserves, one obtains minimal URR estimates of ≳1100 Gt of hard coal and ≲500 Gt of lignite. The reserves correspond to ∼33000 EJ for hard coal and ≲5000 for lignite, i.e., ∼38 000 EJ for both. In these conversions, 30 GJ/t was assumed for hard coal and 10 GJ/t for lignite.

In a now somewhat old review, Rogner (1997) mentions that proven reserves estimates have been stable in the 20th century at ∼ 1000 Gt and also gives a URR estimate of ∼10 000 Gt,

[14]Data directly read off Laherrère's (2025) figures for hard coal and lignite and converted with the energy densities given right below. See footnote 8.

$\sim$300 000 EJ. This in fact is more in line with BGR (2023) total resources estimate of $\sim$16600 Gt (excluding past production) or EUR (estimated ultimate recovery, including past production) $\sim$17000 Gt.

Another, very conservative URR estimate, has been given by Rutledge (2011) based on region by region logistic fits to past production, at $\sim$680 Gt, but this is unreliable due to the extent of undeveloped regions, ignored in the analysis.

Finally, Mohr et al. (2015) provide low, best guess and high estimates of $\sim$660 Gt $\sim$14500 EJ, $\sim$1160 Gt $\sim$21400 EJ and $\sim$1720 Gt $\sim$31600 EJ (for all types of coal). The low and best estimates are rather small compared to the BGR ones, and the high one is comparable to BGR's proven reserves.

Two other pieces of information are available. IEA (2013) gives coal break-even up to 720 Gt, with a sharp increase starting around 650 Gt, which is more or less consistent with low end of the figure just quoted. Laherrère[15] finds URRs of $\sim$ 17000 EJ for hard coal and 2500 – 3000 for lignite, from Hubbert linearization estimates. This is two-thirds of the above BGR estimate.

We now turn to breakeven vs market prices to see if one can obtain further insight[16]. The current hard coal price[17], $\sim$100\$/t $\sim$20\$/boe is still quite low. The mean break-even remains at 100\$/t up to $\sim$500 Gt of production, which, if one includes producers and speculators margins, gives a price higher than the current one; however, the lower bound to the break-even is about a factor of 2 lower than the mean (IEA, 2013). If one assumes for the sake of discussion that the lower bound is a more realistic break-even and that margins lead to double the cost to reach the price (adopting the same rule of thumb as for oil), the mean break-even then becomes a realistic coal market price, and is at least consistent with the current market price for the current cumulative coal production. Beyond the 650 Gt of cumulative production mark, the mean coal price slope is 1.28\$/t/Gt, starting at a price of $\sim$250\$/t[18]. Again, for the sake of discussion, let us take 150\$/boe as the maximum price affordable macroeconomically. Adopting an equivalence of one ton of coal with 5 boe, this translates to a maximum price of 750\$/t for coal. A simple linear extrapolation implies thus that an extra $\sim$400 Gt of coal can be produced beyond 650 before reaching the price limit, i.e., a cumulated URR of $\sim$1050 Gt. Taken at face value, this implies as for oil that BGR data indeed provide a reasonable URR estimate for hard coal.

From this discussion, and from the fact that BGR's proven reserves + past production for oil also gave a sensible URR estimate for a resource that has long been exploited, we keep the BGR figures quoted above.

As we are still far from having retrieved half of these reserves, coal is not likely to peak soon. This can be tested with a Hubbert (logistic) fit on hard coal past production, constrained by the URR estimate of $\sim$ 33000 EJ just selected, gives in terms of estimates peak production and peak production date. This is shown on figure 2.4. The peak occurs around 2067 for a production slightly below 200 EJ/yr, only $\sim$ 20 EJ/yr above current production. For a 17000 EJ URR, Laherrère (as quoted above) did find a peak in $2037 - 2038$ and a maximum production of $\sim$ 190 EJ/yr. Thus, increasing the coal URR to 33000 EJ/yr delays the peak quite significantly, but the maximum production increases by only 5%. Still, the peak delay leaves a significantly total larger production before the peak, $\sim$ 660 EJ instead of $\sim$ 180 EJ for Laherrère's projection.

Finally the remarks that are made below in the oil discussion section on the role of a 10% variation in estimated URR apply here as well (see section 2.3.1.1).

[15] See footnote 8.

[16] The usefulness of this angle of analysis has been discussed more extensively for oil and gas (see section 2.3.1 and Appendix 2.A).

[17] There is no global market price for lignite. Because its energy density is so much lower than coal, transporting it far from production sites would make its price larger than hard coal's. It is mainly used locally, at whatever current local price.

[18] 1.28\$ per ton refers to the price increase per ton, for the added production in Gt.

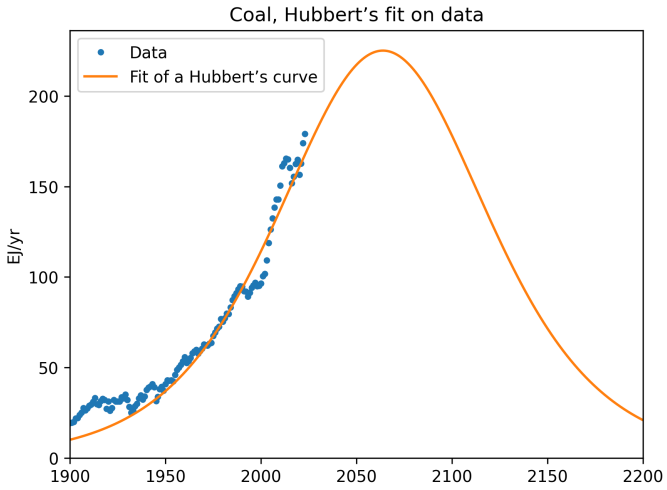


FIGURE 2.4: Hubbert logistic fit to coal production for a 33000 EJ URR. Coal supply data retrieved from OurWorldInData (Our World In Data, 2024).

2.3.3. SOLAR AND WIND RENEWABLE POTENTIALS AND ANNUAL PRODUCTION PROJECTIONS

The potential[19] of wind and solar electricity has been highly debated in the literature, with a huge range of estimates, from 32 EJ/yr (de Castro et al., 2011) to more than 3000 EJ/yr for wind farms, and 1300 (Hoogwijk, 2004) to 280 000 EJ/yr (Global Energy Assessment, 2012) for solar photovoltaic panels, as reviewed by Dupont et al. (2018) and Dupont et al. (2020).

In this work, we base ourselves on these two pieces of work by Dupont et al., due to the care displayed in their methodology to obtain more reliable estimates. They actually provide an EROI-dependent potential (standard EROI, at the outlet of the wind and solar panel farms). For wind energy, this ranges from[20] 530 (EROI of 8) to $\sim$ 750 EJ/yr (EROI of 4), with a maximum of $\sim$ 760 EJ/yr (EROI of 1). For photovoltaic panel energy production, the potential ranges from $\sim$ 720 EJ/yr (EROI of 8) to $\sim$ 1200 EJ/yr (EROI of 4 and nearly the same for an EROI of 1).

This is a rather high level of potential production (which takes into account realistic capacity/efficiency factors). For comparison, summing the maximum expected production of fossil fuels (oil, gas and coal, which do not happen at the same time) leads to $\sim$ 700 EJ/yr, more than 2.5 times less than the estimated potential at an EROI of 4 for wind and solar energy, and $\sim$ 1.8 times less at an EROI of 8. Another point of comparison is the annual worldwide electricity production, $\sim$ 110 EJ/yr. Moreover, the primary to useful energy conversion is most commonly more efficient in the case of technologies consuming electricity produced from renewable energies rather than fossil fuels, by approximately a factor of 2. This is pointed out in Appendix 2.E.

However, at least one qualification is in order. The suitability factor of various locations (measuring the fraction of area suitable for generating electricity) is taken from the literature and is unrealistically high in some locations[21]. Also, an EROI of 4 at the wind farm or solar PV panel plant seems rather low, even with moderate losses in the electric network in the 8 –

[19] Clearly, URRs are irrelevant here, as these sources are virtually infinite for all practical purposes. Instead, the maximum expected annual production is used.

[20] We take an EROI range of 4 to 8 as a characteristic and useful range of EROI at the production sites.

[21] For example, the deep Sahara or Australian deserts are unsuitable for both wind and solar farms, due to the maintenance needs of these facilities and the difficulty or impossibility of access of these locations, not mentioning the harsh conditions (e.g., night/day temperature variations, sand storms, etc) to which they would be subjected.

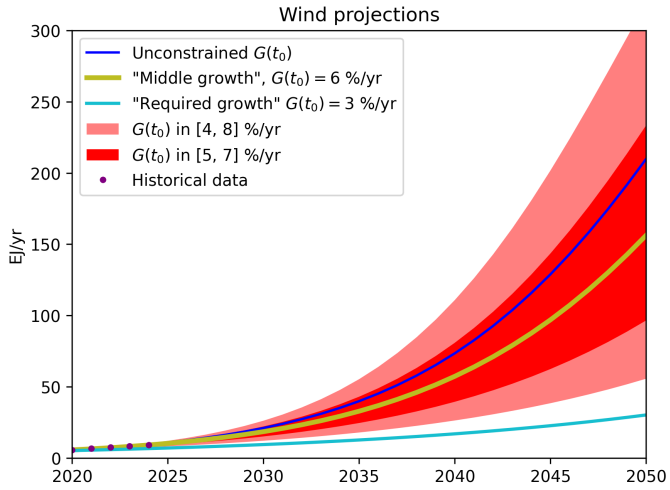


FIGURE 2.5: Annual energy production as a function of time from wind turbines. All projections use a logistic fit to the data, for an imposed maximum corresponding to 80% (640 EJ/yr) of Dupont et al. (2018) maximum potential.
The normalized growth rate is constrained at values indicated in the legend. The cyan curve represents the "required growth" scenario of section 2.4.1, the green yellow curve the "middle growth", and the outer lower and higher red bounds the "low growth" and the "high growth" scenarios respectively.

10% range. We conservatively estimate that the potential of both wind and solar farms may be overestimated by $\sim$ 20% because of these two factors.

Based on this potential estimate and past wind and solar farm development, we have modeled future projections of wind and solar production capacity with logistic functions, fixing the maximum production parameter of the fit at 80% of the maximum potentials quoted above (see Appendix 2.F for details on the fit procedure). For reasons explained below, we have also made other fits with normalized growth rates G constrained in the 4 – 10%/yr range (see Appendix 2.F for the definition of this quantity), on top of the saturation level of the logistic function. These various fits are shown up to 2050, as shown on figures 2.5 and 2.6.

We now discuss the issue of normalized growth rates G mentioned above. $G(t_0)$, shortened G, is the growth rate of the logistic function at its inflection point. In the case of the unconstrained logistical fits, $G \sim 12.5$%/yr for photovoltaic panels (PV) and $G \sim 6.5$%/yr for wind. The inflection point dates are 2045 for PV panels at 80% of maximum production; and 2055 for wind. These normalized growth rates correspond to maximum relative growth rates (in the very initial phases of deployment) twice as large, i.e., 25%/yr for PV and 13% for wind.

A recent publication has compiled normalized growth rates for nearly 150 historical technological deployments (Nemet et al., 2023). The authors indicate that all their growth rates G fall within the 1 – 12 %/yr range, with a median of 6%/yr and the two middle quartiles being bounded in the 3 – 8%/yr range[22]. For comparison, from our analysis of oil, gas and coal, we obtain much lower normalized growth rates G of 1.7 %/yr for oil, 2.3 %/yr for gas and 1.2%/yr for coal.

This suggests that the growth rate of wind is possibly within expectations, while PV's is high but not necessarily suspiciously so. On the other hand, as the deployment of both renewable energy sources is still in its early stages, not only is the maximum production level badly constrained by existing data, but the normalized growth rate and its date as well. For example, when

[22]Note that the deployment rate of ICTs such as smartphones was large but on short period. Between 2010 and 2015, the number of smartphone produced and sold per year has undergone an (exponential, not linear) deployment rate of $\sim$ 30%/yr, a seven-fold increase. However, ICTs have always been the exception, not the rule, and they are not heavy industry products.

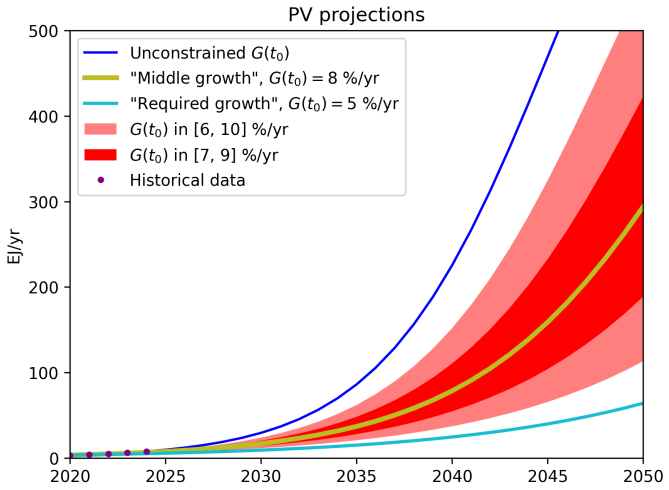


FIGURE 2.6: Annual energy production as a function of time from photovoltaic panels. All projections use a logistic fit to the data, for an imposed maximum corresponding to 80% (960 EJ/yr) of Dupont et al. (2020) maximum potential.
The normalized growth rate is constrained at values indicated in the legend. The cyan curve represents the "required growth" scenario of section 2.4.1, the green yellow curve the "middle growth", and the outer lower and higher red bounds the "low growth" and the "high growth" scenarios respectively.

performing a free logistic fit on the wind and solar PV data[23], one obtains saturation levels of 16 and 45 EJ/yr, normalized deployment growth rates of 9.5 and 12.5%/yr in 2023 and 2030, respectively (not shown on graphs).

This is unlikely. These considerations prompted us to add fits with both constrained normalized growth rates $G = k/2$ and logistic saturation amplitude L (see Appendix 2.F for a definition of these quantities). Such fits imply that the available data are not precisely representative of a long term logistic behavior, which is consistent with the fact that in early stages, too many factors enter into play on the deployment of too few sites to allow reliable long term trends to emerge.

Based on this analysis, four logistic projections with different normalized growth rate G assumptions are used:

REQUIRED GROWTH SCENARIO

This scenario corresponds to a set of normalized growth rates meeting the gap between high supply and demand, i.e., 3% for wind and 5% for PV. This is discussed in section 2.4.

LOW GROWTH SCENARIO

Lowest scenario of Figs. 2.5 and 2.6 and , i.e., 4% for wind and 6% for PV.

MIDDLE GROWTH SCENARIO

Middle scenario (yellow lines) of Figs. 2.5 and 2.6, i.e., 6% for wind and 8% for PV.

HIGH GROWTH SCENARIO

Highest scenario of Figs. 2.5 and 2.6, i.e., 8% for wind and 10% for PV.

The annual growth rates associated with different scenarios are shown in Appendix 2.D.

[23] A similar approach but on production capacities instead of actual annual production has been undertaken by Hansen et al. (2017), with similar results.

2.3.4. Nuclear energy

The energy supply from nuclear fission — which currently represent 30EJ of primary energy — is expected to grow in all institutional scenarios. This growth is primarily driven by the deployment in China (IAEA, 2023; IEA, 2024d; US EIA, 2023; BP, 2024; OPEC, 2025), which currently constitutes 16% of the nuclear production (Bernardi and Huang, 2024). Still, the expected growth between 2023 and 2050 varies significantly across these scenarios, ranging from +25% in the reference scenario of US EIA (2023) to +195% in the "high" scenario of IAEA (2023). Furthermore, several barriers to the deployment of nuclear energy are anticipated.

First, 20 EJ/yr of nuclear energy production capacity was built between 1970 and 1990 in advanced economies (IEA, 2024b). Assuming a 60-year lifetime of the plants, this means that an equivalent of 20 EJ/yr of nuclear power must be built between 2030 and 2050 simply to replace plants reaching end-of-life. Moreover, due to the limited number of new projects in these advanced economies since 2000, they may have lost expertise and industrial capacity for building new power stations. Furthermore, this energy source is controversial among the population, primarily due to safety concerns (Moriarty and Honnery, 2022; Moriarty, 2021). Nuclear projects involve the State to commit to the project over the lifetime of the project, of the order of a century (including dismantling), and even longer because of nuclear waste management. Although resources and costs are not of concern, the supply chain of uranium also faces challenges (Muellner et al., 2021; NEA and IAEA, 2024; Monnet, 2016). All these issues lead the projects to be considered as highly risky, which has financing implications. Small modular reactors (SMR), although not facing several of these issues, do not benefit from the economies of scale of large projects (Ramana, 2021; Thomas and Ramana, 2022; Mignacca et al., 2020) and are not expected to represent an important proportion of future nuclear deployment by 2050, according to previous institutional scenarios.

In this paper, we assume that nuclear energy production will increase by +60% by 2050, corresponding to BAU projections of the IEA (IEA, 2024d), as well as to the higher value found in the scenarios from the US EIA (US EIA, 2023), and the lowest value of the scenarios from the IAEA (IAEA, 2023). This still could be an optimistic projection, considering the aforementioned barriers and that most scenario projections from EPRI (2022) forecast a stable nuclear capacity value. The "low" supply scenario therefore reduces this increase to +20%, which approximately represent the addition due to the chinese prospective capacity until 2030. The projections of nuclear energy supply are shown in Figs. 2.7 and 2.8.

2.3.5. Hydropower

The hydroelectric energy production in 2022 was 16 EJ. The energy potential which is economically viable is assumed to be between 29—54EJ/yr (IPCC, 2023). Most of the remaining potential is in non-OECD countries which have not yet exploited their available potential. In line with this limited potential, the IEA (IEA, 2024d) forecasts a growth to values between 23 and 28 EJ/yr in 2050 among their different scenarios. This 23 EJ production in 2050 is kept as the high (reference) scenario while this is reduced to 20EJ in the "low" supply scenario.

2.3.6. Bioenergies

The production of bio-energies reaches 54EJ in 2022 (IEA, 2024b). These include the traditional use of biomass. IEA (2024d) forecasts an evolution of bioenergy production in the 72

– 83 EJ range in 2050 in the STEPS and APS scenario respectively. BP and OPEC (BP, 2024; OPEC, 2025) only quantify the evolution of the modern use of biomass, which is expected to increase by +70% (from 31 EJ/yr to 52EJ/yr) and 25% (from 29 EJ/yr to 37 EJ/yr) respectively in the "current trajectory" from BP (2024) and the scenario from OPEC (2025).

However, bioenergy production raise several issues, the main one due to the pressure on land-use. Indeed, land used to grow crops or trees competes with forests, meadows and agricultural land, which is a major issue and barrier to their deployment (IPCC, 2023; de Castro et al., 2014; Searchinger et al., 2017; Moriarty, 2022). They may also raise tensions regarding water and fertilizer use. Searchinger et al. (2017) and de Castro et al. (2014) also mention that the generation of bioenergy has a far lower surface energy density than solar PV. Moreover, carbon emissions of biofuels are controversial, as discussed in Moriarty (2022).

The projection of bioenergy production is based on IEA's STEPS projection. As biofuels are already accounted for in Globalshift's projections for liquid fuels, the amount of biofuels in the projections from the IEA is deducted. The projection is therefore linear towards 68 EJ by 2050. This value for 2050 is reduced to 60 EJ in the "low" supply scenario.

2.3.7. Other energies

In 2022, the energy supply from the remaining energy sources represented a growing 7EJ, dominated by geothermal energy. Although the geothermal energy potential is often considered to be limited (Moriarty and Honnery, 2020), this source grows quickly, and would probably be complemented by thermal solar and other minor renewable sources, such as tide energy, to a lesser extent. In the long term, new geothermal technologies could extend the supply potential (IEA, 2024).

The growth of the remaining energy sources is projected to be linear, with a linear fit from 2018 to 2023 included. This reaches 14 EJ by 2050. The "low" supply scenario projects a linear increase to 10EJ by 2050.

2.3.8. Total energy supply

The resulting energy supply projected up to 2050 is summarized on Figs. 2.7 (non-cumulative), 2.8 (non-cumulative, focused on non fossil energies) and 2.9 (cumulative) for the high and low supply scenarios.

2.4. Discussion

A superficial look at and comparison of our fossil fuel projections on the one hand, and wind and solar energy on the other, would leave us undecided on whether the latter may compensate for the expected decline of the former, especially under the constraint imposed by type of BAU GDP growth expectation quantified in Appendix 2.B. The purpose of this section is to discuss this point in some detail.

Economists may object that any potential energy resource tension will translate on prices which in turn will provide an economic incentive for substitution with other energy sources, thus making the problem (if real) produce its own solution. While Europeans have had first-hand experience with the first part of this statement as recently 2023-2024, from the rise in

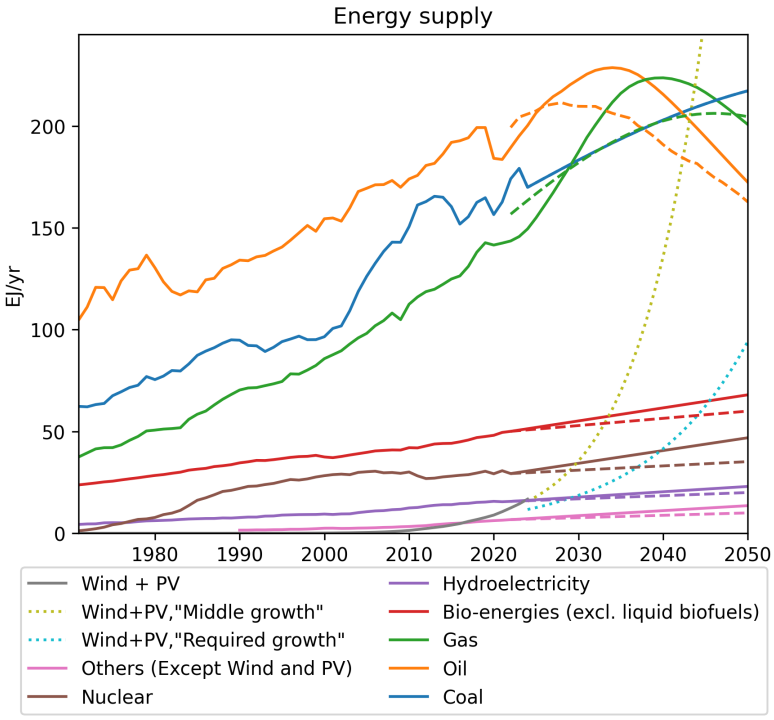


FIGURE 2.7: Energy supply data and projection of this study. Plain lines (resp. dashed lines) represent the projections of the "'high supply" scenario (resp. "low supply" scenario). Projections begin in 2023 except for wind and PV production for which the data are based on Energy Institute (2025) and extend to 2024.

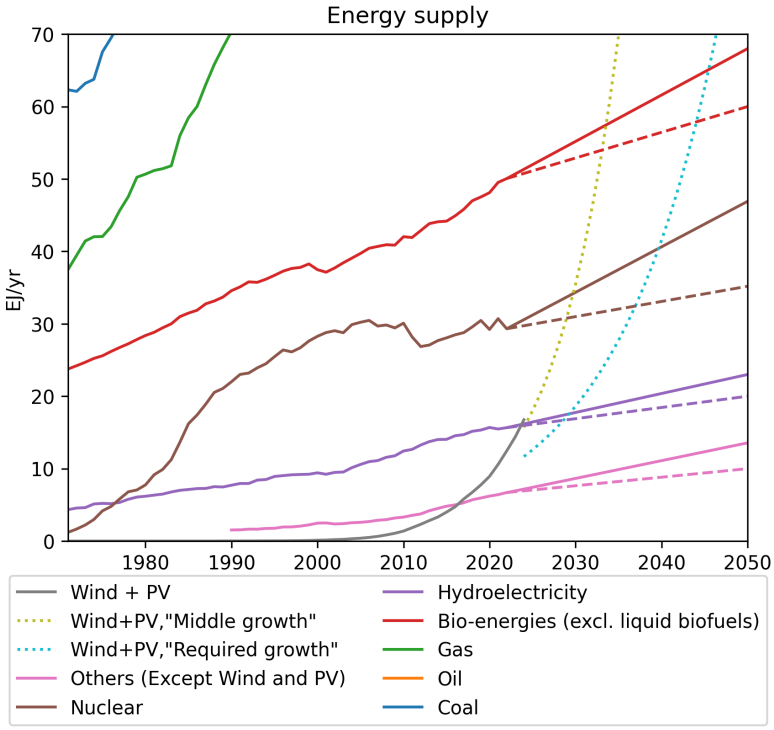


FIGURE 2.8: Energy supply data and projection of this study, zoomed on minor energy sources. Dashed curves represent the projections of the "low supply" scenario.

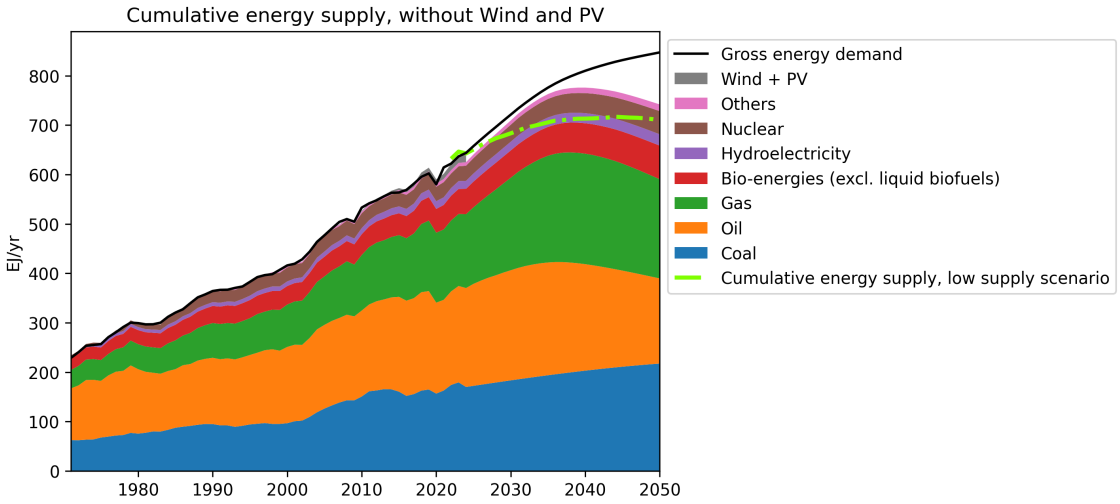


FIGURE 2.9: Cumulative energy supply from all sources, historical data and projections of this study. Wind and PV projections have not been shown because they are quite uncertain as discussed in section 2.3.3. The gross energy demand is computed in Appendix 2.B and is based on our GDP projections combined with the empirical GDP/energy correlation. The historical data of the total energy supply comes from the IEA (IEA, 2024b), while the data for oil and gas supply come from Globalshift, which explains the slight mismatch between the black curve and the top of the colored curves in historical data.

energy prices due to the Russia-Ukraine conflict, the second part of the statement is all but certain. Energy is not something the economy can do without, as amply demonstrated by the well-known GDP/energy correlation, and the deployment of new energy sources (or further development of existing ones) always takes time. The problem of whether renewable energy may rise fast enough to compensate for oil and gas gross supply declines is therefore not so easily dispelled.

2.4.1. DECLINE OF THE OIL AND GAS SUPPLY CHAINS VS ENERGY TRANSITION

From our gross and net oil and gas energy analysis, one needs to examine separately the energy supply before and after 2035, as this is the tipping point of oil gross supply. The remaining decade before the oil supply peak is very short for the development of other alternatives, e.g., fusion energy. One may therefore question if the energy system will be able to cope with the subsequent decline in oil first and then gas, considering the short time left to anticipate such a shift.

The comparison of the four scenarios described in section 2.3.3 (called "required", "low", "middle" and "high" growth scenarios) with the gap between gross energy demand and low/high gross energy supply is shown on Fig. 2.10. The "low", "middle" and "high" scenarios are defined based on the plausible normalized growth rates as explained in section 2.3.3. The normalized growth rates G of the "Required" growth scenarios for wind and PV are specifically chosen in order for supply to meet demand.

These results are illustrative, as we have not explored all couples of normalized growth rates that could meet the gap between demand and low/high supply. In this analysis, the "required energy supply from wind+PV" is computed taking into account the average difference of energy efficiencies between renewables and fossil fuels at the useful energy stage. It is considered that 2 EJ of fossil energy can be substituted by 1 EJ of electric energy, as described in Appendix 2.E.

The resulting required ranges of normalized growth rates (3 – 6%/yr for PV and 4 – 5%/yr for

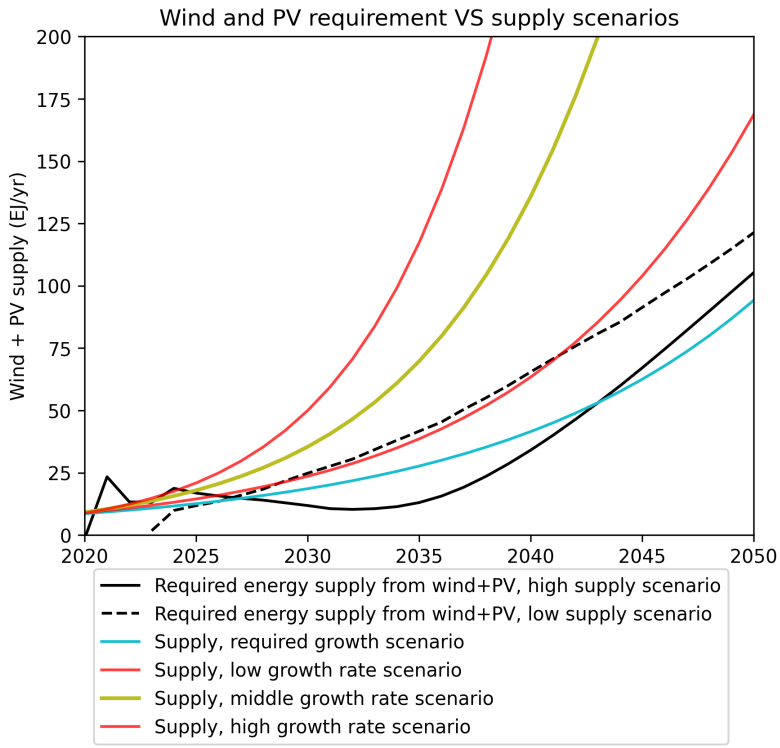


FIGURE 2.10: Required energy supply from wind+PV in the high supply and in the low supply scenarios, shown along with the energy supply of wind and PV in different deployment scenarios.
The color code for the growth scenarios is the same as in Figs. 2.5 and 2.6. The required energy supply from wind+PV are derived from the difference between the gross energy demand of Fig. 2.9 and the cumulative supply of all energy sources, with a correction due to the higher efficiency of the primary to useful energy conversion of renewables compared to fossil energies.

wind) may seem moderate in light of the discussion of section 2.3.3. In the "required growth" scenario with normalized growth rates of 3%/yr and 5%/yr for wind and PV, the actual annual growth rates stay close to 6%/yr and 10%/yr up to 2050 for wind and PV respectively. One should note that meeting the required energy supply from wind and PV requires approximately 100—125 EJ/yr of wind and PV supply in 2050 in both high and low supply scenarios. The current global electricity production is about 110 EJ/yr. Consequently, the deployment of electric grids would have to undergo a more than twofold increase in the next 25 years in order to integrate these renewable energies as well as the increase in electricity production from nuclear and hydroelectricity. Still, this may be plausible as the electric production has actually doubled in the last 25 years.

2.4.2. Critical discussion and concluding remarks

The projection of the deployment of wind and PV power made only integrate two barriers: a limit on the global potential, and a limit on the normalized growth rate at point of inflection. However, one could expect additional barriers to the deployment of wind and PV power, particularly in the most ambitious scenarios.

The deployment of wind power has already left an exponential trend toward a linear one, which indicate the presence of barriers in its deployment (GWEC, 2025; IRENA, 2025), partially due to competition on land use, geographical suitability limits, regulations and electric grid connection.

The deployment of wind and PV is contingent upon their integration in the electric grid. The electric grid has to grow in size and to adapt to these spread sources, but the timescale of the grid deployment is identified as much longer than this of wind and PV which make it a current barrier to their deployment (Guo et al., 2023; IEA, 2023; Grimault, 2021). Moreover, grid balancing would require investing in equipment to compensate reactive power, generate virtual inertia and store energy (Obuseh et al., 2025; Pithwa et al., 2024). This would entail non-linear additional costs when wind and PV would reach a significant penetration on the electric grid, which may significantly reduce the profitability of wind and PV, thus their deployment.

Deploying wind and PV also requires an increase in the electricity demand, therefore an electrification of the consumption technologies (cars, heating, etc). Still, one may expect limits in the deployment of electric vehicles due to their higher purchasing prices, but also to other technical and economical barriers (IEA, 2025b; Virmani et al., 2023; Muratori et al., 2021; Rajper and Albrecht, 2020; Zhuge and Shao, 2019; Fevang et al., 2021; Purwanto and Irawan, 2024; Naseri et al., 2024; Soszynska et al., 2024; Pulido-Sánchez et al., 2022). More generally, the lack of maturity (or readiness level), combined with technical and economical barriers affect is observed in many (if not most) sectors (Gailani et al., 2024) such as concrete production (Pisciotta et al., 2022; Busch et al., 2022), steel making (Holappa, 2020; Vogl, 2023; Pisciotta et al., 2022; Wang et al., 2021), fertilizers (Olabi et al., 2023) or aviation and shipping Bergero et al. (2023); Detsios et al. (2023); Balcombe et al. (2019); Ansell (2023); Bauen et al. (2020); Cabrera and de Sousa (2022); Afonso et al. (2023); Islam Rony et al. (2023); Prussi et al. (2021); Foretich et al. (2021). Actually, most technologies aiming to use di-hydrogen suffer these technical, economical and maturity barriers at the 2050 horizon, besides the fact that green hydrogen (di-hydrogen from renewable energy sources) itself suffer these barriers, that its production was negligible in 2024 and not anticipated to scale following the IEA (IEA, 2024,d).

Finally, a steady deployment of wind, PV and electricity-consuming technologies aforementioned would require a supported effort from industries, from the raw material extraction sector

(IEA, 2025a) particularly for some such as copper or lithium, from related financial investments (Jacques et al., 2023; Gonzalez-Redin et al., 2018), from job creation (IEA, 2024c; Černý et al., 2024; Lucas et al., 2018; IPCC, 2023; Xie et al., 2023) and from institutions and regulations (Palle, 2021; Brutschin et al., 2021; Stammer et al., 2021). There is a lack of robust quantitative elements in the literature on these barriers and uncertainties on the development of technologies that prevent us to model these barriers. Still, supporting ambitious energy transition scenarios may be challenging in the given timescales (less than 25 years), and may require tremendous efforts from multiple actors.

Some quantitative elements allow to put our assumptions on the normalized growth rate and the global wind and PV potential:
Normalized growth rates of fossil fuels are in the $\sim$ 1 – 3%/yr (see section 2.3.3), although the relevance of the comparison with renewable energies is limited as the context between both deployment differ: fossil fuel consumption historically evolved with the gradual growth of the energy demand in a context in which the increase in incomes resulted in an evolution of consumption patterns of the population, whereas wind and PV are deployed in a context in which the consumption of electricity is already well-established. Conversely the fastest growing worldwide technological deployment — smartphones — reached $\sim$ 30%/yr (in exponential growth) but only for a few years. It appears that smartphones have reached their saturation limit[24]. However, and although comparison with ICTs is popular, it is in fact misleading, as developments in ICTs (information and communication technologies) depend most on conceptual breakthroughs in design and miniaturization than on the massive heavy industry investments needed for wind farms, for example. In this respect, another, more relevant example, is the growth of the commercial tanker fleet, of $\sim$ 3%/yr over the last decade or so[25]. Again, the growth of the commercial tanker fleet may have been limited by the historical evolution of the demand of long-range maritime transport, but this still inform that the deployment of heavy infrastructures has historically been relatively slow. Most of the technologies discussed in Nemet et al. (2023) do not require either heavy industry deployment.

Finally, the potential of renewable energy production is a sensitive parameter of the analysis. Although the results of Dupont et al. (2018) and Dupont et al. (2020) used in this work — and supported by the results from Papagianni et al. (2020) — seem reasonably robust, the wide range of estimates found in the literature and summarized in these two articles suggests that some caution might be in order. In particular, there seems to be a tendency towards reducing the potential as more and more physical constraints are included in the analyses. This trend is possibly not over, which may question the possibility for the potential of wind and PV to be higher than the energy demand without energy demand reduction as the estimations of Papagianni et al. (2020) resulted in regional potential for wind and PV of the order of magnitude of the current energy demand[26].

To conclude this discussion, it is of some interest to point out that IEA's STEPS scenario projection of demand decline in fossil fuel energies (in particular oil) is strangely similar to our projected supply decline[27]. A similar remark holds for major fossil fuel producers' projections, such as BP. In fact, there is a tendency in the fossil fuel industry to transform a supply-side peak (which they cannot ignore is looming) into a demand side one, especially that an actual energy transition scenario has never happened in the past in absolute terms: we use much more

[24] https://www.weforum.org/stories/2021/08/smartphone-growth-peak-5g-apple-samsung-iphone-tech/.
[25] https://www.hellenicshippingnews.com/global-fleet-grows-by-at-least-30-over-the-past-decade/
[26] One should keep in mind that 1EJ of wind or PV would displace more than 1EJ of fossil fuels, as explained in section 2.E.
[27] STEPS stands for "Stated Policies". See, e.g., https://www.iea.org/reports/global-energy-and-climate-model/understanding-gec-model-scenarios.

coal now than in the 19th century, and fossil fuel energy use has increased by $\sim 50\%$ since the turn of the century (although it has decreased by a few percents in relative terms over the same period). Of course, demand *will* adjust to declining supply. However, whether the decline is anticipated or not makes a major difference in the way the global world economy will cope with the problem.

As a final note, we have computed the temperature rise expected as a function of time under the assumption that the projections of fossil fuel production described in this work are fully realized in the future (i.e., without substitution by renewable sources of energy). This leads to $+2^\circ$ in 2050 and $+2.9^\circ$ in 2100. Incidentally, this implies that IPCC's most pessimistic scenarios cannot be realized (see also Höök and Tang 2013). More details are available in Appendix 2.C.

2.5. Conclusion

The present work combines two threads of analysis. The first one bears on energy supply at the 2050 horizon. The second thread of analysis focuses on energy supply vs demand at the 2050 horizon under a mild business-as-usual (BAU) scenario. As this second thread is to some extent less robust than the first, it was dealt with in the discussion section rather than the results section. The BAU demand scenario itself was built in Appendix 2.B.

On the supply side, this brings together our supply analysis for oil and gas (the two fossil fuels to decline soonest), completed by a less detailed supply analysis of coal and renewable energy due from wind and solar photovoltaic panels (PV), and the other, minor sources of energy. On the demand side, we simply extrapolate the past world GDP growth linearly and translate this into gross energy demand on the basis of the well-known GDP/gross energy correlation, corrected by the deployment of wind and PV. The purpose is to analyze whether the present slow-down and future expected decline in gross oil and gas energy beyond 2035-2040 can be balanced by renewable energies.

In these two threads of analysis, we have adopted a somewhat "optimistic" bias: BAU demand is moderated, while gross fossil energy supply is critically estimated, in particular in terms of URRs of fossil fuels (the most important source uncertainty when projecting future supply), which are extensively and critically analyzed in this work.

The main results are the following. We first summarize gross energy issues:

- Oil gross energy supply is expected to peak around 2028—2035 and gas around 2040, both at ~ 220 EJ/yr.
- Coal will peak later, around 2067 at ~ 200 EJ/yr, at a similar level.
- From the literature, we estimate that the combined potential of solar PV and wind energy is rather large, ~ 1600 EJ/yr, i.e., between 2 and 3 times present day gross energy use.
- The main issue however bears on the rate of deployment of these energy sources. As we are still in the early stages of deployment compared to this potential, the past rates are most likely not reliable for future projections. Instead, we constrained the rates of deployment of solar PV and wind energies. We find that normalized growth rates of 3 – 6%/yr for PV and 4 – 5%/yr for wind are needed to bridge the remaining gap between gross energy demand and supply, in our mild energy demand growth scenario. We have

argued that such normalized rates are more demanding than they appear for the large potentials of renewables mentioned above, and represent a sizeable fraction of the present day world electricity capacity in additional annual production capacity, over at least one or two decades.

Our supply vs demand analysis has been performed at the gross energy level. It would be important and possibly critical to perform the same analysis at the net energy level (Delannoy et al., 2024). Indeed, the growth of the economy does not only rely on gross energy growth, but net energy as well, as net energy is what the economy relies on for its production[28].

A final issue must be mentioned to close this discussion. Looking at supply vs demand at the aggregated level hides the fact that not all energy sources are substitutable. However, they are not always substitutable, at least on the short time-scale of interest in this work. This is particularly true for oil, the fossil fuel closest to supply peak. This question constitutes a bottleneck of its own, as oil comes into play in one way or another in 90% of everything produced, and some oil uses cannot be substituted by other resources on the short run. Moreover, the post-peak oil supply decline may be steeper than the past increase, which would increase the tension on oil supply over time. This point calls for a detailed supply vs demand analysis focused on oil.

One may believe that tensions in fossil fuels in the next decade or so is good news for climate change. We believe however that this just displaces the conundrum: we may face instead a major structural and long lasting macroeconomic crisis if the energy transition is not addressed more swiftly and seriously than is presently the case. The worst case scenario would leave us with *both* a major long-lasting crisis *and* severe climate change issues (already underway) in a context where not enough energy would actually be available for society to face them.

[28] In the absence of net energy increase (for production of everything besides energy), there can hardly be any growth in production, at least in the absence of decoupling between GDP and energy.

Appendices to chapter 2

2.A. Critical discussion of all oil liquides ultimate recoverable reserves

In this discussion, we follow the classification of Laherrère et al. (2022), for ease of comparison. Part of this was inspired by the Supplementary Information of Bentley et al. (2025).

2.A.1. Conventional and offshore

2.A.1.1. URR estimates in the gray and academic literature

Laherrère et al. (2022) URR estimate for conventional and offshore oil is 2500 Gbbl, in the 2300-2700 range of most recent estimates (see table in the appendix of the article). There is little doubt that Hubbert linearization is reliable for this category of oil, as most of its oil subcategories have peaked nearly twenty years ago. For comparison, GlobalShift's URR (obtained from a simple extrapolation of their data) is $\sim$ 2300 – 2400 Gbbl, slightly less the Laherrère et al. (2022). Interestingly, Mohr et al. (2015) gives estimates (low, best guess and high) by subcategories; for conventional oil, these are $\sim$ 2480, $\sim$ 2540 and $\sim$ 3700; respectively. The high estimate is in fact comparable to the IEA's TRR one (right below) while the first two narrowly bracket the estimate of Laherrère et al. (2022).

IEA evaluates technically recoverable reserves to 4200 Gbbl in 2013 (IEA, 2013) and to 3600 Gbbl in 2024[29], about 1000 Gbbl higher than other estimates.

However, one must keep in mind that IEA's published technically recoverable reserves (TRRs) cannot be directly compared with URRs for at least two reasons: the difference between 'technical" and "ultimate", pointed out earlier makes IEA estimates always significantly larger than URRs; and, for conventional oil, IEA included an increase in declared reserves by many countries outside USA at the turn of the century, although such declared increases did not reflect actual reserve increases[30]. This most probably explains in part or in totality the large excess of IEA estimates with respect to available independent estimates, in particular estimates from oil intelligence companies such as IHS, Rystad or GlobalShift.

[29] See figure 8.3 of IEA (2013), summing the "already produced", "MENA conventional oil", "other conventional oil", "non CO_2 and CO_2 EORs", "Arctic" and "ultra-deep water" on the graph. Alternatively, IEA (2024), as reproduced on figure 1 of Art Berman's blog post mentioned above (footnote 9) gives, 2100 Gbbl yet to produce; adding $\sim$ 1500 Gbbl already produced (estimated from GlobalShift data) leads to $\sim$ 3600 Gbbl.

[30] Roger Bentley, private communication. This is also briefly mentioned in Laherrère et al. (2022).

2.A.1.2. Constraints from break-even and prices

It is nevertheless useful, for the discussion of conventional as well as other oil categories, to examine oil production cost and spot price issues. This is partly for completeness and pedagogical purposes for this oil category, where they do not yet play a major role, but this purely economic aspect of the problem becomes more and more relevant as one moves towards less and less conventional fuels. IEA (2013) provides a range of break-even for conventional oil, which spans the 10 – 80+$/bbl range. Interestingly, Rystad provides both remaining reserves and break-even data, evaluated in 2024[31]. Without surprise, the remaining reserves quoted by Rystad Energy are much lower than IEA's 2100 Gbbl in 2024 (once already produced oil has been subtracted) but the break-even price is also lower, in the 10 – 50+$/bbl range. Rystad's break-even range represents 60% of the actual total range (i.e., covers most of the available reserve), so that the highest expected break-even would be of 65 – 70$/bbl, closer to the highest estimate of IEA (2013), but still reasonably lower, not a surprise for this oil category. Furthermore, in the same web post, Rystad Energy provides break-even for new developments for different oil categories, including OPEC production (among the cheapest conventional oil sources), shelf and deep-water. For the most expensive categories (the last two), the mean break-even is $\sim$ 50$/bbl, making the earlier IEA higher estimate of $\sim$ 80$/bbl realistic, in spite of the decrease in mean break-even also noted by Rystad energy.

The other aspect of this economic discussion bears on the comparison of break-even to crude oil prices. A common practice is to equate the break-even to the price to understand the conditions under which a particular oil source becomes profitable. This is misleading. In fact, oil prices exceeding break-even is a necessary but not sufficient condition, as oil prices include not only the production costs, but the margins of oil producers and speculators. Needless to say, these are quite difficult to quantify, due to the financial sector opacity[32]. One may however have an idea of the difference between break-even and oil prices nowadays. For example, current crude oil prices ($\sim$ 75$/bbl on average over the last six months at the time of writing) are substantially higher than the current mean break-even of conventional oil ($\sim$ 25$/bbl according to the same post by Rystad Energy) or, e.g., current light tight oil mean break-even ($\sim$ 45$/bbl, again from Rystad Energy). From this we conclude that the added margins between mean price and mean break-even account for anything between a factor of 1.5 (to be on the safe side) to a factor of 3 of the beak-even cost, on average for the most important sources of oil today, to reach the oil spot price. This may have been lower in the past, in particular before the major increase of activity on the oil derivatives market observed since the 2008 economic crisis[33], and there is little prospect of this decreasing in the future, especially in a BAU scenario where constraining regulations on financial markets are not in order. As an example, taking a factor of 2 as typical rule of thumb, the mean break-even of IEA's "other conventional oil" category climbs to 80$/bbl.

The historical tendency is clear: oil prices increase because the cheapest oil sources become less and less abundant; this tends to maintain margins for oil sources that are in the mean break-even vicinity, which increases with time. Oil sources with break-even close to oil prices are in fact not exploited (or marginally) for a number of reasons: sizable investments, long times of return over investment (years or even a decade, except for LTO, but this is an exception), oil price volatility (largely a recent phenomenon due to speculation on oil derivatives) which requires a sufficient "margin buffer", as volatility provides only a very limited horizon of predictability on actual prices (days or weeks).

[31] See footnote 2.

[32] Producers also invest in oil financial markets, either for hedging or for speculation.

[33] Daily "virtual" barrels exchanges on oil derivatives markets nowadays amount to $\sim$ 50 times the actual daily sales of oil Bouchouev (2023).

Because conventional oil sources have a low to moderate break-even (in comparison to the 100$ oil price milestone), even for some not in use yet, the economic constraint remains moderate. We have discussed it to some extent for completeness and in order to pave the way for the other oil categories. Some of the future conventional oil is not going to be competitive for prices lower the 80 – 100$/bbl, or even more, but in the end the economic constraint is expected to have a limited impact on the transformation of TRRs in URRs for conventional oil. However, if one adds other types of obstacles to oil exploitation (protected areas, etc) to the two points mentioned above to the differences between TRRs and URRs, one has a solid basis to understand why most URRs of conventional and offshore oil are at least 1000 Gbbl lower than IEA's TRRs, on top of the intrinsic robustness of Hubbert linearization for this oil category, which remains the strongest argument.

2.A.2. Shale/tight oil

2.A.2.1. URR estimates in the gray and academic literature

Laherrère et al. (2022) ascribe a URR of 3000 Gbbl to their second category, or equivalently, estimate that shale and light tight oil (LTO) represent an extra 500 Gbbl of ultimate recoverable resources. Hubbert linearization is also most probably reliable here, considering the extent of the linear regime visible in figure 7 of Laherrère et al. (2022), but, as for the previous category, examining other estimates is useful.

Shale oils has been discovered a long time ago, but is still little exploited to date, due to their high cost of extraction and low EROI. This implies that lumping them together with LTO will tend to make their contribution to this category uncertain.

Rystad Energy[34] estimates that $\sim$ 100 Gbbl of LTO remains to be exploited, and $\sim$ 80 Gbbl for shale oil. Adding $\sim$ 40 Gbbl already produced in these two categories[35] gives a combined URR of $\sim$ 220 Gbbl, less than half the Laherrère et al. (2022) result. For comparison, GlobalShift's URR is also substantially lower, at $\sim$ 200 Gbbl.

On the other hand, IEA's TRRs estimates are $\sim$ 1100 Gbbl for shale oil (both in 2013 and 2024[36]), $\sim$ 250 for LTO in 2013 and $\sim$ 500 in 2024, for a total of $\sim$ 1350 to 1600 Gbbl, way above the previous URRs estimates. Mohr et al. (2015) low, best guess and high amount, for shale/tight oil to $\sim$ 340 (LTO almost exclusively), $\sim$ 1140 ($\sim$ 370 for LTO) and $\sim$ 2600 (LTO: $\sim$ 640) Gbbl, respectively (shale/tight oil). Except for the low estimate, these are in the same range as IEA's TRR; shale oil URRs in particular are particularly high in this last reference.

The discrepancy for LTO is probably the easiest to understand, as much of the technically recoverable reserves are in countries with adverse legislative dispositions and grassroots movements, even though the break-even is not so large, as already pointed out[37].

2.A.2.2. Constraints from break-even and prices

For shale oil, however, IEA (2013), gives a break-even range of 60 – 100$, and Rystad (2024), 35 – 85$[38]. With our conservative rule of thumb (factor 1.5 to 2) this yields an expected crude oil price of 50 – 125$ range and 70 – 170 (high range) when this oil is brought to market.

[34] See footnote 2.

[35] From GlobalShift data, as for all other such numbers of produced volumes to date.

[36] IEA (2013) and footnote 9.

[37] Roger Bentley, private communication.

[38] Once the 60% range has been extended to 100%. The difference with IEA's break-even is largely explained by the decrease in break-even pointed out by Rystad Ebergy over the 2014-2024 decade. Most of the decrease has occurred during the 2014-2020 period, and break-even have been stable since, for all major oil categories.

The low range is expected to apply when these are still a secondary source, but they cannot become a major one without even higher sources becoming more widely exploited, in which case the high range should apply. Oil prices above 120 – 150$ are unsustainable as these can only lead to high and generalized energy prices (and many other commodities as well) whatever the source, which in turn drives large segments of the population to both cuts in expenditures, and may lead companies across many sectors of activities to bankruptcy if such high prices are maintained long enough. As a consequence, one form of economic crisis or another is triggered, bringing down oil prices, through temporary GDP declines and/or oil prices/oil consumption reductions. This is actually what happened in 2008 (Hamilton, 2009). In all likelihood, because of this, large fractions of shale oil will never be able to reach the market.

This discussion implies that IEA's TRRs estimates are probably much beyond realistic oil exploitation levels in this category, although it is difficult to say precisely by how much. Still, and in the absence of more information, the fact that Hubbert linearization yields believable results is strong enough in our view to adopt – as for conventional oil – Laherrère et al. (2022) estimate of 500 Gbbl. For the same reasons, we find the two higher estimates of Mohr et al. (2015) unrealistic, especially for shale (kerogen) oil.

2.A.3. Extra-heavy oil

2.A.3.1. URR estimates in the gray and academic literature

This is probably the most contentious category, with no clear consensus on the definition, and huge differences between IEA's TRRs estimate[39] ($\sim$ 1500 Gbbl in 2013 and $\sim$ 1900 in 2024 for "heavy oil and bitumen"), Laherrère et al. (2022) URR of 500 Gbbl, Rystad (2024) estimate[40] of $\sim$ 20 (remaining) + $\sim$ 20 (already produced) leading to a URR of $\sim$ 40 Gbbl, and $\sim$ 90 for GlobalShift. Mohr et al. (2015) completes the picture with $\sim$ 670 (low), $\sim$ 760 (best guess) and $\sim$ 1300 (high) Gbbl.

We are entering here a zone of larger uncertainty, not only because of the huge range of estimates just quoted, but also because the Hubbert linearization method becomes sensibly less precise for this oil category, as the cumulative production to date of extra-heavy oil is only a small fraction of the potentially recoverable oil, if one excludes the very low estimate of Rystad Energy. As a matter of fact, the cumulative category of Laherrère et al. (2022) (which is the one quantified) is largely dominated by the two previous categories (this is actually visible by comparing the two relevant sub-graphs of their figure 7). In fact, the extra-heavy oil category alone has been analyzed by Laherrère[41] (2025). Hubbert linearization is uncertain, as the linear data domain is nearly absent, and rather noisy. Laherrère finds a URR range of $\sim$ 60 – 80 Gbbl, roughly consistent with GlobalShift's and Rystad's, which were obtained from aggregation from individual wells. The agreement may or may not be a strengthening argument, as well by well estimates of future production also suffer from the same low level of exploitation compared to potential reserves, on worldwide average.

To get a better grasp of such potential recoverable reserves, it is useful to look at estimates for the two largest sources of extra-heavy oil, the Canadian tar sands and Venezuela's "Orinoco Belt", compared to worldwide resources. For Venezuela, a USGS publication gives a TRRs range of $\sim$ 380 - 650 Gbbl (Schenk et al., 2009). By comparison, Dusseault (2001) gives $\sim$ 270 Gbbl for the same resource and also $\sim$ 200 Gbbl for the Alberta tar sand (bitumen) oil. This

[39] See IEA (2013) and footnote 9.
[40] See footnote 2.
[41] See footnote 8.

gives a range of $\sim$ 470 – 850 Gbbl for these two oil sources only. To give an idea of their share in extra-heavy oil worldwide, one may compare the Canada and Venezuela *(original oil in place* (OOIP) (a measure of the total resource) to the world OOIP for extra heavy oil. Dusseault (2001) quotes 1200 Gbbl (OOIP) for Venezuela and 2200 Gbbl (OOIP) for Canada. Another USGS report distinguishes two types of oil, heavy oil and bitumen. Focusing on bitumen (extracted from tar sands), this report gives 2100 Gbbl (OOIP) for Venezuela and 2400 Gbbl (OIP) for Canada, for a total known and prospective discovery of 6400 Gbbl (OOIP) (Meyer et al., 2007). Original rates of recovery were rather small. Current recovery rates are of the order of 10%. Dusseault (2001) estimates (from a survey of geologists and his own expertise) that an ultimate rate of 20% is likely. From (Meyer et al., 2007) OOIP estimates, this yields TRRs of 420 Gbbl (Venezuela), 480 Gbbl (Canada) and $\sim$ 1300 Gbbl (Worldwide), which is similar to the high end quoted by Mohr et al. (2015). If one pushes recovery rates up to 30% (which Dusseault 2001 considers as still possible but less probable), one obtains $\sim$ 2000 Gbbl worlwide. This last figure is comparable to IEA's 2024 TRR estimates, which indicates that IEA's expectations are on the high end of the spectrum.

2.A.3.2. Constraints from break-even and prices

The next question, as previously, is what insights can be obtained from a look at the economic viability of tar sands. IEA gives a break-even in the $\sim$ 50 – 90$ range. Rystad Energy gives $\sim$ 35 – 85$ (complete range). We will not repeat here the previous argument, but it is clear that a significant fraction of the TTR and higher URR estimates will never become economically viable.

From these arguments, we estimate that about half of the 1300 Gbbl TRR is a reasonable educated guess for a URR of extra-heavy oil, that is, $\sim$ 650 Gbbl, i.e., higher but in the same range as Laherrère et al. (2022) (which may, however, be a coincidence in light of the previous discussion), and comparable albeit slightly smaller than the low estimate of Mohr et al. (2015). However, we must keep in mind that an oil intelligence company like Rystad energy, with inside knowledge and much more manpower than GlobalShift or Mohr et al. (2015), sees very small prospects for extra-heavy oil. On this basis, it seems prudent to keep a range and not only some crude estimate for this highly uncertain oil category, say 100 – 650 Gbbl (still substantially higher than Rystad Energy to be on the safe side).

2.A.4. NGL, CTL and GTL

2.A.4.1. URR estimates in the gray and academic literature

For these oil liquids sources, Laherrère et al. (2022) gives a substantially higher URR than for other non conventional oil sources, of $\sim$ 1500 Gbbl. This is also the least believable of the four estimates provided in the article, with a narrow Hubbert linearization domain.

In this discussion, it is useful to consider NGLs on the one hand and CTL/GTL on the other. For one thing NGLs are a by-product of oil and gas exploitation, and their historical production would give by itself a much better reliability to Hubbert linearization. Conversely, Hubbert's model (and the linearization method that stems from it) does not make much sense for CTL and GTL, in our view. These are not provided by direct exploitation of coal and gas (they are not necessary by-products of this exploitation) but instead depend on a decision to use — or not — coal and gas for this purpose. The constraints coming from Hubbert model and related supply peaks are indirect at best. Actually IEA (2013) does not provide prospective

volumes of production for CTL/GTL, only break-even.

Let us first examine CTL and GTL, as only GlobalShift gives future production estimates for these two oil liquids.

The very low levels of future production estimated by GlobalShft for CTL can be understood once the energy cost of the known processes to liquefy coal is factored in; this is even more the case when $C0_2$ capture is included, as this brings the EROI of such processes very close to one, or even below (see Table 4 of Delannoy et al. 2021a). Even taking into account recent technological advances, the EROI remains quite low ($\lesssim 1.5$) for a break-even of 90 – 100$ and a current coal price of 100$/ton (Li et al., 2023). There is very little prospect of coal prices decreasing noticeably in the future. First the expected tension on oil that is already noticeable results in an increased demand for the other fossil fuels, which maintains pressure on coal and gas prices. Second, the declining oil EROI trend puts further pressure on gas and coal for oil production, as pointed out earlier. Finally the high break-even of CTL implies it will remain a niche market in the future, even if the expected/needed margin is lower, say 50%, short of a major technological breakthrough.

The same arguments apply to GTL to a large extent. The EROI of the process is comparable to CTL's, and gas is under pressure as well, even ignoring the growing demand of gas in the oil supply chain (in any case, gas and oil prices are well-known to be coupled). The break-even is however somewhat lower (Braide et al., 2024).

This leaves us with NGLs[42]. As for other fossil fuels, Laherrère (2025) has made a direct Hubbert linearization estimate of NGLs URR; the data allow for the procedure to give a sensible result, although somewhat less robust than for the two first categories of oil examined in this discussion. The estimate is ~ 650 Gbbl (URR). IEA (2013) does not give an estimate but in 2024, this agency projected 700 Gbbl of NGLs for the future. Adding the 150 Gbbl already produced yields a TRR estimate of 850 Gbbl. For once, this does not exceed the available URR estimate by a large margin. Mohr et al. (2015) provide no estimates for this category (but it is included in their natural gas URR estimates).

2.A.4.2. Constraints from break-even and prices

We do not have break-even estimes for NGLs, but as these are byproducts of gas extraction (2/3 of the annual world production) and oil refining (1/3), the arguments made above (and including gas) would apply. However, these is no need to dig any further in this direction considering the closeness of the TRR and URR estimate, and we keep 650 Gbbl as a URR estimate of NGLs.

2.B. Demand projection

A projection of the total energy demand is made in this Appendix, based on a moderate GDP growth scenario and on the GDP/energy correlation empirically observed. For this purpose, we have used the World Bank deflated world GDP data and IEA's World Energy Balances (WEB) gross primary energy data (IEA, 2024b).

First, the global GDP is projected. This consists just of a linear extrapolation of the linear fit on the historical data performed between 1990 and 2020. The global GDP is shown in

[42] Refinery gains apply only in volume, not energy, at least not to any noticeable level. Biofuels are intrinsically limited: converting biomass to fuels is an inefficient process and would require way too much arable land to be a game changer.

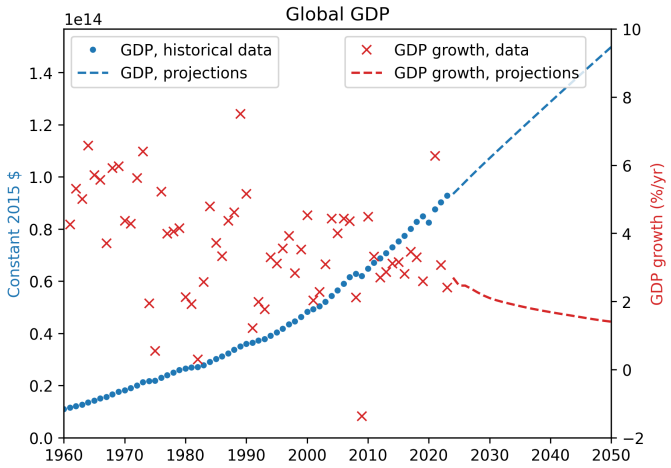


FIGURE 2.B1: Evolution of the global GDP (blue, left axis) and its growth (red, right axis).

figure 2.B1. This is by design somewhat less optimistic than OECD's (OECD, 2023), which expects a small exponential growth rate in the next decades. The difference however is small, even in 2050. Similarly, it is less optimistic than IEA's 2.7% average annual growth rate to 2050[43]. This reflects our slight bias towards a moderate growth paradigm, due to the new area of world turmoil and uncertainties on resources (including energy resources) that started with the peak of conventional oil around 2006, and that has been observed through the accelerated pace of crises of various sources since then. This bias makes future energy demand easier to satisfy.

Second, a projection of the total energy demand is made based on the well-known GDP/energy correlation. The correlation between GDP and the primary energy consumption has been extensively studied in many countries in the literature (see, e.g., Haberl et al. 2020). However, projecting the future trend is not straightforward due to the deployment of renewable energies. Indeed, Haberl et al. (2020) point out that the relevant correlation is between GDP and useful energy rather than primary energy. This difference become an issue when the penetration of renewable energies in the energy mix increase, in which case the GDP/energy correlation would not follow linearly. This is due to the fact that the primary to useful energy conversion has a far better efficiency in the case of renewable energies than for fossil fuels, as explained in Appendix 2.E.

In order to account for this effect while keeping the model quite simple, it has been chosen to project the GDP/energy correlation linearly based on historical trends between 1991 and 2022, and then correct the projections considering the penetration of wind and photovoltaic power in the energy mix. As discussed in Appendix 2.E, it is assumed that 1 EJ of wind and PV could substitute 2EJ of primary energy from fossil fuels. The energy supply from wind and PV is thus assumed to be the required quantity in order for supply to meet demand, either in the "high supply" or the "low supply" scenarios. The resulting GDP/energy correlation projections are shown in Fig. 2.B2. The "low supply" scenario assumes a higher wind and photovoltaic penetration in the energy mix, which explains why the energy demand is slightly lower than in the "high supply" scenario. Their deployment is shown in Fig. 2.10.

The energy demand is then derived from the previous GDP and GDP/energy correlation projections, and shown in Fig. 3.E3. The energy demand in the low supply scenario is lower

[43]IEA uses a purchasing power parity (PPP) GDP whereas we simply use a deflated one. Therefore, our projections cannot be directly compared to theirs. OECD's projections are in PPP unit, and they provide a PPP conversion factor that allows us to convert PPP units into non-PPP ones. The GDP projections from OECD (OECD, 2023) are slightly more optimistic than ours, but less than the IEA's 2.7%/yr growth. We conclude that our deflated GDP projections are somewhat more moderate than IEA's equivalent deflated non-PPP projections.

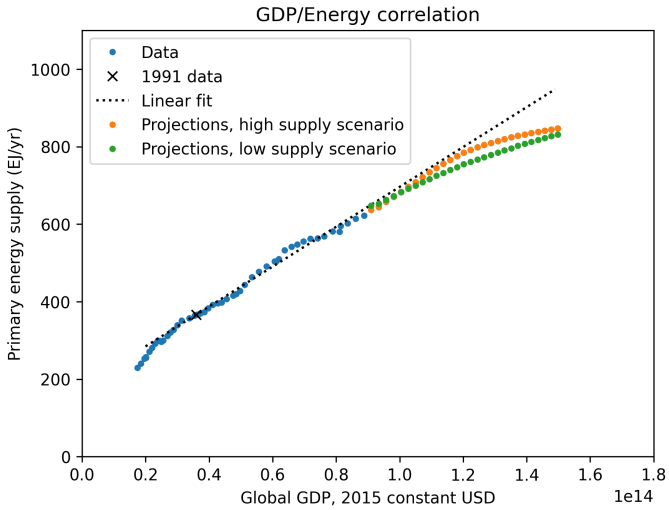


FIGURE 2.B2: GDP/Energy correlation from 1970 onward and our BAU projections.

than this of the high supply one due to the higher wind and PV penetration in the energy mix, as explained previously and in Appendix 2.E.

The total energy demand is thus found about 10% higher than these of the IEA's STEPS (IEA, 2024d) scenario when a similar correction than done previously to the energy accounting has been performed. As the GDP projections of the IEA are higher than these of this article, it is deduced that the GDP/energy correlation from the IEA increases slower this of this article.

In this article, the projections on the energy demand is only used to estimate and discuss the order of magnitude of the renewable energy deployment required.

2.C. CLIMATE CHANGE PROJECTIONS

As fossil fuels represent three quarters of the greenhouse gases emissions (IPCC, 2023), Hubbert's projections of fossil fuels allow us to compute a first-order estimation of future CO_2 emissions and of climate change. The aim is to provide an estimate of the global rise in temperature if all available fossil fuels (as described in this work) were consumed.

Hubbert's fits for gas and coal as well as the median 4000 Gboe Hubbert's fit for oil are used in order to produce production estimates up to 2200. Globalshift's projections up to 2050 could also be used, but we seek to model emissions to a longer time horizon. We then assume that the emission intensity coefficients for oil, gas and coal are constant over time, at 59 Mt CO_2/EJ for oil, 55 Mt CO_2/EJ for gas and 91 Mt CO_2/EJ for coal. These values are retrieved from dividing CO_2 emissions due to the energy source by its energy production, with data of IEA (2024d).

CO_2 emission data from land-use change and concrete carbonation are included (retrieved from Friedlingstein et al. 2025). Land-use emissions are projected linearly based on historical trends since 1850, and carbonation is projected as a bell-shaped curve.

The combination of these three contributions gives the total CO_2 emissions.

Finally, the transient climate response to cumulative emissions of carbone dioxide (TCRE) concept is used to calculate the global rise in temperature from cumulative CO_2 emissions. Despite the fact that CO_2 is not the only greenhouse gas and that the earth climate system is com-

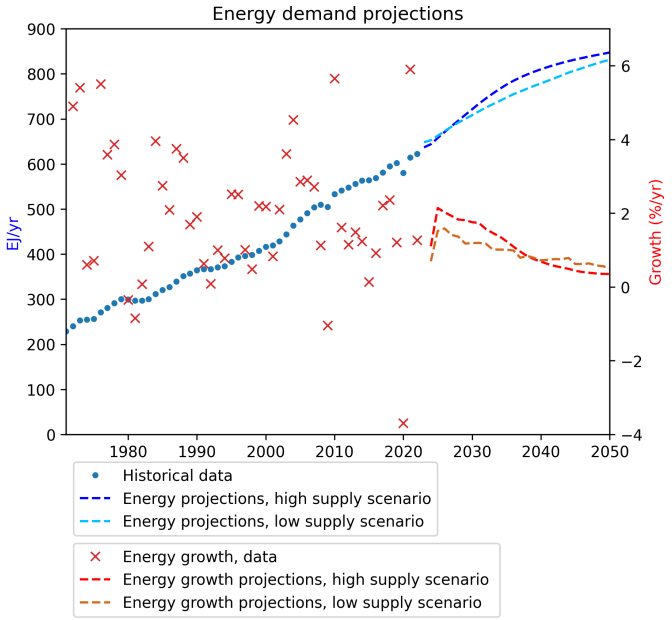


FIGURE 2.B3: Total primary energy demand projections (blue left axis), with associated growt rates (red right axis). The difference in the energy demand in the scenarios come from the difference in penetration assumptions of wind and photovoltaic in the energy mix, see text for more details.

plex, it is observed that the temperature rise can be quite linearly correlated with cumulative CO_2 emissions following IPCC (2023) (see Box 3.4 page 321). A linear regression is performed on data from the working group I (WG I) of IPCC in the scenario in which cumulative emissions have a 50% chance of limiting peak warming to the designated temperature. Peak surface warming are taken from HadCRUT5 (Morice et al., 2021)[44] and are relative to the 1850—1900 temperature average.

Projections of the CO2 emissions and temperatures rise are shown in figures 2.C1 and 2.C2.

Projections of the CO_2 emissions and temperatures rise are shown in figures 2.C1 and 2.C2. Not surprisingly, global warming still reaches 1.5°C in 2032, 2°C in 2051, +3.1°C in 2100 and saturates close to 4°C at the end of the fossil fuels era. This confirms that one needs to shift away from fossil fuels rather fast and at any rate much sooner than their expected supply exhaustion in order to contain the global rise in temperature under +2°C. This also indicates that the worse IPCC scenarios cannot be reached by GHG emissions alone, a point argued in more detail in Höök and Tang (2013).

2.D. WIND AND PV DEPLOYMENT GROWTH RATES

The figure 2.D1 shows the historical growth rates of the wind and PV annual energy supply, and the growth rates of several projections: the logistic fit with all parameters being unconstrained, the "middle growth" and "required growth" scenarios.

[44] Updated data were found at `https://www.eea.europa.eu/en/analysis/indicators/global-and-european-temperatures/global-and-european-annual-average`.

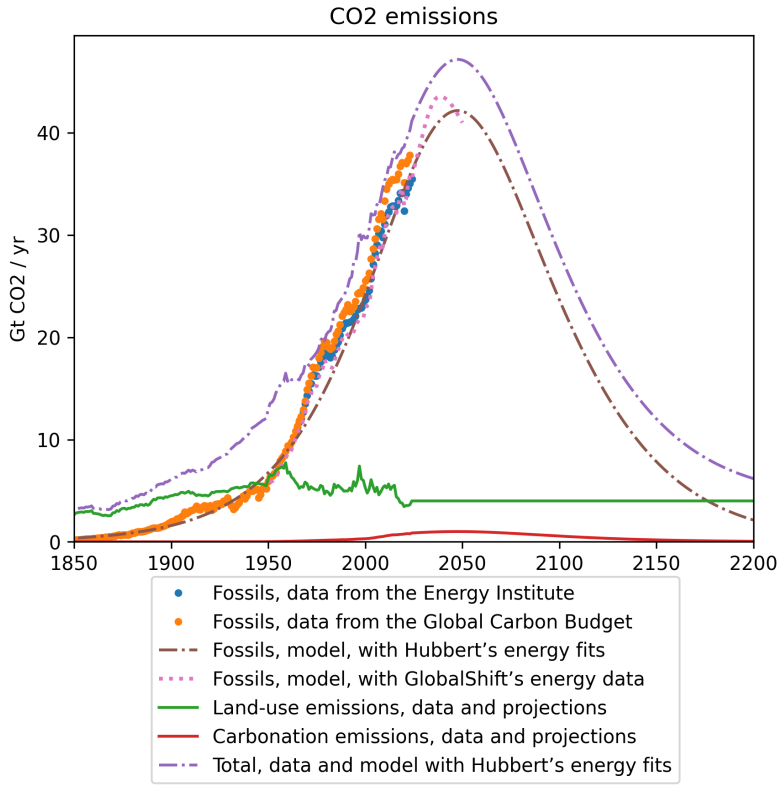


FIGURE 2.C1: Projections on global CO2 emissions.
Dashed and dotted curves from Hubbert's fits on oil, gas and coal energy supply. Dotted line from GlobalShift's data for oil and gas, and Hubbert's fit for coal energy supply.

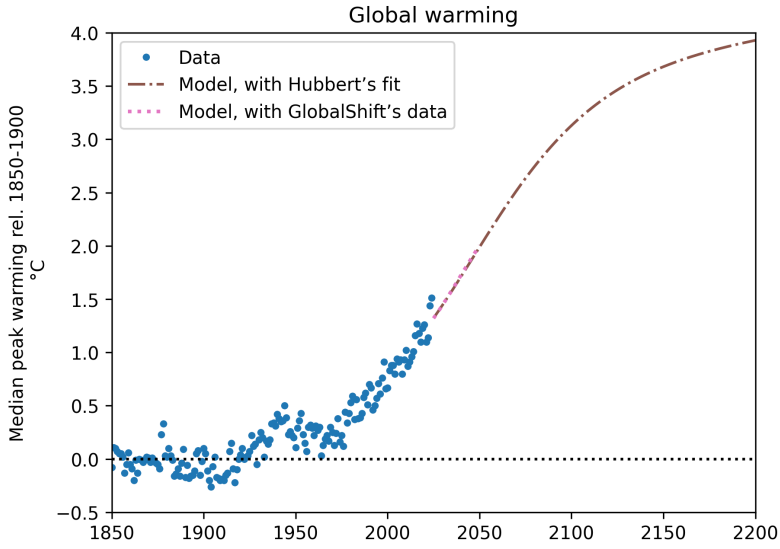


FIGURE 2.C2: Projections on the median temperature rise, relative to the 1850—1900 average.
Data from HadCRUT5. Dashed and dotted curves from Hubbert's fits on oil, gas and coal energy supply. Dotted line from GlobalShift's data for oil and gas, and Hubbert's fit for coal energy supply.

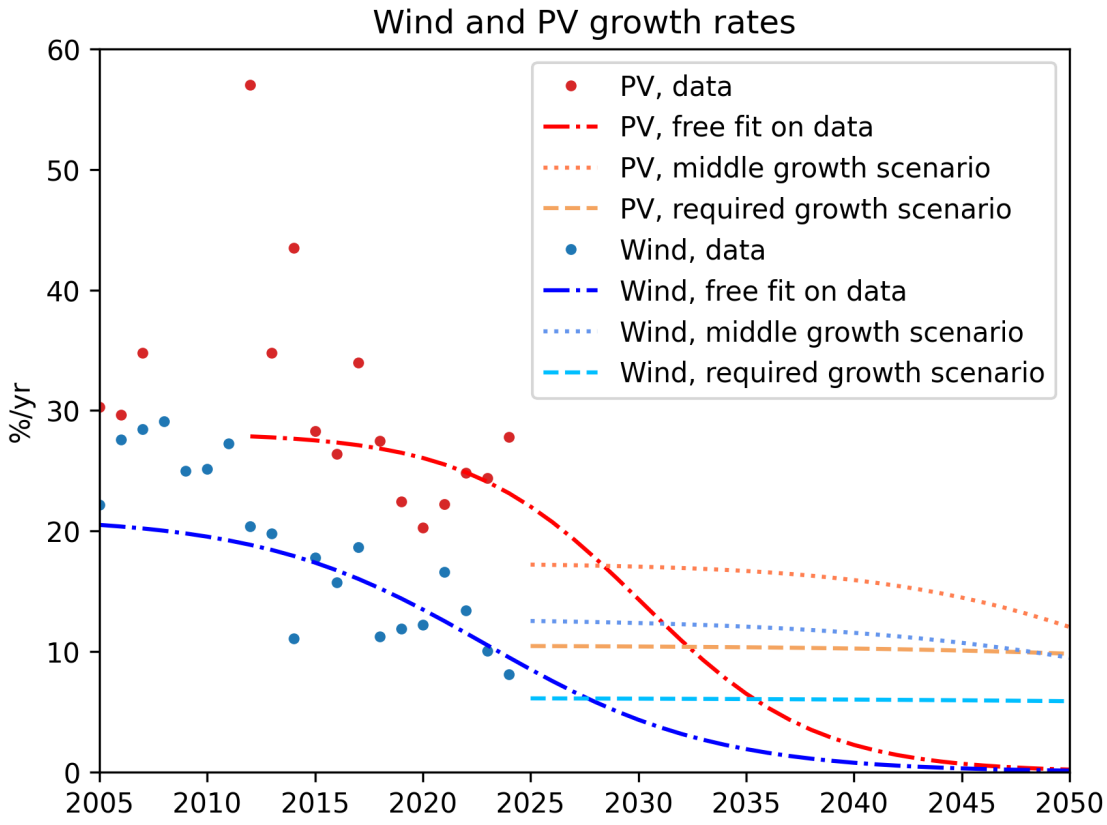


FIGURE 2.D1: Annual growth rates of wind and PV energy supply among scenarios discussed in section 2.3.3. Note that our scenarios do not seek to best project historical growth rates, but depict different possible trends over the long-term.

2.E. Energy substitution between wind/PV and fossil fuels

A core goal of deploying wind and PV is to substitute fossil energies, primarily because of their climate impacts and of the anticipated decline in their supply. However, substituting 1 EJ of fossil energy requires less than 1 EJ of wind or PV, on average, due to different energy efficiencies in conversion processes.

Indeed, primary energy is used to quantify the energy content of fossil fuels. In the case of wind and PV, the energy produced is grossly equivalent to the electricity generated by the wind turbine or the PV cell. The efficiency of the subsequent steps in the energy conversion chain then differ. In particular, fossil fuels are mostly associated with low-efficiency processes, whereas the use of electricity for the same applications has higher efficiency[45]. In all substitutions, the useful energy — the energy of the process ultimately sough (i.e. the mechanical energy moving a car) — is sought to remain the same. This means that, for a given amount of fossil fuel to be substituted, one should find the quantity of renewable energy that would be required to produce the same useful energy. Such an estimation requires a precise model that quantify the conversion of all energy use into useful energy for all applications, as done by Aramendia et al. (2024), as well as a model of the evolution of the activities in which renewable energy will substitute fossil fuels. This is far beyond the scope of the present study.

Brockway et al. (2024) states that the current global conversion of primary energy into useful energy has a 47% averaged efficiency. Based on this last article, on Aramendia et al. (2024) and on typical conversion factors in the applications of electricity, we estimate that wind and PV production could produce approximately twice the useful energy of the same amount primary energy from fossil fuels. In other words, that 1 EJ of oil, gas or coal could be substituted by 0.5 EJ of wind or PV.

Although this estimation is not precise, it is sufficient for the purpose of the present work, and allows us to assess the feasibility of the required deployment of wind and PV.

2.F. Logistic fits on fossil fuels and renewable energy data

In the results presented in section 2.3, a number of logistic fits have been performed on energy supply data, for various purposes. On the conceptual level, these logistic fits are identical to the procedure followed by Hubbert in his well-known forecasts of oil production peaks and URRs.

2.F.1. Logistic and Hubbert functions

The main idea is to fit a logistic function to the cumulative production of an energy source, such as oil or coal. The logistic function has a simple form. Denoting by p the instantaneous production assimilated to the annual production[46], $P(t)$ the cumulative production function,

[45] Fossil energies are mostly used in processes that convert heat into mechanical energy, i.e. in electric thermal plants and vehicles engine which have a low efficiency, i.e. approximately 30% for vehicles's engine and around 50% for most efficient steam turbines producing electricity. Conversely, the efficiency of electric engines is of the order of even exceeds 95%.

[46] This formulation is continuous in time. Usually one uses a discrete time data set, e.g., annual production time series. In practice, the production changes very little from one year to the next, so that fitting the continuous production to the data is a very accurate procedure. This amounts to assume that the annual production is simply the mean instantaneous one (a rate of production in energy unit per second)

L the total production once the resource is depleted, i.e., the asymptotic cumulative production, t the time, t_0 the time of maximum annual production and k the characteristic growth-time scale, the logistic function reads

$$P(t) = \int_{-\infty}^{t} dup(u) = \frac{L}{1 + \exp\left[-k(t - t_0)\right]}. \tag{2.F1}$$

For fossil fuels, L is identical to their ultimate recoverable reserve (URR) — at least when the logistic fit provides a faithful representation of the data. For renewable energy sources L is the maximum production per year, or the maximum production capacity per year (depending on the modeler purpose). In this work, we model the annual production (windmills and solar PV panels, independently).

The resulting curve has an S shape, starting from 0 and increasing asymptotically to L, with t_0 being its inflection point.

From this, the annual production $p(t)$ follows and reads

$$p(t) = \frac{kL \exp\left[-k(t - t_0)\right]}{\left(1 + \exp\left[-k(t - t_0)\right]\right)^2}. \tag{2.F2}$$

This is the definition of the Hubbert function. One can check that t_0 is indeed the time of maximum annual production, in line with the fact that it is the date of the inflection point of its integral (cumulative production).

Thus, logistic/Hubbert fits have three free parameters: L, t_0 and k. The first two have direct meaning as already pointed out: L is the saturation level of the logistic function, and t_0 is both the date of the inflection point of the cumulative production for fossil fuels (and the annual production for renewable energy sources), and of the maximum of the annual production in the case of fossil fuels (Hubbert fits are not used for renewable energies). Note that at t_0 the cumulative production $P(t_0) = L/2$ (this is a consequence of the symmetry properties of the logistic curve but can also be checked immediately from Eq. 2.F1). The final parameter, k, is a growth rate (inverse of a characteristic time-scale), whose meaning is discussed in more detail later on in subsection 2.F.2.

Logistic fits can be made directly on the cumulative data if the data are sufficiently constraining by themselves, e.g., by fitting the three parameters to the data in the least square sense. This returns the values of the three parameters of the logistic and Hubbert functions. In practice, this can be done when the inflection point of the cumulative curve has been reached or nearly so (i.e., if the annual production data extend long enough and not too far from the maximum annual production, or at least sufficiently far from the initial purely exponential growth phase). If this condition is not satisfied, the saturation level L of the logistic function may be poorly constrained by the data, even though the fitting procedure will always return a value. Ideally, if estimates of this saturation level (URR of fossil fuels) are known, it is advisable to use them and remove L from the fit parameters. Additional constraints may be used on top or instead of the saturation level, e.g., the normalized growth rate (see section 2.F.2 below) of the cumulative production (not to be confused with the maximum growth rate of the annual production), as was done in section 2.3.3.

We now illustrate the logistic fitting procedure on the case of natural gas, discussed in section 2.3.1.2. For this fit, we have imposed the saturation parameter to the URR estimate obtained

multiplied by a year ($\sim 3.1 \times 10^7$ s), instead of the formal and somewhat pedantic procedure that would require to integrate the instantaneous production over a year around the point of interest in time. Assimilating this integral to the product of the instantaneous production by the time span (a year) introduces a negligible error.

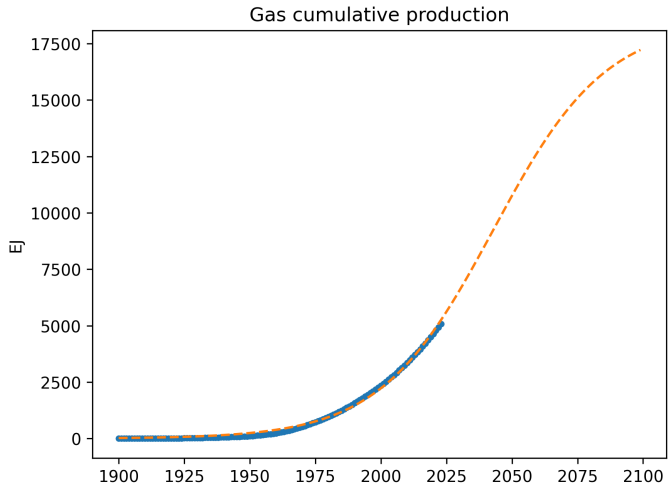


FIGURE 2.F1: Hubbert logistic fit to gas cumulative production for an imposed URR of 18500 EJ (see section 2.3.1.2). Gas supply data from GlobalShift.

in this section.

Figure 2.F1 shows the logistic fit, Eq. (2.F1). The related Hubbert function for gas annual production, Eq. (2.F2), is shown on figure 2.3. This fit gives a peak production date in 2042 and maximum production of $\sim$ 230 EJ/yr. By comparison, GlobalShift's projection corresponding figures are 2040 and 225 EJ/yr, respectively.

One may note that the fit of the cumulative data appears to be of a higher quality than the resulting fit of the annual production data. This feature is generic, because a data based derivative is always "noisier" than the integral data. Noisier here does not imply that the data are not well determined or contain an unknown source of noise. The fluctuations are in fact physical, due to variations in annual demand and supply. However, the higher quality of the fit of the cumulative data is the main reason why the date of maximum production and associated peak production may be well constrained, especially if the saturation level and/or normalized growth rate is independently constrained.

This being said, one should keep in mind that in some circumstances a logistic fit will be a poor model of the data. The most severe failure occurs when the production undergoes several peaks. This is the case when a source that was previously unreachable for any kind of reason (e.g., geological, technological, financial, etc) becomes accessible. A famous case in point is oil production in the US, who reached their conventional oil peak in the 1970's, and then saw oil production steeply increasing again in the 2010's due to the tight oil made accessible through hydraulic fracturing. The obvious workaround in such cases, as discussed in section 2.3.1.1, is to make independent analyses by oil type (more generally, by resource type for given energy source). Another, less critical problem, is that applying a Hubbert model to individual well productions, for example, may not be extremely precise because the production is usually asymmetrical (the production decline does not mirror the production increase). Similarly and even if individual well productions follow a Hubbert curve, their aggregate result does not necessarily do. This is in fact one of the main reasons behind the deviations from the Hubbert fit of the global oil, gas and coal productions. However, these deviations are not critical in light of uncertainties on URRs.

2.F.2. Normalized and relative growth rates

To make the meaning of k (inverse of a time) more transparent, it is useful to look at the derivative of the logistic function at its inflection point (maximum annual production). In practice, this derivative (the largest one along the logistic curve) is in fact normalized to make it comparable between different logistic functions for different quantities in different contexts. The normalization consists in expressing the growth rate at the inflection point as a fraction of increase of the quantity of interest at the inflection point per year.

For the logistic function of Eq. (2.F1) $P(t) = L/(1+\exp[-k(t-t_0)])$ with characteristic growth rate k, saturation amplitude L and inflection point time t_0, the normalized growth rate G reads

$$G = \frac{P'(t_0)}{P(t_0)} = \frac{k(L/4)}{L/2} = k/2, \tag{2.F3}$$

where $P'(t_0)$ is the derivative of P at t_0, i.e., $p(t_0)$. This equation gives a direct physical meaning to the parameter k.

G is expressed in %/yr unit. This procedure corresponds to the intuitive way normalized growth rates are usually expressed, once on takes into account that $P'(t_0) \simeq \delta P/\delta t$, with $\delta t = 1$ yr and δP being the change in P over one year at $t = t_0$, so that $G \simeq [\delta P/P(t_0)]/\delta t$, i.e., the relative change in P per year at time t_0.

This normalized growth rate is used extensively in section 2.3.3. Note that G is not the maximum of such relative growth rates, defined as $p(t)/P(t)$. In fact, one can check from Eq. (2.F4) below that for $t \ll t_0$, $p(t)/P(t) \simeq k$. The same equation also implies that as t increases, $p(t)/P(t)$ decreases continuously, as $P(t)$ is a monotonically increasing function of time by construction.

2.F.3. Hubbert linearization procedure

One may explain the Hubbert linearization procedure mentioned and discussed in section 2.3.1.1. Indeed, one can check that Eqs. (2.F1) and (2.F2) can be combined to yield

$$\frac{p(t)}{P(t)} = \frac{k}{L}[L - P(t)], \tag{2.F4}$$

i.e. that the ratio of annual to cumulative production is a linear function of the cumulative production. This last relation is exact for a logistic function and provides a model for p/P as a function of P. This model becomes more and more precise as one approaches the peak production, $L/2$, and L is obtained by extrapolating the linear fit on the data p/P as a function of P, on the portion of data that does behave linearly as a function of P: when this linear extrapolation reaches the horizontal axis, one has an estimate of L, i.e., of the considered fossil fuel URR.

CHAPTER 3 | ESCALATING ENERGY INVESTMENTS IN THE OIL AND GAS SUPPLY CHAINS CALL FOR CHOOSING A RAPID OIL PHASE OUT OVER A RACE FOR FUELING OIL SUPPLY

Chapter 2 critically assessed the future gross energy supply. However, the energy return on investment (EROI) of oil and gas are expected to decline in the forthcoming years. This implies that the net energy retrieved from oil and gas decline faster than their gross energy. This was first ignored in Chapter 2 and should be considered when modeling the energy demand of a BAU scenario. The present chapter thus models the evolution of the energy investments required in the oil and gas supply chains.

This material has been submitted to Applied Energy.

Abstract

Oil and gas supplies are expected to peak in the next decade, while their energy return on investment (EROI) will keep declining. This work models the energy investments in the oil and gas supply chains up to 2050, to the point of use and up to the auxiliary boundary. These are disaggregated by sources, leading to the definition of a "source-based" net energy completing the usual "EROI-based" one.

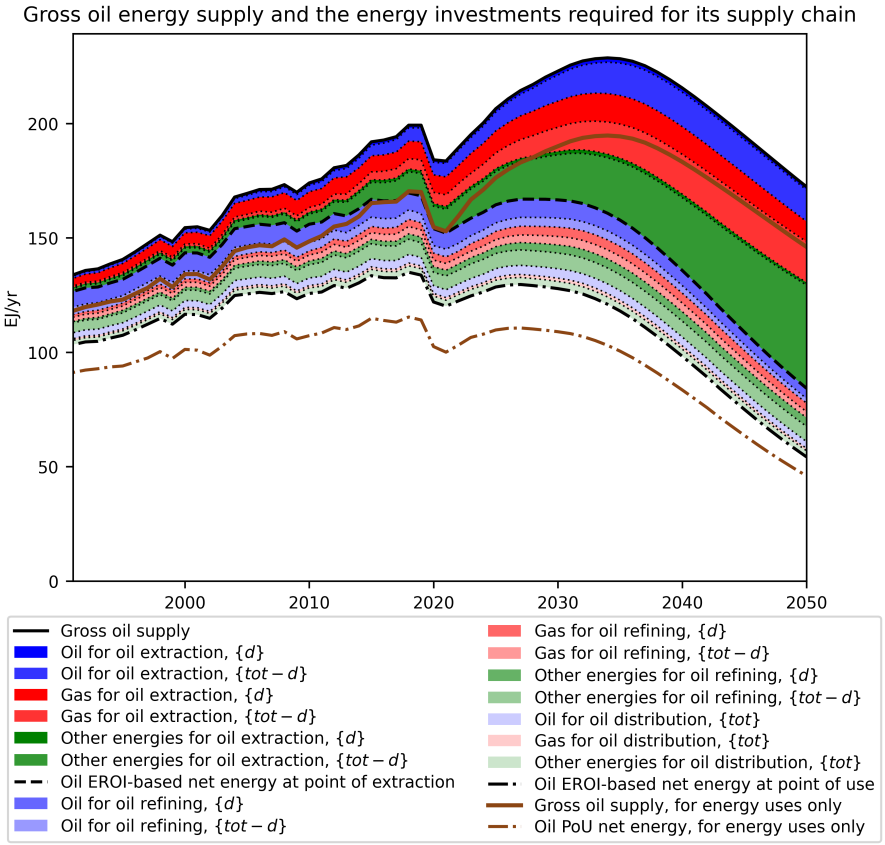
This new source-based net energy allows us to pinpoint the contribution of energy industry on future tensions on fossil sources. It is also the energy available by source outside the energy sector. Because the oil source-based net energy keeps growing up to 2035, the global world economy most likely fails to perceive the need to shift out of oil for energetic reasons and faster than anticipated by its supply peak.

Indeed, energy investment in the oil and gas supply chains are respectively expected to increase by +75% and +100% between 2022 and 2040 in a business-as-usual (BAU) scenario,

which represent a total addition of +100 EJ, while the oil EROI-based net energy has already peaked. The EROI of oil and gas, respectively, decrease from 2.8 and 2.9 in 2022 to 1.5 and 2.0 in 2050.

This puts a unexpectedly large pressure on other energy sources to compensate for the oil and gas declines. Accelerating the deployment of wind and photovoltaic power is therefore critical, not only for climate change but also to avoid the effect of a bottleneck on oil supply.

Graphical abstract



3.1. Introduction

Net energy issues have attracted a lot of attention in the recent years, in relation to the growing body of analyses of energy return on investment (EROI). The best and most accessible fossil fuels' sources have been exploited in priority in the past, progressively leading producers to exploit sources of lesser quality, or more difficult to access. This in turn induced to a decline in standard[1] EROI that has been going on for a few decades (Brockway et al., 2019; Aramendia et al., 2024; Feng et al., 2018a; Slameršak et al., 2022).

This energy issue can be viewed from two different perspectives. Firstly, EROI is an indi-

[1] Measured at the wellhead. It may include various boundaries of direct and indirect energy use for fossils extraction. See Murphy et al. (2011) for more details on the various EROI perimeters and their rationale.

cator of societal metabolism. Therefore its decline may impact society, e.g., its economy (Hall et al., 2009; Brandt, 2017; Fizaine and Court, 2016) or its level of complexity (Tainter, 1988). Moreover, this raises questions on the level of net energy available from these sources in the future, on top of the upcoming resource limited production peak. Delannoy et al. (2021a,b) present the most extensive recent investigation of the issue of peak oil and gas taking EROI issues into account, from a supply side perspective. These authors have estimated the maximum net energy at the point of extraction for these two fossil fuels, from the maximum gross oil and gas production historical data and projections of GlobalShift[2].

Secondly, the decrease in EROI implies an increase in energy investments in the oil and gas supply chains, also pointed out in Delannoy et al. (2021a,b). This adds to the energy demand required to compensate for future peaks in oil and gas supply as well as to the energy required to meet a business-as-usual (BAU) global energy demand growth. This questions whether the energy supply may indeed match demand in a BAU scenario. This is of particular concern in the case of oil given that its supply peak will occur soonest and that oil cannot be easily substituted in a number of uses.

The first and novel contribution of this work is to disaggregate the energy investments by energy sources. Although the precision of this disaggregation is limited by the availability of relevant data, this allows us to look at another form of net energy, i.e., the net oil and gas energy remaining after all uses of oil and gas for energy production have been subtracted from their gross energy. We dub this alternative form of net energy "source-based net energy". It is in some way opposite to the usual, "EROI-based" one: in the evaluation of EROI-based net energy, all the energy invested to produce a given source of energy is subtracted from its gross energy, whereas source-based net energy subtracts all the uses of a given source of energy for energy production from its gross energy. Evaluating this source-based net energy from oil (or gas) is a necessary first step in the comparison of oil or gas demand and supply outside the energy industry, and therefore in the identification of potential tensions between supply and demand, in particular for oil, whose potential of substitution is limited in the short- and mid-term (decade).

The second contribution of the present work is to clarify and extend the analyses of Delannoy et al. (2021a,b) in a number of directions. The point of net energy evaluation adopted in these works (point of extraction) is not the most informative to understand the effects of the upcoming oil and gas peak supply, although this is definitely the easiest and most precise to evaluate. The point of use is by design much more informative. Although uncertainties increase when increasing the scope in this way, it is essential to subtract the energy used in the refining process and in transportation, in the whole supply chain up to the point of use. This is the objective of our in first line of inquiry.

In relation to this, we point out that the net energy evaluated by Delannoy et al. (2021a) and Delannoy et al. (2021b) subtracts direct and indirect energy uses from the gross energy. However, this relies on various EROI estimates found in the literature, with inconsistent EROI boundaries. On the other hand, it is difficult to do much better on the basis of the existing literature. We circumvent this issue by pointing out that these works underestimate the energy cost at the largest (cumulative) boundary and overestimate it at the standard one. We adopt the same strategy in extending the analysis from the extraction point to the point of use. The conservative underestimates obtained in this way at the cumulative boundary turn out to be already quite substantial and informative on the issue of potential tensions between oil/gas energy supply and demand.

In our analysis, slightly conservative assumptions are made when needed, to provide robust

[2] `https://globalshift.co.uk/`.

estimates of potential tensions between energy supply and demand. Namely, an optimistic but realistic view of oil and gas supply has been adopted (in particular for computing net energies), in conjunction with a mild, somewhat pessimistic but also realistic BAU growth scenario.

Finally, it may be worth pointing out that the current peak oil discussion differs in an essential way from the discussion that took place at the turn of the century. The latter debate was focused on *conventional oil*, whereas the former bears on *all oil liquids*. Peak-oilists of the 90s correctly predicted the peak of conventional oil gross production to occur in the mid-2000s (which indeed occurred in 2006, as can be seen retrospectively on oil data, see, e.g., Fig. 1 of Delannoy et al. 2021a). Furthermore, we are now so close to the all-liquids production peak that uncertainties on this point are quite limited.

The present paper is organized as follows. Section 3.2 introduces our data sources and our models. However, the models needed to extricate oil and gas use in their supply chains up to the point of use are somewhat involved. In order to provide the reader with several levels of reading, the method used is first described in section 3.2.1.2, while the models themselves are presented in much more detail in Appendices 3.A and 3.B; finally, the most involved details are described in dedicated Appendices (3.D, 3.E, and 3.F). Our results are exposed in section 3.3, with the energy investments in the oil and gas supply chains (section 3.3.1), the EROI-based net energy (section 3.3.2) and then the source-based one (in section 3.3.3). Discussions follow in section 3.4. First, modeling uncertainties on EROI values and the extrapolations are presented in sections 3.4.1, 3.4.1.1 and 3.4.1.2 — a dedicated Appendix addresses a number of subtle issues in the modeling of the EROI of conventional oil (Appendix 3.G) — followed by a comparison of our results on EROIs with the literature (section 3.4.3). The conclusion (section 3.5) summarizes our most important results and outlines some points of focus for future work.

3.2. Materials and methods

3.2.1. Methods

The bulk of the work performed in this article focuses on the evaluation of net energies for oil and gas. To this effect, it is necessary to recall the definitions of the quantities and various perimeters of energy cost used in the evaluation of oil and gas EROI.

3.2.1.1. Energy perimeters

Obtaining net energy from gross energy requires to quantify the energy invested or equivalently the energy return over investment (EROI). This leads us to introduce a few definitions.

Denoting EROI by ξ, one has

$$\xi \equiv \frac{E_G}{E_r}, \tag{3.1}$$

where E_G is the gross energy delivered and E_r the energy required in the process. Consequently, the net energy E_N is obtained by

$$E_N = E_G - E_r = E_G \left(1 - \frac{1}{\xi}\right). \tag{3.2}$$

Eq. (3.1) allows us to express E_r as a fraction of the gross energy: $E_r = E_G/\xi$. It is also useful to express it as a fraction of net energy, with the help of Eq. (3.2) ($\xi > 1$ by assumption):

$$E_r = \frac{E_G}{\xi} = \frac{E_N}{\xi - 1}. \tag{3.3}$$

These principles are simple enough, but, as clarified by Murphy et al. (2011), some complexity comes in when one notices that this requires to define a perimeter along two dimensions: one for energy inputs, referred to as a "boundary", and one for energy outputs, referred to as a "point" (in the remainder of this article the term perimeter is used to designate the combination of a point and a boundary). More precisely, for inputs, the following various boundaries are defined:

- direct energy invested onsite (for extraction, etc);
- indirect energy input (i.e., energy invested offsite for the production of materials — engines, etc — used onsite, itself a recursive quantity due to machines and materials needed to produce machines and materials);
- indirect labor energy use (i.e., energy needed to produce all goods and services employees consume);
- auxiliary services energy use (these include all services not provided by the company labor, e.g., financial services from banks, government services such as public roads but more generally all services connected to the State action required for all private operations to be possible, etc);
- finally, we define a cumulative energy use boundary, which sums all the energy invested at the various boundaries just defined.

This leads us to introduce a superscript b for E_r: E_r^b, with $b = d$ for direct, $b = i$ for indirect, $b = st$ for standard (which is by definition the sum of direct and indirect energy uses at the extraction point), $b = lab$ for labor, $b = aux$ for auxiliary energy use, and $b = tot$ for the cumulative boundary. The energy needed to compensate for environmental externalities is usually not taken into account. But even with this simplification, evaluating EROI at the cumulative boundary can be a quite complex and daunting task, which, when undertaken, usually relies on the use of proxies.

The various points of energy output of relevance in this work are the following:

- the extraction point (the wellhead for an oil field, for example);
- the processing point (e.g., refining for oil);
- the end use point, or point of use (e.g., a gas station for oil).

This is taken into account by adding a second superscript a to E_r^b: $E_r^{a,b}$ (e.g., $a = ex$ for the extraction point, $a = ref$ for the refining process for oil or $a = trans$ for the transmission process of gas, and $a = pou$ for the point of use).

With these definitions, the EROI parameter at the cumulative boundary is given by

$$\xi^{a,tot} = \frac{E_G}{\sum_b E_r^{a,b}}, \tag{3.4}$$

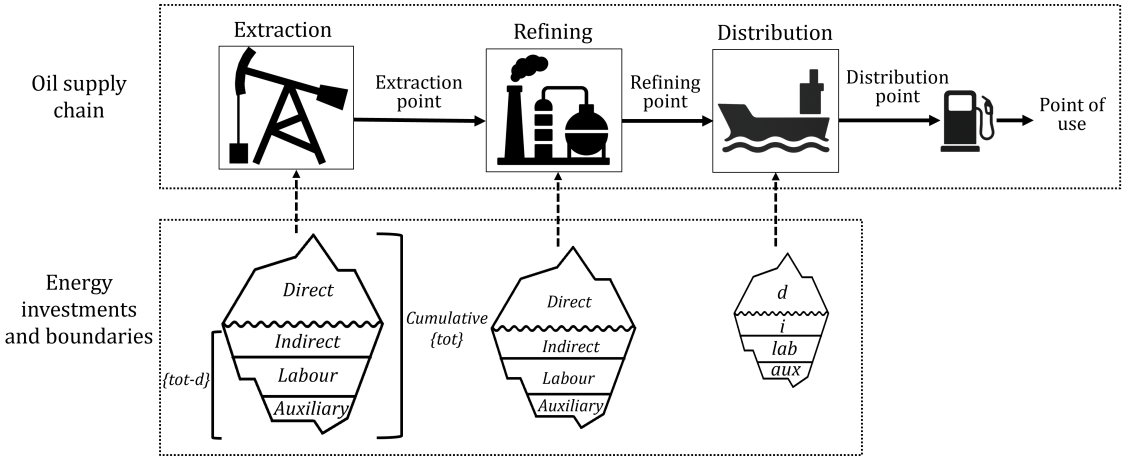


FIGURE 3.1: Different processes of the oil supply chain, with the different points at which the net energy can be computed. The energy investments at each stage of the supply chain are depicted by icebergs, the tip of which is the direct energy and the submerged part the $\{tot - d\}$ energy investments.

where $b \in \{d, i, lab, aux\}$.

Finally, Eq. (3.3) implies that the relevant average for the energy cost of extraction is the weighted average $1/\xi_o^{ex,tot}$ for the various types of oil at the point of extraction:

$$\frac{1}{\xi_o^{ex,tot}} = \frac{1}{E_{G,o}} \sum_k \frac{E_{G,k}}{\xi_k^{ex,tot}}, \tag{3.5}$$

where the dummy index k refers to the different types of oil and $E_{G,o}$ is the gross production of oil (measured in energy unit, even for the fraction of oil devoted to non-energy uses).

Figure 3.1 summarizes the different points and boundaries mentioned in the case of oil.

3.2.1.2. METHODOLOGICAL OUTLINE

The gross oil and gas energy supply data used in our analysis of the energy use in the oil and gas supply chain are taken from GlobalShift, following Delannoy et al. (2021a,b), for reasons explained in section 3.2.2.

These authors state that they quantify the EROI of oil and gas at the standard boundary. However, a more careful inspection of the various methodologies used in the papers referenced in Delannoy et al. (2021a) shows that the energy output boundary varies between the standard $\{st\}$ and $\{tot\}$ boundaries defined above. In particular, the cumulative boundary is the actual one used for onshore and shallow offshore conventional sources which constitute the lion share of past and present oil and gas productions, whereas the EROI of some other forms of oil and gas are evaluated at various other points, with some prominence for the standard point.

Thus in effect, the Delannoy et al. (2021a,b) results provide a *minimum* estimate of the energy invested at the extraction point for the cumulative boundary ($E_{r,o}^{ex,tot}$ for oil and $E_{r,g}^{ex,tot}$ for gas as described in section 3.2.1.3), or, equivalently, a *maximum* estimate of the EROI-based net energy at the same perimeter ($E_{N,o}^{ex,tot}$ for oil and $E_{N,g}^{ex,tot}$ for gas). For the same reason, their EROI value is a maximum estimate of the EROI at the point of extraction for the cumulative boundary $\xi^{ex,tot}$. We use this feature as a starting point in our own analysis.

The energy invested at the extraction point is next disaggregated between oil, gas and "other" energy sources with the help of the IEA World Energy Balances database (IEA, 2024b), as explained in more detail below.

Finally, the data quoted in Table 2 of Murphy et al. (2022) is used to characterize the other energy input points. The energy investments are labeled $E_{r,x}^{a,tot}$ with a taken in $\{ref, dist, trans\}$ designating the process and $x \in \{o, g\}$ the appropriate oil and gas supply chain. This data is in fact given at the standard boundary by Murphy et al. (2022). No information was found in the literature on the quantification of the energy investments at the $\{lab + aux\}$ boundary. In order to estimate the investment at the cumulative boundary, we decided to apply a (conservative) +50% increase on these values. This choice is an educated guess, suggested by our results at the extraction perimeter where EROI data of conventional oil sources are in fact evaluated at the cumulative boundary as just pointed out, and by other sparse elements of information. In any case, the impact of this 50% increase on the final results is relatively moderate.

We apply the same overall logic at all points in our analysis: first, the energy investment required at the considered point for the tot (cumulative) boundary is obtained in absolute terms from the EROI data sources mentioned above (Delannoy et al., 2021a,b; Murphy et al., 2022). Next this invested energy is fractionally distributed between the various energy sources (oil, gas, other energy sources), in a modeling step that relies mostly on the IEA World Energy Balances database (IEA, 2024b). The actual procedure at every point closely follows the extraction point one. Details about this procedure are provided in Appendices 3.A and 3.B. The disaggregation between oil, gas and other sources is assumed proportional to the world energy mix, in order to reflect the variety of goods and services required, in particular at the auxiliary boundary. In practice, this energy mix is determined from a simple, moderate, business-as-usual (BAU) energy demand extrapolation, and and from the projections of oil and gas. This is explained in detail in Appendix 3.E.

3.2.1.3. Notations for energy investments

The energy investments are denoted $E_{r,x}^{a,b,y}$, where a is the point ($a \in \{ex, ref, dist, trans, pou\}$) and b the boundary of the energy investments ($b \in \{d, i, st, lab, aux, tot\}$); $y \in \{o, g, e\}$ is the type of energy invested (e refers to all forms of energy besides gas and oil); $x \in \{o, g\}$ designates the supply chain in which this energy is invested. This is summarized in a possibly more easily grasped manner in Table 3.1.

Processus	**Boundary of energy investments**		
	Direct	total - direct	total
Oil supply chain			
Extraction	$E_{r,o}^{ex,d}$	$E_{r,o}^{ex,tot-d}$	$E_{r,o}^{ex,tot}$
Refining	$E_{r,o}^{ref,d}$	$E_{r,o}^{ref,tot-d}$	$E_{r,o}^{ref,tot}$
Distribution	$E_{r,o}^{dist,d}$	$E_{r,o}^{dist,tot-d}$	$E_{r,o}^{dist,tot}$
Point of use	$E_{r,o}^{pou,d}$	$E_{r,o}^{pou,tot-d}$	$E_{r,o}^{pou,tot}$
Gas supply chain			
Extraction	$E_{r,g}^{ex,d}$	$E_{r,g}^{ex,tot-d}$	$E_{r,g}^{ex,tot}$
Transmission	$E_{r,g}^{trans,d}$	$E_{r,g}^{trans,tot-d}$	$E_{r,g}^{trans,tot}$
Point of use	$E_{r,g}^{pou,d}$	$E_{r,g}^{pou,tot-d}$	$E_{r,g}^{pou,tot}$

Table 3.1: Quantities designating the energy investments made in the oil and gas supply chains. $E_{r,o}^{pou,tot}$ and $E_{r,g}^{pou,tot}$ are the main focus of the present study. Each quantity in this table can be further disaggregated according to the various energy sources $y \in \{o, g, e\}$ at need.

The energy investments of different processes — extraction, refining and distribution for oil, and extraction and transmission for gas as detailed in Appendices 3.A and 3.B — collectively amount to the investments at the point of use, both in the oil or in the gas supply chain[3]:

$$E_{r,o}^{pou,b} = E_{r,o}^{ex,b} + E_{r,o}^{ref,b} + E_{r,o}^{dist,b}, \tag{3.6}$$

$$E_{r,g}^{pou,b} = E_{r,g}^{ex,b} + E_{r,g}^{trans,b}. \tag{3.7}$$

The different perimeters at which energy is accounted — direct, indirect, labor, auxiliary — sum up to the total one:

$$E_{r,x}^{a,tot} = E_{r,x}^{a,d} + E_{r,x}^{a,i} + E_{r,x}^{a,lab} + E_{r,x}^{a,aux}. \tag{3.8}$$

The type of energies invested — oil, gas and the others grouped in a unique category — sum up as well:

$$E_{r,x}^{a,b} = E_{r,x}^{a,b,o} + E_{r,x}^{a,b,g} + E_{r,x}^{a,b,e}, \tag{3.9}$$

and the EROI-based net energy follows simply for oil and gas, as a consequence of energy conservation:

$$E_{N,x}^{pou,tot} = E_{G,x} - E_{r,x}^{pou,tot}. \tag{3.10}$$

Finally, as presented in the introduction, we define an other type of net energy, called "source-based net energy". This is the quantity of any given energy source remaining after all uses in the supply chain of all energy sources are subtracted. Denoting $E_{S,x}^{pou,tot}$ this source-based net energy, one has:

$$E_{S,y}^{pou,tot} = E_{G,y} - \sum_{x \in \{o,g,e\}} E_{r,x}^{pou,tot,y}. \tag{3.11}$$

The energy investments in the supply chain of the other energy sources $E_{r,e}^{pou,tot}$ are not modeled in the present article.

3.2.2. Oil and gas past supply data and future supply projections

Following Delannoy et al. (2021a) and Delannoy et al. (2021b), we make use of the GlobalShift oil and gas supply data, for ease of comparison with their earlier work, but also because the disaggregated data of GlobalShift are already at our disposal[4]. This data series starts in 1950 and the projections are given up to 2050. We also use two other sources at the aggregated level for oil: Rystad Energy's and Jean Laherrère data and projections (these were also used in Delannoy et al. 2021a), as a point of comparison of oil production projections and estimate of the associated uncertainties.

Rystad Energy is a highly reputed oil intelligence company, while Jean Laherrère is a well-known expert with decades of experience in and with the oil industry. GlobalShift also relies on decades-long expertise in the oil sector. It may be worth noting at this point that data from oil (and gas) producers themselves may be misleading, and in any case may not be reliable due to various (geo)political, economic or technical considerations (see, e.g., Laherrère et al. 2022 for explanations on this point). Furthermore oil producers themselves do rely on projections

[3] We neglect the small amount of energy needed at the point of use itself.

[4] One of the present authors coauthored these earlier pieces of work. This reuse is done with the agreement of GlobalShift. Note that GlobalShift follows the common convention of counting NGLs (natural gas liquids), CTL (coal to liquid) and GTL (gas to liquid) as oil liquids. Double counting is avoided by excluding them from gas and coal. Similarly, a fraction of NGLs is obtained as refinery products, but are not included in the NGLs included in oil liquids to avoid double counting.

such as those of Rystad Energy; considering the high annual price tag of such oil databases, this indicates that producers do consider these data are reliable.

These are our major sources of data for gross production. Other data are used for modeling (see section 3.2.3).

3.2.2.1. Oil data conversion

In this work, we adopt a different strategy than Delannoy et al. (2021a) to convert oil production in volume to oil production in energy. These authors subtracted first the oil non-energy uses[5], and then converted the rest in gross energy using appropriate conversion coefficients for the different types of oil, namely 4.06 GJ/bbl for NGLs and 5.9 GJ/bbl $\simeq$ 1 boe/bbl (= 6.12 JG/bbl) for all other liquids (see their section 3.2). Here, instead, we directly convert the total volumetric production into a gross energy content. Although at first sight this may seem less precise (a point discussed further below), this choice is motivated by the following considerations:

- The (inverse) EROI displayed on figure 3 (which is the correct average for the purpose of quantifying the energy invested in the oil production process) is an EROI of all liquids including non-energy uses[6].

- We also convert Rystad Energy's and Laherrère's data on gross oil liquids production in energy using the same method. Thus, the comparison of all three production projections is made on the same basis. If we had used Delannoy et al. (2021a) method instead, such an informative comparison would not have been possible.

We now explain our conversion procedure. The GlobalShift data on oil production are given in kbbl/d (kilo barrel per day). The volumetric energy density varies between different categories of oil and evolves a little over time. For this reason, in principle, converting volumetric data into energetic data requires specific knowledge of these energy densities for the different oil categories. In effect, however, most oil types have very similar energy densities, leaving out natural gas liquids (NGLs) and biofuels which have somewhat different energy contents[7]. This is the main reason why our assumption of a unique, time-independent, average coefficient to convert volumes (barrels) into energy is precise enough for our purposes. This conversion coefficient is calibrated from a fit of the GlobalShift historical oil production data in kbbl/d on the IAE historical total energy supply, in EJ/y (these data incorporate oil non energy uses, as does GlobalShift's; see IEA 2024b, pp. 13[8] and 20).

More quantitatively, the proportion of NGLs (natural gas liquids) in the gross oil in GlobalShift's data is low and remains almost unchanged between 2020 and 2050 (12.7% in 2020 compared to 14.6% in 2050). For their energy content, Delannoy et al. (2021a) use 4.06 GJ/bbl (0.66 boe/bbl), from a privately communicated GlobalShift estimate. In the remainder of this work, we retain this characteristic value of 4.06 GJ/bbl, as other estimates are difficult to find in the published (academic or gray) literature.

[5] They assume that non-energy uses of oil account for 40% of NGLs (natural gas liquids) and 8% of all other oil types.

[6] This incidentally raises a subtle question on the validity of the results of Delannoy et al. (2021a), as they use an EROI defined and computed in the same way, but for all oil liquids energy uses only. This point is addressed in Appendix 3.D, where it is shown that the results of this earlier publication are nevertheless valid to a reasonable degree of precision, with respect to this issue.

[7] This is compounded by the fact that these two categories of fluids represent a not negligible but still small enough fraction of the total, from $\sim$ 16% at peak production to $\sim$ 22% in 2050.

[8] Although the definition refers to production without more specification, it is clear that this is the total oil production, including its eventual non-energy uses, as production data are provided by producers.

Turning to biofuels, the energy volumetric density of ethanol is 0.58 boe/bbl, and 0.86 boe/bbl for biodiesel[9]. From the IEA World Energy Balance database, we found that the proportion of biodiesel in biofuels has increased at a constant rate since 2020, raising the energy density of biofuels from 0.60 to 0.72 boe/bbl. In practice, we assume that the latter value will be a precise enough characteristic value for the future. Indeed, on the one hand, the energy density is obviously limited to the biodiesel's one, and it is unlikely that biodiesel will constitute the entirety of biofuels in the future. On the other hand, the share of biofuels in present and future projected oil liquids production is small enough that a further increase from 0.72 boe/bbl will have negligible impact on the total.

Using a constant average conversion coefficient from volume to gross energy implies that, as NGL and biofuels conversion coefficients are lower than 1, the small increase of their shares in the oil mix results in a small decrease in the total oil energy supply compared to the oil volumetric supply evolution. As a result, our hypothesis of constant conversion coefficients leads to a slightly optimistic projection of the oil energy supply. We have quantified the error made in this way by comparing the constant coefficient conversion with the varying coefficient one adopted by Delannoy et al. (2021a). Between 2020 and 2040, the constant coefficient conversion increases progressively over the varying coefficient conversion, and reaches a maximum relative difference of 4%. Over historical data, the discrepancy is negligible as a consequence of our fitting procedure on IEA data. This small projected difference is negligible, in light of the uncertainty in the projection itself (see Fig. 3.2).

As indicated above, we proceeded in the same way to convert Rystad's and Laherrere's aggregated gross oil supply volumes into energy. The various supply curves obtained in this way are shown on Fig. 3.2 along with the IEA's total energy supply data. As the fit is performed between 1971 and 2019, the supply projections of Rystad and Laherrere are slightly overestimated between 2015 and 2021. As mentioned, this leads to slightly optimistic gross oil supply projections. Still, because conventional oil dominates oil production over the fit period, a constant conversion coefficient results in very good fits over this period. Fig. 3.2 can also be used as an indication of the associated uncertainties at the gross energy level, and does show that it is quite limited.

Finally one should keep in mind that the projections shown correspond to the *maximum* worldwide production, at least for GlobalShift data, which results essentially from a supply-side constraint[10]. Note that this is a *flow* and not a *stock* supply side limit. Oil reserves are extremely large if one includes forms of oil that are difficult to exploit. But precisely because of this difficulty, they are unlikely for both economic and practical reasons to be exploited to a significant extent, leading to the future flow projections shown.

As a consequence, the GlobalShift data may not exactly represent actual oil production in the future. In fact, at any given time, there are unused production capacities, in order for producers to react to variations in demand but also to exert some control on oil prices. However since the turn of the century, these unused capacity represent most of the time $\lesssim 5\%$ of oil demand and sometimes as little as 2%, as opposed to 10% or more before 1990 (EIA, 2022). Unused production capacities are expected to remain low in the near to mid-term future (up to the 2040 horizon), due to growing demand (even in an energy transition period), and more and more limited future supply. This point will be shown in more detail in a future publication.

[9] `https://www.bp.com/content/dam/bp/business-sites/en/global/corporate/pdfs/energy-economics/statistical-review/bp-stats-review-2022-approximate-conversion-factors.pdf`

[10] For more details about GlobalShift methodology and assumptions, see `https://globalshift.co.uk/mode.html`.

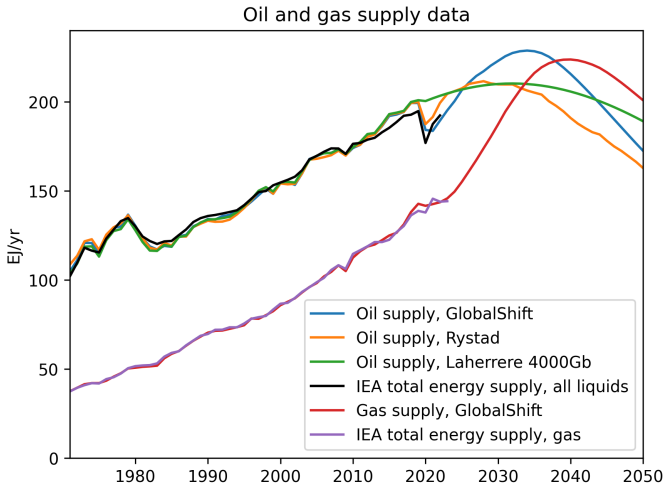


FIGURE 3.2: Oil and gas supply data from multiple sources as indicated in the figure legend. The projections data begin at year 2020 or 2021, which explains why the decline in oil consumption in 2020 (due to the COVID pandemics) is not reflected in Laherrere's data.

3.2.2.2. GAS DATA

For gas, we make use of the GlobalShift database only. As for oil, we rely on Delannoy et al. (2021b) to convert gas volumes into gross energy at the extraction point. This question is however much simpler than for oil, as methane (the sole product of sales gas) has a well-known energy conversion coefficient. The conversion factor used is 39.7 PJ per million cubic meter of gas (under standardized conditions of temperature and pressure).

The gas supply converted in EJ/yr and fitted on the IEA total energy supply data is also shown in figure 3.2.

3.2.3. OTHER DATA

This work also makes use of the IEA World Energy Balances data (IEA, 2024b) ranging from 1971 to 2022 included, and some aggregate data provided by Murphy et al. (2022), in particular from their Table 2. These will be quoted more precisely later on as we present our methodology.

3.3. RESULTS

Some color conventions are used in our figures:

- Shades of blue and cyan respectively represent various forms of oil investments in the oil and gas supply chain.
- Shades of red and magenta respectively represent various forms of gas investments in the oil and gas supply chain.
- Shades of green and yellow-green respectively represent various forms of investments of all other energy sources in the oil and gas supply chain.

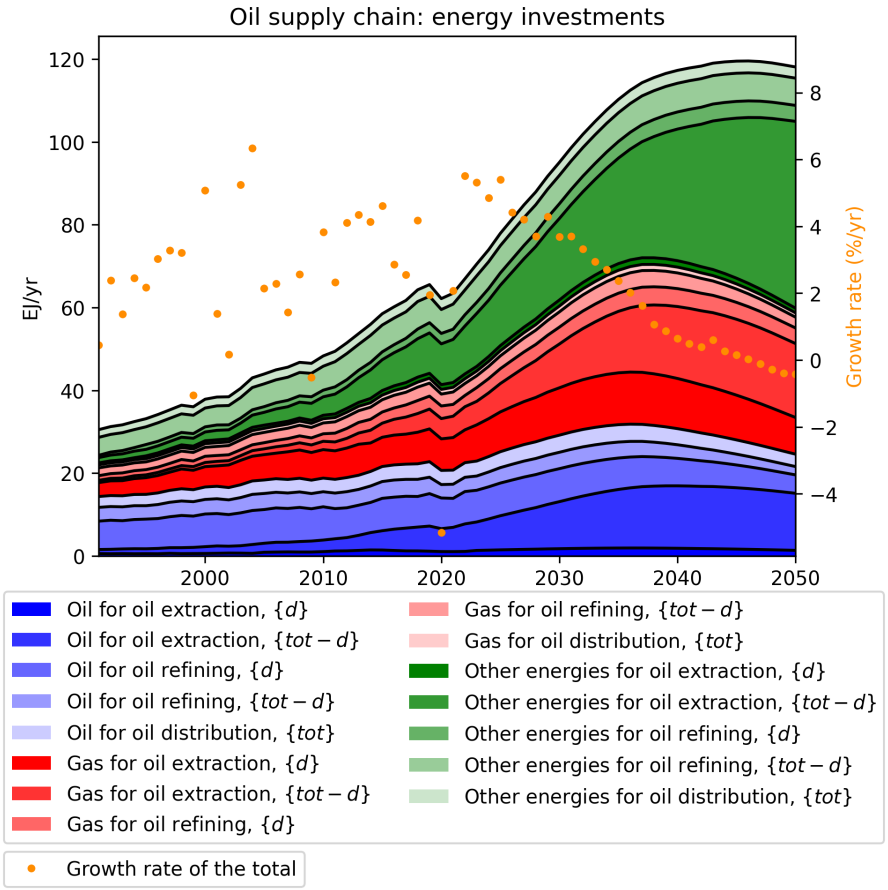


FIGURE 3.3: Absolute cumulative energy investments in the oil supply chain, and growth rate of the shell (right axis). The different boundaries of each flows are explained in section 3.2.1.

The different forms of energy investment are separated by black lines in figures except in the net energy ones where dotted lines are used instead. Both choices were made for the sake of readability. The figures are displayed from 1991 onward in order to avoid a discontinuity present in IEA's WEB database between 1990 and 1991.

3.3.1. ENERGY INVESTMENTS IN THE OIL AND GAS SUPPLY CHAIN

Figs. 3.3 and 3.4 illustrate the absolute cumulative energy investments in the oil and gas supply chains. These grow steadily and represent significant amounts of energy: 117 EJ/yr in the oil supply chain in 2040 (for a total gross production of 216 EJ/yr) and 97 EJ/yr for gas (for 224 EJ/yr of gross production), i.e., +96% for gas and +75% for oil compared to 2022, or a total +98 EJ addition. The values of the energy invested in the oil supply chain will reach 118 EJ in 2050 (for 172 EJ/yr of total production), which will represent 69% of the gross oil supply (from which the non-energy uses have not been subtracted), compared to 35% in 2022. In the case of gas, the energy invested will reach 102 EJ in 2050, for a total production of 201 EJ/yr, which represents 51% of the gross gas supply (compared to 34% in 2022).

Other energy sources consumption will skyrocket, reaching 116 EJ in 2050 from 45EJ in 2022, as shown on Fig. 3.5. This is mostly because of the $\{tot - d\}$ energy growth needed in oil and gas extraction. The $\{tot - d\}$ energy investments from the other energy sources are modeled as being proportional to the share of the other energies in the energy mix (quantified in

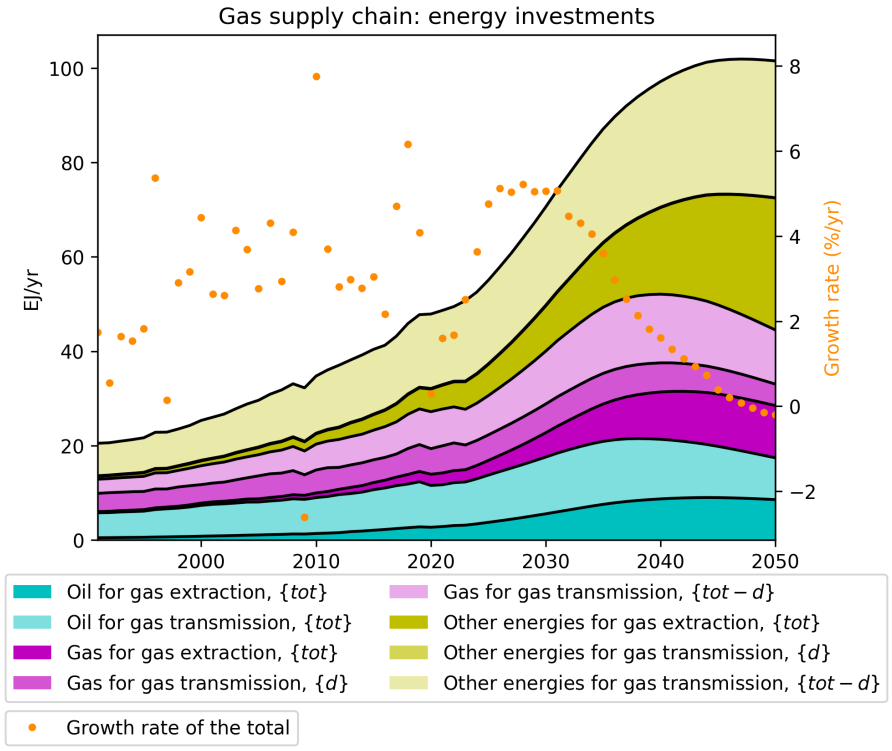


FIGURE 3.4: Absolute cumulative energy investments in the gas supply chain, and growth rate of the shell (right axis). The different boundaries of each flows are explained in section 3.2.1.

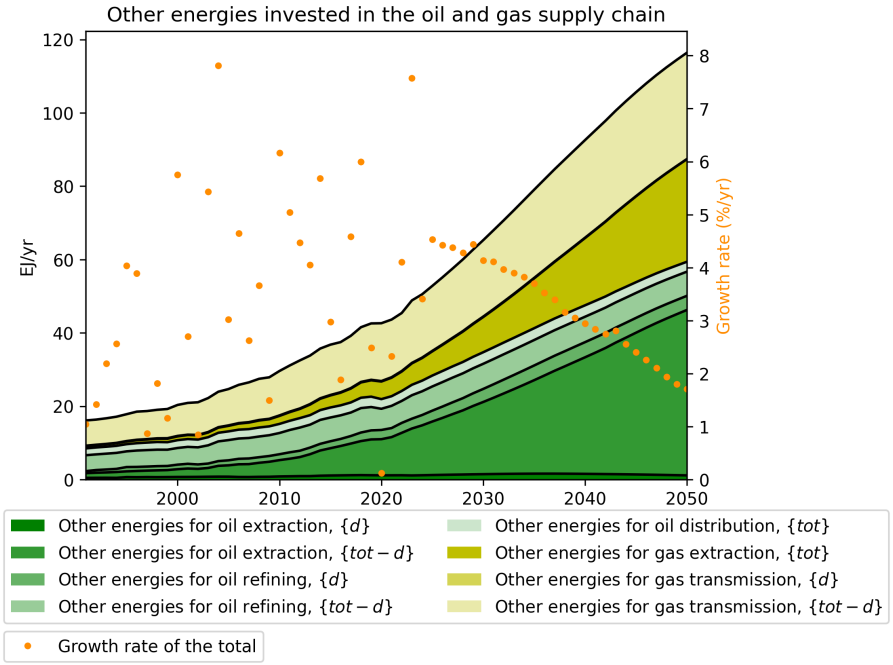


FIGURE 3.5: Other energies investments in the oil and gas supply chains, and growth rate of the shell (right axis).

Appendix 3.E), due to the variety of goods and services they are used for in the oil and gas supply chain. The increasing share of the other energy sources in the energy mix after 2035 (shown in Fig. 3.E4) explains these energy investments increase while the total energy investments in the oil and gas supply chains stagnate after 2035. Overall, the compound annual growth rate of the energy investments from other sources was 3.7%/yr between 2000 and 2022, and should be 3.4% between 2022 and 2050. These 71 EJ of additional energy from the other energy sources must be taken into account when quantifying future energy demands in models. Indeed, this is slightly more than the addition from other energy sources to the total energy supply achieved between 2006 (218 EJ) and 2022 (286 EJ).

Approximately 60% of these other energies nowadays comes from coal, the remainder being attributed to nuclear, hydroelectricity, wind and photovoltaic (PV) power, and bio-energies. Given the limited deployment potential for nuclear energy, hydroelectricity and bio-energies (IEA, 2024d; IAEA, 2023; IPCC, 2023), we anticipate that the additional energy requirements in the oil and gas supply chain will most likely primarily lead to an increased pressure on coal and on world-wide wind and PV deployment, even in the mild BAU scenario envisioned here. Whether these renewable energy sources may deploy fast enough or not in the decade or so left for this energy demand expansion to take place is an open question at this point.

In the case of the oil supply chain, the energy investments from the $\{tot - d\}$ boundary of the extraction processes represent the larger share of the investments: 36% in 2022 to 65% in 2050. The gas investment in the direct energy of oil extraction is also rather large. In the case of the gas supply chain, the energy investments are more evenly distributed across its various points, and in different types of energy. Appendix 3.C discusses in more detail the importance of the $\{tot - d\}$ energy investments in total energy investments.

A plateau and an eventual decline in the oil and gas investments in their supply chains are seen on Fig.3.3 and 3.4 from around 2035-2040 onward. This is predominantly driven by the decline in oil and gas gross supply. At the same time energy investments must keep growing until 2050, due to the steady decline in mean EROI of both gas and oil. The difference must then be provided by other energy sources, unless oil and gas demand decreases faster than the maximum possible net supply. This will be further discussed in section 3.4.1.1.

3.3.2. EROI AND "EROI-BASED" NET ENERGY IN THE OIL AND GAS SUPPLY CHAINS

The relative shares of the various energy investments sources at the direct $\{d\}$ and cumulative minus direct $\{tot - d\}$ boundaries are shown on Figs. 3.6 and 3.7 in a cumulative way in the oil and gas supply chains. The cumulative envelope is the inverse of the oil and gas EROIs at the point of use, $1/\xi_o^{pou,tot}$ and $1/\xi_g^{pou,tot}$. Although oil and gas investments reach a plateau in absolute terms past 2035-2040, this is not the case in relative numbers for the oil supply chain, and to a lesser extent for the gas supply chain as well.

The EROIs of oil and gas at the point of use and cumulative boundary are shown in Fig. 3.8. The EROI of oil is decreasing from 5.0 in 1950 to 2.8 in 2022 and 1.5 in 2050. The EROI of gas — lower than oil's before 2020 — slowly decreases, from 3.6 in 1950 to 2.9 in 2022 and 2.0 in 2050.

The decline of the EROI of oil and gas beyond 2010 has implications for the societal EROI (defined as the EROI of the whole energy system). Fossil fuels constitute nowadays 81% of the global primary energy mix, with oil, gas and coal accounting for approximately equal shares. For coal, energy investments are dominated by preparation (washing) and transport, with a relatively small contribution from extraction. According to Murphy et al. (2022), energy in-

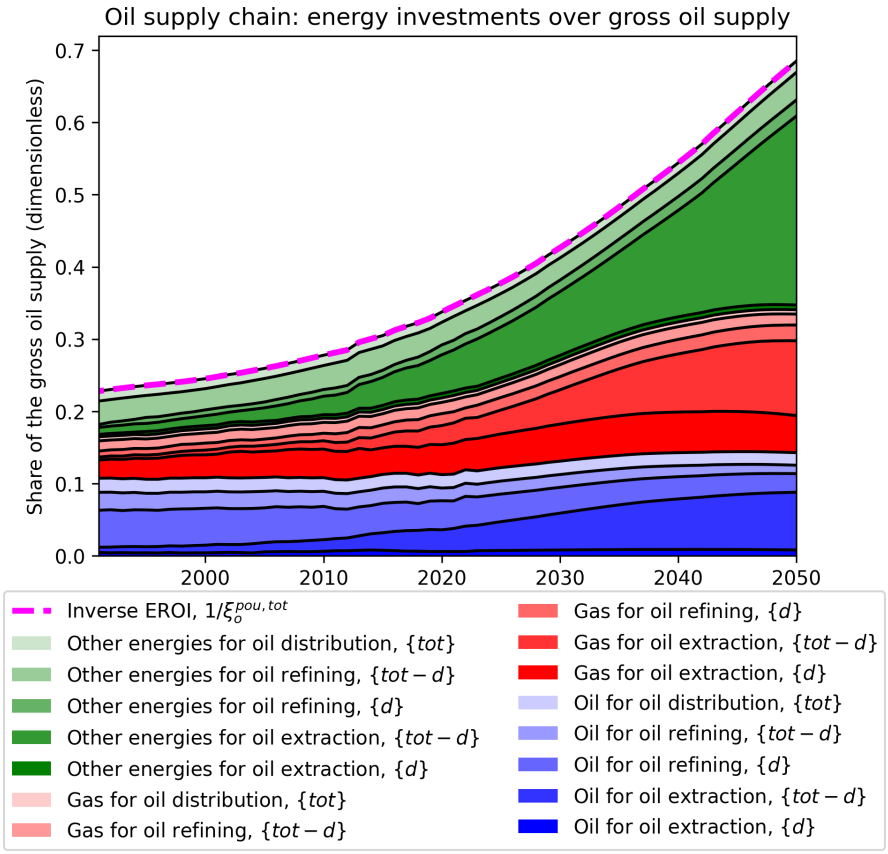


FIGURE 3.6: Energy investments into the oil supply chain, expressed as a share of the gross oil supply. $\xi_o^{pou,tot}$ designates the EROI of oil at the point of use.

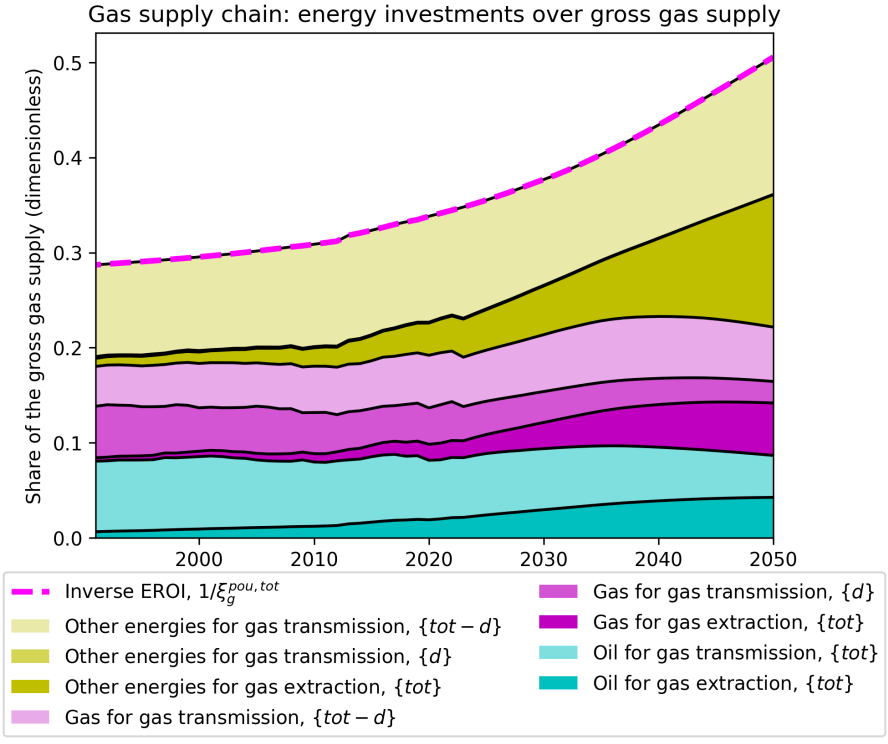


FIGURE 3.7: Energy investments into the gas supply chain, expressed as a share of the gross gas supply. $\xi_g^{pou,tot}$ designates the EROI of oil at the point of use.

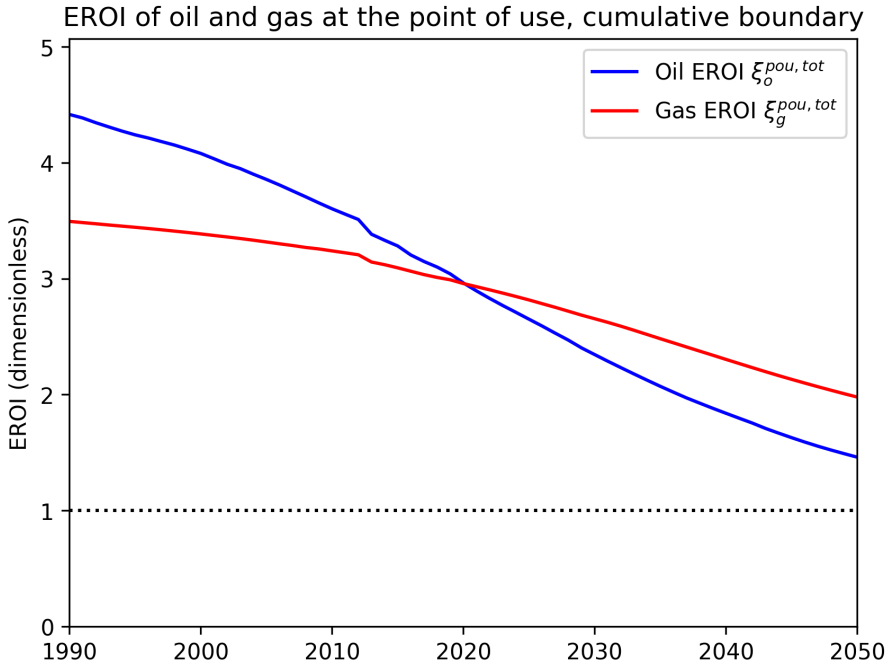


FIGURE 3.8: Evolution of the EROIs of oil and gas at the point of use and at the total cumulative boundary.

vestments in the preparation and transport represent 10% of the energy content of coal output, which implies that at the point of use, the EROI of coal is necessarily lower than 10. Under the simplifying assumption that this EROI remains constant as well as the share of coal in other energy sources, our societal EROI would thus amount to ∼5.5 in 1950, decreasing to ∼4 in 2022 and ∼3 as soon as ∼2035[11]. In other words, the share of the energy investments in the energy industry over the gross energy supply was ∼18% in 1950, ∼25% in 2022 and will be ∼33% in ∼2035 — a significant acceleration. We do not provide societal EROI estimates beyond 2035 as the uncertainty on the deployment of renewable energies and the peak in gross oil and gas supply add too much uncertainty in the energy system for these back-of-an-envelope estimates.

Some authors (Hall et al., 2009; Fizaine and Court, 2016; Brandt, 2017) have argued that a societal EROI decline below some level would render the pursuit of economic growth unfeasible. In this respect, the societal EROI we estimated is expected to decrease as much in the ∼10—15 years between 2022 and ∼2035 as during the 30 years between 1990 and 2022, which may raise a concern for growth policies. Finally, another burden may further reduce societal EROI in the short term, as the deployment of wind and solar PV (photovoltaic) energies is very energy-intensive (see Capellán-Pérez et al. 2019; Sgouridis et al. 2016; Slameršak et al. 2022; Jacques et al. 2023), although their EROIs may be higher than those of fossil energy sources in the longer term (Aramendia et al., 2024) (see footnote 22).

The concept of EROI becomes less immediately useful when EROI scores get closer to unity. Indeed, small changes in EROI in this regime represent much larger changes in net energy. It is more informative to focus on energy investments and net energy at low EROI values (smaller than a few). Figs. 3.9 and 3.10 show energy investments in the oil and gas supply chains in comparison with the oil and gas gross energies. This makes these figures more directly comparable to the same figures of Delannoy et al. (2021a,b), although our gross oil supply is not exactly computed in the same way.

[11] The comparison of absolute societal EROI values with the literature is not very relevant as the boundary of what is computed is different.

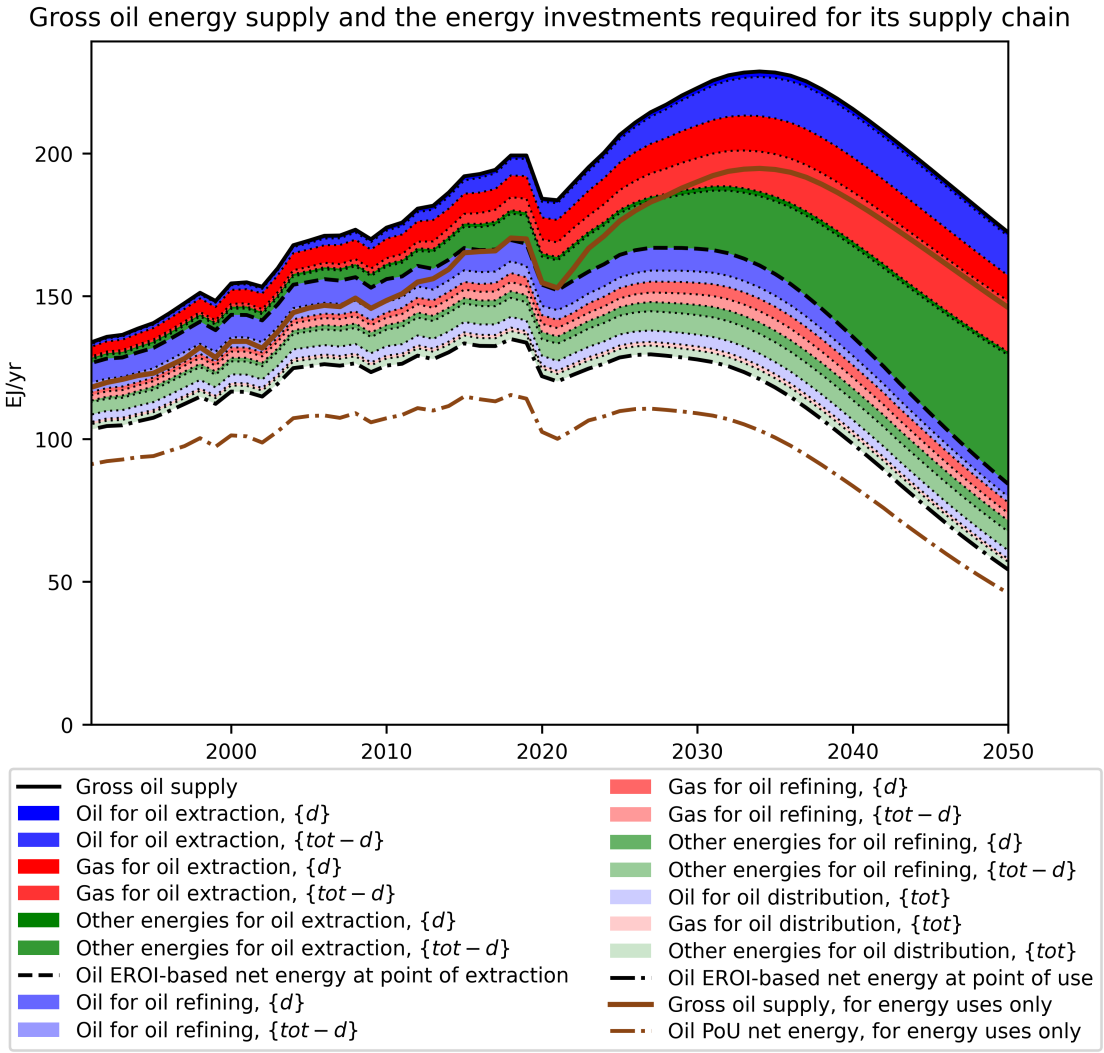


FIGURE 3.9: Oil gross supply, and all energy investments in its supply chain. The legend presents the curves from top to bottom.
The top curve is the gross supply, the dashed curve the net energy at point of extraction ($E_{N,o}^{ex,tot}$) computed in Delannoy et al. (2021a), and the dash-dotted curve the net energy ($E_{N,o}^{pou,tot}$) at the point of use. The curves in brown represent the gross oil supply and the EROI-based net oil energy supply computed for energy uses only, when non-energy uses are excluded. Small dotted lines delineate borders between quantities.

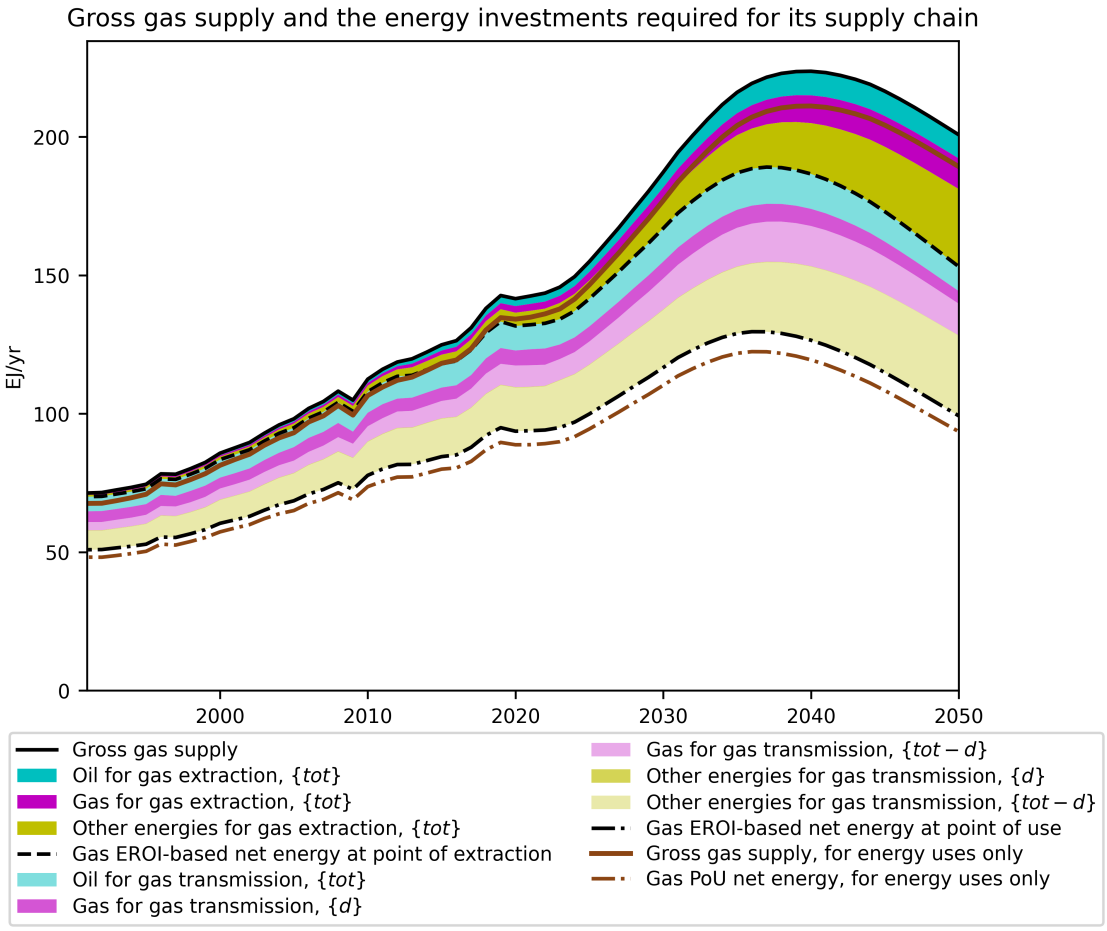


FIGURE 3.10: Gas gross supply, and all energy investments in its supply chain. The legend presents the curves from top to bottom.
The top curve is the gross supply, the dashed curve the net energy at point of extraction ($E_{N,g}^{ex,tot}$) computed in Delannoy et al. (2021b), and the dash-dotted curve the net energy recovered from gas exploitation ($E_{N,g}^{pou,tot}$) at the point of use. The curves in brown represent the gross gas supply and the EROI-based net oil energy supply computed for energy uses only, when non-energy uses are excluded.

As in Fig. 3.3, the energy invested in refining and distribution of oil leads to a net energy at the point of use that is substantially reduced with respect to the net energy at the extraction point. Moreover, it shows clearly energy investments keep increasing steadily as a fraction of gross energy while the gross oil supply itself decreases. The same phenomenon is observed for gas. Possibly the most important conclusion drawn from our extension to the point of use is that *oil net energy has already peaked and is on a slowly decreasing plateau, until 2030-2035 where the effect of the gross energy peak leads to a faster and faster decline. In relation to this energy investments (including non-energy uses) increase from 37% to nearly 70% of oil gross energy between now and 2050*. Similar but milder conclusions hold for gas as well, except that net energy has not yet peaked. This result for oil is most likely robust, as GolbalShift's gross energy projections are the ones that keep increasing fastest until the peak among the various available projections (see Fig. 3.2). If the approach to the peak is shallower instead, the present oil net energy slow decrease is expected to steepen.

As seen in section 3.3.1, between 2035 and 2050, oil and gas production and processing will require an increase of 45 EJ/yr from other sources of energies. Additionally, as seen in this section, compensating for the decline of oil and gas EROIbased net energy will require an increase in energy supply of 64 EJ/yr for oil and 30 EJ/yr for gas, i.e., ∼140 EJ/yr over 15 years, just to maintain the economy at a constant level. This can be compared, e.g., to the peak oil and gas EROI-based net energy, ∼225 each (about 60%). This also represents about 1/3 of today's EROI-based net fossil fuel energy (whose gross energy provides 81% of today's primary gross energy production). This requirement is what is needed to maintain the economic production stable, not growing[12]. This is a rather steep requirement over 15 years, and may turn out to be taxing for wind and PV energies especially if pro-growth policies are pursued.

3.3.3. Energy investments and "source-based" net energy in the oil and gas supply chains

We now turn to the second concept of net energy defined in the introduction, i.e., the oil and gas energy remaining once all oil and gas used for all forms of energy production are subtracted from their respective gross energy. Although other sources of energy provide energy to society, subtracting oil and gas investments in these other energy supply chains is informative as all sources of energy are not substitutable in the short to mid-term (from a couple of years to a couple of decades in the future).

In practice, we have only quantified in detail the oil and gas investments in oil and gas supply chains. A more accurate view would be provided by evaluating more precisely than done here their investments in the supply chain of other energy sources (coal, nuclear energy, renewable energy...). However, this would require substantial additional work.

The first results of this analysis are shown on Figs. 3.11 and 3.12, where the bottom curves represent the source-based net oil and gas after oil and gas investments in their supply chains have been subtracted from their gross energy.

The oil investments in the oil and gas supply chain reach 53 EJ in 2035 (at the gross oil supply peak); this is higher than but roughly comparable to the other energy investments in the oil supply chain at the same date. The gas investments reach 70 EJ in 2040 (gross gas supply peak), 50% higher than other energy investments in its supply chain at the same date. All in all, one uses more oil and gas to produce oil and gas than one uses other types of energy, in spite of the substantial increase in these other energy uses pointed out in the previous subsection.

To proceed somewhat further, let us make a semi-quantitative evaluation of oil and gas use

[12] We neglect the small annual energy efficiency gain per GDP point in this order of magnitude argument.

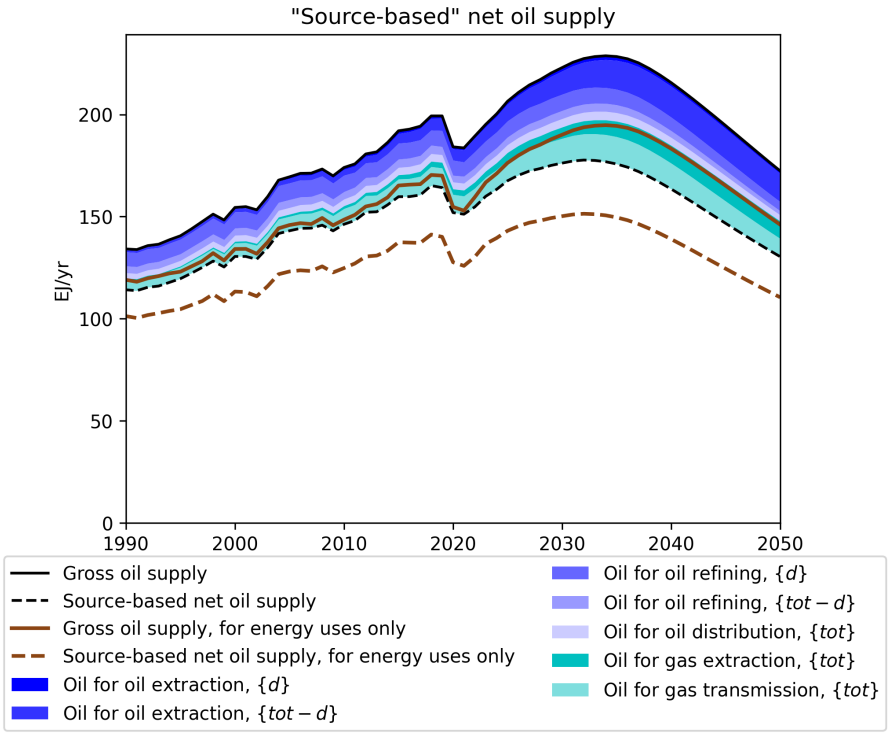


FIGURE 3.11: Partial "source-based" net oil supply energy, obtained by subtracting all oil invested in the oil and gas supply chains from the gross oil supply, including (black curves) and excluding (brown curves) non-energy uses (see legend).

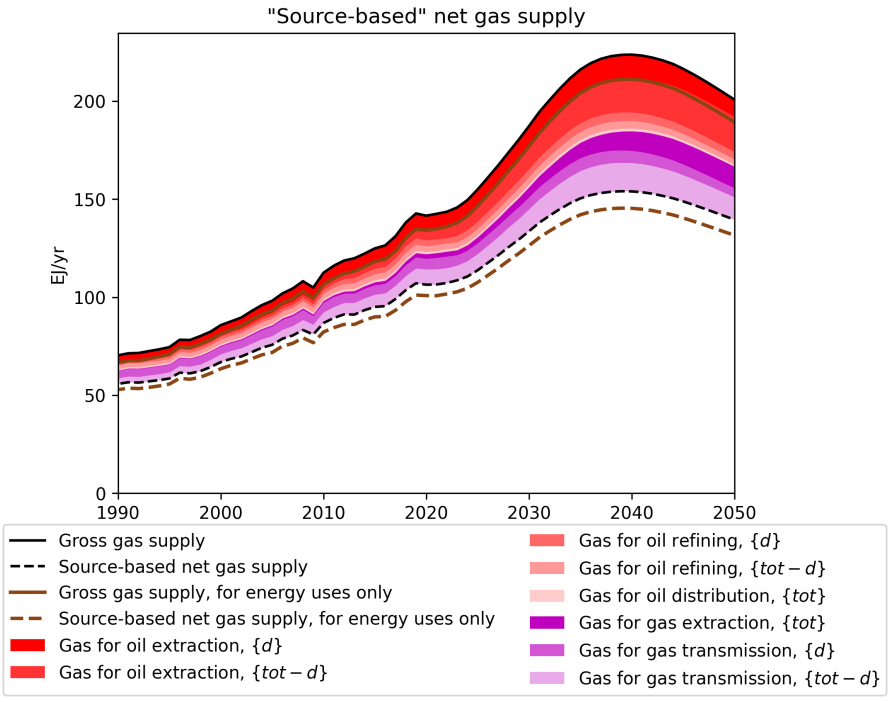


FIGURE 3.12: Partial "source-based" net gas supply energy, obtained by subtracting all gas invested in the oil and gas supply chains from the gross gas supply, including (black curves) and excluding (brown curves) non-energy uses (see legend).

in the production of coal, as fossil fuels still constituted 81% of primary energy supply in 2022.

The direct use of oil and gas in coal extraction is negligible (less than 1EJ/yr for each according to IEA 2024b). In fact, it appears that coal is still the major direct energy source in coal production. From Murphy et al. (2022), we can expect about 16EJ/yr of oil and 7EJ/yr of gas to be invested in the rest of its supply chain.[13]. This represents 60% of the oil consumed in the oil and gas supply chains. Furthermore, the time evolution of the energy investments in the coal supply chain may be slow as the EROI at extraction of coal is not expected to decrease in a significant manner in the future years. In the absence of more information, this is not modeled more precisely here.

The energy investments required for the deployment of wind and PV infrastructures are also discussed in section 3.4.2. The oil and gas investments are thus expected to increase continuously, reaching 4 to 5 EJ/yr by 2050 in the mild BAU scenario assumed in this work, as the investments mainly come from other energy sources. Consequently, the source-based net oil supply is overestimated by approximately 10 to 15% from 2022 to 2050, and 5 to 10% for gas.

This discussion has a number of implications.

First, the net "source-based" oil supply shown on figure 3.11 shows a lack of tension on oil availability for uses outside energy production until 2035 (but one should keep in mind Fig. 3.9, which shows that this oil flow comes at the expense of other sources of energy, with a negative global balance). In any case, the turning point in figure 3.11 also occurs in 2035, a mere decade away. The continued increase in oil and gas source-based net energy pointed does not favor an early anticipation of the production peak, and therefore, the need to phase out oil at an accelerated pace for reasons independent from climate change mitigation.

Secondly, the anticipated peak in the net source-based oil and gas supplies outside energy production, suggests that there may be an important tension on oil and gas supply in the next decades, particularly for oil. The peak in net source-based gas supply could be compensated by a partial substitution by coal and renewable energies as an important share of its uses could be substituted (heating and electricity production) if appropriate transformations are operated in the required timescale. However, this is not the case for oil (which is the fossil most immediately in potential tension in terms of net energy). Additionally, the tension on gas supply would limit the potential substitutions of gas for oil in the next decade.

Finally, at present, less gas and oil is used in other forms of energy production than other energies in the production of oil and gas, and the difference will keep growing even after reaching oil and gas supply peaks. This means that the decline of oil and gas will decrease the net EROI-based energy left to society by *more* than the gross supply decline as discussed in section 3.3.2, unless oil and gas can be phased out much faster than their maximum possible production decline.

[13] This follows from the following line of reasoning. We deduce from its EROI at the extraction that about 3EJ/yr of indirect energy are also invested in the extraction of coal, thus probably about 1EJ/yr of oil and 1EJ/yr of gas considering again the energy mix as representative of the share of investments among the various sources of energy. The share of the energy invested in the preparation — washing coal — over the total coal supply thus amounts to 4.2%. It can be assumed that it is mainly provided by electricity at the direct boundary. The global energy mix is again assumed to be representative of indirect energy investment shares. Finally, the transportation energy investment represents 5.6% of the total coal energy supply. In all likelihood, this comes mostly from oil, which constitutes more than 95% of the energy used in transportation, and as we can expect the direct energy investments in oil to be dominant over indirect ones. We then apply the +50% factor discussed above in section 3.2.1.2 to estimate the $\{lab + aux\}$ energy investments. We then expect that oil investments in the coal supply chain represent $\sim$10% of the total coal supply, and gas investments less than 4%. Excluding the non energy uses of coal in the computation, this represents in 2022 $\sim$16EJ for oil and $\sim$7EJ for gas.

3.4. Discussion

3.4.1. Modeling uncertainties

Let us briefly recall that our model uses the cumulative ($\{tot\}$) energy investments calculated in Delannoy et al. (2021a) and Delannoy et al. (2021b) at the extraction stage and adds the direct + indirect ($\{d+i\}$) energy investments within the remainder of the supply chain (processing and transport) from the data of Murphy et al. (2022), itself produced using the EcoInvent life cycle analysis database; finally, we extend this direct+indirect boundary to the cumulative (tot) boundary in a simplified, conservative manner. The sum of all the energy investments at the various points accounts in the end for the cumulative (tot) energy investments at the point of use of oil and gas.

This implies that modeling uncertainties fall under one of two categories[14] for oil and gas:

1. Uncertainties in EROIs themselves (or equivalently, in energy investments).
2. Uncertainties in the extrapolations done for the modeling presented in section 3.2.1.2 and detailed in Appendices 3.A and 3.B.

Let us start with the latter, i.e., the most easily dealt with.

3.4.1.1. Extrapolation uncertainties

These extrapolations have been mostly discussed and graphically shown in Appendices 3.A and 3.B. Extrapolation of past trends is a common procedure. The question is how far in the future can simple extrapolations be reliably performed.

Most of these extrapolations are either constant or linear trends with small absolute annual changes; because of this mild change, we expect these extrapolations to be reliable up to the time limit of the present analysis (2050). Some extrapolations however imply more substantial changes in 2050. For example the share of energy invested in gas pipelines for gas, shown on figure 3.B3, displays a substantial drop between now and 2050. This in turn implies a related decrease in the overall energy investment in gas transmission, Eq. (3.B6). We have checked in all such cases that changing the form of the extrapolation has little influence on the overall results. In this specific case, we have tested a constant share of energy investment in gas pipelines instead of a decreasing one. This changed the net gas energy by ~ 1 – 2%.

This last remark is valid for all our extrapolations. Furthermore, the vast majorities of these bear on shares of investments that are given from EROIs or directly in energy before being distributed among various uses[15]. Thus, errors in these shares do not affect the end results on net energy. Only EROI uncertainties (discussed next) matter in this case.

A consequence of our extrapolation strategy is that the oil and gas energy investments in their supply chains decrease once these energy sources have reached their production peak, while the energy requirement increases because the EROI of oil and gas decreases steadily (before and after their production peak). Therefore, within our extrapolation, other energy sources must contribute substantially to both supply chains past the oil and gas production peak. These points have been shown quantitatively in section 3.3.1. One may question whether oil and gas

[14] These are modeling uncertainties, not data uncertainties. The uncertainty on the data used in (Murphy et al., 2022) are unknown. The uncertainties on the gross oil and gas supply are bracketed by the three different projections of Fig. 3.2; a more extensive analysis on gross energy projection uncertainties is performed in Chapter 2.

[15] This is not the case of the gas pipeline share.

may not in fact contribute more to the required energy investments than suggested by our simple extrapolations. We consider this unlikely, because the demand pressure on oil (for transport and petrochemistry) and gas (for electricity production) is unlikely to decrease within the next ten or fifteen years[16]. This point of view will be self-consistently justified in a future publication. For now, it can be considered as a working hypothesis. Note that in any case, the total energy investment from all energy sources is constrained from the oil and gas EROIs. A higher oil and gas investment in their supply chain would result in a lesser demand on coal and renewables to bridge the gap. This would not affect the major conclusions of our analysis, in particular on EROI and source-based net energy.

Yet another hidden source of error related to our extrapolations comes from a possible underestimation of the weight of heavy and extra-heavy oils in the refining process. These are energetically more costly to process, and extrapolations from the past may not be reliable, as the share of these oil sources increases faster in the future than in the past in the global gross oil supply. To estimate the magnitude of this error, we point out that these constitute less than half of the gross net supply, including in 2050, and that the refining of heavy/extra-heavy oil requires $\sim$ 40% more energy than conventional oil (this is deduced from Fig. 1 and Eq. (1) of Karras 2010, one of the scant publications addressing this issue). As these oil fluids constitute less than 30% of the projected oil supply in 2050, and as refining constitutes less than 30% of energy investments, we conclude that neglecting this issue leads to an overestimate of net available energy by less than 3 or 4%. In all likeliness, there is a wide margin in this upper bound, as all factors mentioned above are themselves upper bounds, and as it was derived with the implicit assumption that no heavy oil sources were present in the past. This is also in line with our adopted bias towards slightly overestimating net energy supply in this work.

From this discussion we conclude that extrapolation uncertainties are small, and in fact negligible in first approximation compared to other sources of uncertainties (projection data and EROI uncertainties).

3.4.1.2. EROI UNCERTAINTIES

In the case of the oil supply chain, energy investments at the extraction point play an instrumental role, constituting 50% of all investments in 2020 and 75% in 2050 (see Fig. 3.9). The estimates of the EROI of the different types of oil at the extraction stage are discussed in the section 3.3 of Delannoy et al. (2021a). In particular these authors have made an extensive sensitivity analysis of their major results on EROI decline modeling assumptions, and found that it affected little the main results (date and amplitude of the net supply peak), even though these authors investigated different forms of EROI decline. These results apply here as well.

Delannoy et al. (2021b) tested and discussed the EROI estimates of gas in a similar way, although the extraction stage is less important in the gas supply chain than in the oil's one (see Figs. 3.9 and 3.10).

This still leaves aside two points, for the present purpose:

- Errors related to the energy investments beyond the extraction point (energy investments taken from Murphy et al. 2022).
- For conventional fossil fuels (oil, gas and in fact coal as well), EROI estimates from Court and Fizaine (2017) have been used. These authors evaluated EROIs from prices, which implies that the energy investments for conventional oil are calculated at the cumulative

[16] Except for contextual variations in supply and demand, such as the current slight overproduction which produced a substantial decrease in oil prices over the past year.

boundary, instead of the standard on $(d + i)$. However, on closer inspection, their use of monetary proxies involves erroneous assumptions.

We cannot estimate errors related to the first item, as the figures quoted in Murphy et al. (2022) come from the EcoInvent life cycle analysis database, but the second item is of particular importance due to the share of conventional oil (which in Court and Fizaine 2017 includes both onshore and offshore sources) in oil supply up to 2050.

In Appendix 3.G, we point out and correct the erroneous assumptions made in Court and Fizaine (2017). Combined with a correction of URR pointed out by Delannoy et al. (2021a), we conclude that the correct conventional EROI lies in between the lower and mean values of these latter authors. In practice, we keep the mean value, noting that this overestimates the correct EROI by a factor of order unity, and in agreement with the bias towards (slight) overestimation of net oil supply adopted in this work. This result is convenient but fortuitous considering the number of subtleties involved in the analysis.

Finally, it should be noted that we ignore future changes in capital energy investments in the oil and gas supply chain. We pointed out in Appendix 3.G that capital investments are small compared to operational investments for past and current conventional oil. This may not be the case in the future as the capital investments for oil projects (the $\{tot - d\}$ investments at extraction) may be more significant for non conventional oil and as a number of oil projects are underway or planned to compensate for the decline in conventional fields (Rabas, 2024). Modeling this dynamics would tend to increase the energy investments in the short-term. Again, neglecting this is in line with our bias towards maximizing within reason net available energy.

From this discussion, we conclude that EROI uncertainties do not affect our main results in a noticeable way. In fact, our reasoned bias has been adopted precisely for this objective, i.e., reaching bottom-line conclusions that may only be worsened by new knowledge (except for unforeseen and major technological breakthroughs).

3.4.2. Oil and gas investments in wind and solar renewable energy production

So far in this work we have left aside the question of the energy supply required by the energy transition, part of which must inevitably come from oil and gas. To address this question at the level of detail adopted in our analysis would require a modeling of renewable energies and of the energy system (for modeling the transformation of the end-use technologies and of the electric grids) well beyond the scope of the present paper. Nevertheless, it is interesting to give some semi-quantitative indications on this topic, basing ourselves on the relevant part of our work on gross energy supply at the 2050 horizon performed in Chapter 2. This summary is provided in Appendix 3.H. The outcome of this summary is that wind and PV are expected to collectively produce around 90—100 EJ/yr in 2050, compared to 17 EJ/yr in 2024.

We focus here only on wind and photovoltaic (PV) energy sources. Indeed, the deployment potential for nuclear energy, hydroelectricity and bio-energies is generally projected to be limited up to 2050 (IEA, 2024d; IAEA, 2023; IPCC, 2023). This directly limits the future energy investments in their supply chains, especially when energy costs are concentrated in capital investments that have already been performed, as is the case for hydroelectricity and, to a lesser extent, nuclear energy[17]. Moreover, from the references given above, we estimated the additional energy supply of nuclear energy, bio-energies, hydroelectricity and other minor energy sources to $\sim$50 EJ/yr between 2022 and 2050 in a relatively high supply assumption. In the case

[17]Many nuclear plants were built in the 1980s and will reach end of life before 2050. Investments in new nuclear plants would thus be required just to maintain a global constant energy production capacity.

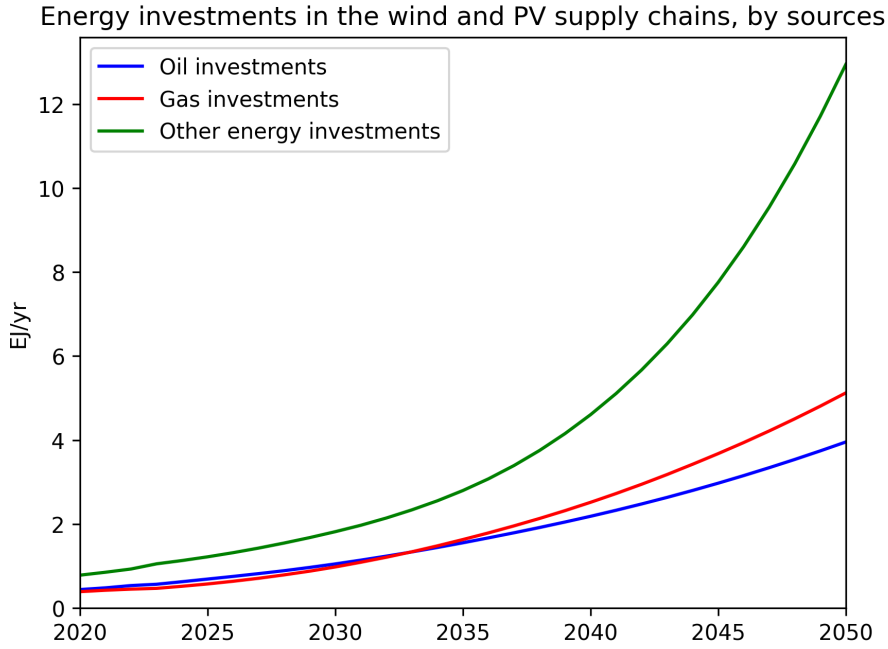


FIGURE 3.13: Oil, gas and other energy sources investments in the wind and PV supply chain in order to provide the energy supply shown in Fig.3.H1.

of wind and PV, it should (and could) be around 80 EJ/yr in the scenario in which wind and PV increase in order to just meet the energy demand while compensating for the decline of oil and gas supplies[18].

The two studies of Dupont et al. (2018) and Dupont et al. (2020) provide information on the operational and capital expenditures (in energy units) of wind and PV. Using our scenario on the deployment of wind and PV described in Appendix 3.H, we find that the share of the annual energy investments over energy production stays relatively constant at 0.31 for PV and 0.10 for wind. The constancy is due to the deployment of wind and PV being close to exponential up to 2050.

These energy investments represent sizable fractions of the energy produced, especially for PV. The very high energy cost for solar PV production is due partially to intrinsic reasons, and partially to the high growth rate of this energy source, which reflects the present large rate of deployment of new facilities. These figures ignores the end-of-life and replacement energy cost of old infrastructure. However, the lifetimes of wind and PV infrastructures are expected to be in the 20-30 years range, which makes the energy required for replacement small or even negligible compared to the energy investment in new infrastructures for the period considered here (2025-2050).

These data can be used to quantify in absolute energy units the oil, gas and other energy investments in these two technologies as a function of time, for PV and wind, in the deployment scenario described before. This is achieved by using the energy mix of our mild BAU scenario, quantified in Appendix 3.E.2, and the logistic projections of wind and PV energy production shown on Fig. 3.H1. The resulting flow of capital and operation energy investment for both types of renewable energy sources is shown on Fig. 3.13.

This whole procedure is less precise than the quantification of section 3.3 especially due to the uncertainties in the actual potentials and normalized growth rates of wind and PV energies.

[18]More ambitious energy transition scenarios, in which wind and PV completely replace fossil fuels, would require further wind and PV deployment in the case of a business-as-usual total energy demand growth.

Nevertheless, it still indicates that the oil, gas and other energy investments in the wind and PV supply chains would respectively represent 4 EJ/yr, 5 EJ/yr and 13 EJ/yr in 2050. This is about 10% of the investments in the oil and gas supply chains for each energy source in 2050. However, it should be noted that it increases quickly after 2035 in absolute values, opposite to the oil and gas investments in the oil and gas supply chain that decline after 2035—2040.

The oil and gas investments in the wind and PV supply chains therefore remain small (but not negligible) compared to the investments in the oil and gas supply chains, for our adopted minimal deployment scenario of Appendix 3.H. These investments do not account the energy investments required for the electric grids to integrate these energy sources, nor the whole investments required in the transformations of the energy infrastructures (on both the production and consumption sides). These may be of particular importance in more ambitious energy transition scenarios.

3.4.3. Comparison of EROI results for the oil and gas chain with the literature

Some existing studies (Brand-Correa et al., 2017; Brockway et al., 2019; Aramendia et al., 2024; Feng et al., 2018a; Gomes Gonçalves and Trotter, 2025; Dupont et al., 2021; Brandt, 2011; Ecclesia et al., 2022; Jackson and Jackson, 2021; Slameršak et al., 2022) also quantify the energy investments required at the point of use in the oil and gas supply chain. However they rarely disaggregate between the different types of energy investments, but rather give results about EROIs and the assumptions made. We will thus mainly compare EROIs at the point of use in this part of the discussion.

In practice comparing EROI results therefore amounts to discussing the hypotheses behind EROI models. Such a comparison is made difficult by a number of factors:

- The boundaries differ: existing studies often compute energy investments at the direct + indirect boundary or at the cumulative ($\{tot = d + i + lab + aux\}$) one, but this may exclude capital investments (as pointed out by Brockway et al. 2019).
- The processes accounted for differ: we included the processing and transport stages of the supply chain, while some articles may not include all of them (as in Brockway et al. 2019 or Brandt 2011).
- The method employed influences the conclusions that can be drawn (as in Gomes Gonçalves and Trotter 2025), or the system studied differs (as in Brandt 2011; Feng et al. 2018a).
- The quality of the results is contingent upon the quality of the data, but it is often difficult to assess the robustness of input data.

For instance, Aramendia et al. (2024) found a stagnating EROI[19] of 8 for oil products, and a gas EROI falling from approximately 25 to 10, between 1971 and 2020. They computed direct energy investments based on the IEA's World Energy Balances (WEB) database (a data source commonly used in the literature). The $\{tot - d\}$ energy investments (called "indirect" energy by these authors) are then estimated using the Exiobase database in conjunction with IEA's WEB in order to obtain the relevant energy intensity coefficients of monetary flows. This is based on the methodology developed in Brockway et al. (2019) from Brand-Correa et al. (2017). Note that multiple articles use a similar methodology (Feng et al., 2018a; Slameršak et al., 2022; Gomes Gonçalves and Trotter, 2025; Jackson and Jackson, 2021).

[19] Their EROI are in fact calculated with the net energy at the numerator. One should then add 1 to their results in order to compare them to ours, defined in Eq. (3.1)

However, the authors do not model the transportation and distribution of oil and gas. This is a key element for gas as transmission constitutes half of the energy investments in the gas supply chain between 1990 and 2020, in our results. Furthermore, the authors indicate that their $\{tot-d\}$ energy investments should be viewed as a lower bound given that their estimation excludes capital expenditures.

In the case of oil, the comparison of Fig. 3 of Brockway et al. (2019) with Fig. 1 of Delannoy et al. (2021a) allows us to deduce that the differences in the estimates of EROIs at the point of use compared to the present study mainly come from estimates of EROIs at the point of extraction. On the contrary, for gas, the EROI at the point of extraction of Brockway et al. (2019) is similar to that of Delannoy et al. (2021b). This implies that the differences in the EROI at point of use necessarily results from the fact that their study neglects the gas transmission in their point of use estimates, while this represent 80% in 2020 and 50% in 2050 of the energy investments in the gas supply chain in our model.

Feng et al. (2018a) found a declining EROI for oil from 8 to 1 between 1990 and 2030, and an EROI of gas between 6 and 2, in China. The methodology is similar to Brockway et al. (2019) article's, but with "indirect" (corresponding to the $\{tot - d\}$ boundary) energy investments being computed based on Chinese national data and appropriate energy intensity coefficients.

Brandt (2011) undertook a comprehensive analysis of the physical energy requirements of the entire supply chain for oil in California, excluding the transportation sector. He obtains a 3.5 EROI in 2010.

Some articles quantify societal EROI, i.e. an EROI for all energy sources at a given time (Feng et al., 2018b; Brand-Correa et al., 2017; Brockway et al., 2019; Gomes Gonçalves and Trotter, 2025; Dupont et al., 2021; Ecclesia et al., 2022). Our own estimate of societal EROI (at point of use and cumulative boundary as always), given in section 3.3.2, ranges from 5.5 in 1971, to 4 in 2022 and 3 in 2035.

Gomes Gonçalves and Trotter (2025) give a global societal EROI between 2 and 1 between 1995 and 2020. However, the authors warn that these absolute values may not be reliable due to the low robustness of using energy intensity coefficients to convert monetary flows into energy one. They point out that although absolute values of EROI may not be reliable, they may be used for relative inter-countries comparison.

The societal EROI is calculated to be 6 in 2010 in Brockway et al. (2019), 9 in 2018 in Dupont et al. (2021), 6 in 2012 in Brand-Correa et al. (2017) for UK, Feng et al. (2018b) 5-7 in 2010 in China, 7-8 in 2010 in Ecclesia et al. (2022) excluding capital investments for Portugal.

We conclude that our point of use EROI at the cumulative boundary is in the lower range of the values documented in the literature. This can be partially explained by the fact that previous analyses frequently omit to account for part of the processes and investments at the labor and auxiliary boundary. Otherwise, the differences is mostly explained by different modeling assumptions for the energy investment in the extraction of oil and gas, and in the transmission of gas.

3.5. Conclusion

3.5.1. Approach

The present work models the energy investments required in oil and gas supply chains by 2050. Particularly, it extends previous analyses by quantifying energy investments to the point of use (a by now common perspective, due to its higher relevance) rather than to the point of extraction, to the cumulative, auxiliary boundary (Murphy and Hall, 2011) rather than the standard one. Energy investments in the oil and gas supply chains are also disaggregated by energy source, a somewhat less robust line of analysis.

In this analysis, a somewhat optimistic view of oil and gas supply has been adopted (in particular for computing net energies), in conjunction with a mild, somewhat pessimistic BAU growth scenario to provide conservative comparisons between energy supply and demand. This in itself strengthens our conclusions on possible upcoming tensions on supply summarized below, in particular for oil.

We have used two different concepts of net energy. The first one is the usual, EROI-based net energy, i.e., gross energy reduced by all energy investments needed to produce it. We introduce in this article a second net energy concept, dubbed source-based net energy, which quantifies the energy available to society and its economy for all uses besides energy production itself. In the context of the present study, this quantifies the remaining oil and gas energy obtained once all oil (respectively gas) used for all forms of energy production is deducted from oil (resp. gas) gross energy. This second form of net energy reflects what the producing economy (outside the energy sector) actually "perceives" as available oil and gas (both in the present and the future), while the former reflects how much energy is really available once oil and gas are processed.

This analysis takes in some ways an opposite stance to uninformed but common opinions, according to which fossil fuels are plentiful and the problem is to shift away from fossil energies to fight climate change. In such a view, there is no issue of fossil energy supply. However, we stress with a number of other authors that although it is true that fossil fuels *stocks* are plentiful (mostly because of uneconomical stocks), *flows* are not. In particular, peaks in oil and gas gross supply are now expected in the near future, opening the possibility that these sources (especially oil) may be difficult to substitute fast enough with other energy sources. Our results indicate that oil (or gas) energy investments exacerbate the decreasing oil (or gas) availability due to their gross supply peak.

In terms of main processes, energy investments in oil supply chain are found to be dominant at the extraction point, whereas energy investments in gas supply chain are more evenly spread between extraction and transmission. Moreover, the $\{tot - d\}$ energy investments represent a significant proportion of the total energy investments.

Beyond these general statements, our main results are the following.

3.5.2. Summary of main results

Energy investments in the oil and gas supply chains are expected to grow steadily until 2035—2040 reaching approximately 120 EJ/yr for oil and 100 EJ/yr for gas[20]. This represents a +75% and +100% increase, respectively, compared to 2022. Their absolute values then stabilize due to the decline in their gross supply, however their relative values continue to increase.

[20] By comparison, for example, the present world electricity use amounts to 105 EJ/yr.

This has two main implications.

First, it raises metabolic concerns. The point-of-use EROI at the cumulative boundary of oil decreases from 2.8 in 2022 to 1.5 in 2050 (4.9 in 1971), and from 2.9 in 2022 to 2.0 in 2050 for gas (3.6 in 1971). The EROI of the energetic system is expected to decrease from ∼4 in 2022 to ∼3 in 2035 (∼5.5 in 1971) in the mild business-as-usual (BAU) scenario adopted in this work. The magnitude of these declines raises questions regarding the value of the societal EROI and its implications on the feasibility of future economic growth (Hall et al., 2009; Brandt, 2017; Fizaine and Court, 2016).

Secondly, the demand for coal and other energy sources (in particular wind and PV) in the oil and gas supply chains increases by 71 EJ by 2050[21], while these sources also have to grow in order to compensate for the decline in oil and gas gross supply — which approximately sums up to 74 EJ in 2050 compared to their peak value. In our BAU scenario, the annual energy supply from other energy sources must increase by 198 EJ (+70%) between 2022 and 2050 (see Fig. 3.E5). This is a quite significant increase in less than 30 years, which may require a continuous effort in terms of coal and renewable deployment, even for our mild BAU growth scenario. Additionally, renewable energy production would need to increase further in order to decrease fossil fuels in the energy mix to reduce CO_2 emissions.

3.5.3. Source-based net energy specific results

On the contrary to EROI-based net energy, the net source-based oil supply still continues to grow up to 2035, in tandem with the oil gross supply itself. This does give a signal of little to no upcoming tension in oil supply in the next decade, while net energy from oil has already peaked. This implies that there may be little economic incentive in most economic sectors to move away from oil in the next ten years, when we should instead move away from oil at an accelerated pace to avoid the structural macroeconomic problems a structural tension on oil would induce.

Another result of source-based net analysis is that at present, less gas and oil is used in the production of other energy sources than other energies in the production of oil and gas, and the difference will keep growing and even accelerating after reaching the oil and gas supply peaks. This implies that once EROI-based net energy of these two sources starts declining faster past 2035, the energy demand from other energy sources for oil and gas extraction and processing will increase *faster* than this decline itself, on top of the energy needed to maintain or stabilize GDP growth.

3.5.4. Policy implications and final thoughts

Furthermore, looking at supply vs demand at the aggregated level (a common stance in the academic and gray literature) hides the fact that not all energy sources are substitutable, especially on short time-scales (a decade or so). This is particularly true for oil, the fossil fuel closest to supply peak. This question constitutes a bottleneck of its own, as oil comes into play in one way or another in nearly everything produced, and some oil uses cannot be substituted by other resources on the short run.

The results summarized in section 3.5.3 have the obvious policy implication that the world economy should phase-out oil as fast as possible, and not only to fight climate change. In fact a tension between oil demand and supply may well flesh out before the most important consequences of climate change unfold. In fact, the climate change debate hides this underlying

[21] Leaving aside the paradox that using renewable sources of energy to produce fossil ones poses!

macroeconomic problem.

More precisely, the metabolic concerns and doubts summarized above about the feasibility of meeting the demand for oil constitute a threat to the feasibility of business-as-usual scenarios: our results suggest that a limit in oil (and to a lesser extent, gas) supply with respect to demand is not out of the question, and this may lead to a global structural economic recession, by making the currently pursued BAU scenarios infeasible. Conversely, fostering the deployment of PV and wind power — the only two energy sources capable of rapid growth — while phasing out oil and gas would contain the decrease in the EROI of the energy system[22] and reduce CO_2 emissions. Still, it is probable that only post-growth policies may avoid the macroeconomic structural recession just mentioned and its consequences.

Our work calls for accelerated and wide-support for the deployment of wind and photovoltaic power and for capping or even decreasing the world energy consumption due to the risks incurred by BAU policies. The worst case scenario would leave us with *both* a major long-lasting crisis *and* severe climate change issues (already underway) in a context where little energy would actually be available for society to face both issues.

[22] Aramendia et al. (2024) indeed suggests that the EROI of renewable energies would be higher than fossil fuels'. However this point of view is not consensual yet (Hall and Palmer, 2025), and the energy investments required in the energy transition must be further modeled to reach more robust conclusions on this front (Nieto et al., 2020; Sgouridis et al., 2016; Dumas et al., 2022).

Appendices to chapter 3

3.A. Energy investments in the oil supply chain

3.A.1. Oil, gas and other energy use at the oil extraction point

A stated earlier, Delannoy et al. (2021a) provide us with EROI estimates at the extraction point for the cumulative perimeter, $\xi_o^{ex,tot}$. We wish to evaluate the shares of oil, gas, and other sources of energy in this EROI perimeter (keeping in mind that this yields a lower bound to the energy investment for this perimeter). The direct oil and gas energy invested in oil extraction can be quantified using data from IEA's World Energy Balances database[23], as shown in absolute fashion on Fig. 3.A1. The same data allow us to represent the same quantity in relative instead of absolute values on Fig. 3.A2.

The first issue is to separate oil and gas extraction in this direct energy use. Oil and gas are aggregated in the WEB database, most probably because they are often found in the same fields. When the field contains mostly oil, it is called an oil field, or a gas field when it contains mostly gas. In most fields, the gas expands naturally once the field is drilled and does not need extra energy to be extracted. This is not the case for oil, which nowadays needs to be pumped to the surface; the higher the oil viscosity and well depth, the larger the pumping energy.

This argument does not apply *a priori* to shale/tight gas, but their gross energy will represent at most 10% of the oil gross energy, and this will occur around 2040 according to the GlobalShift data. Furthermore, shale/tight gas has a rather large extraction EROI, $\sim$50 (Delannoy et al. 2021b and references therein), so that the shale/tight gas extraction energy can be neglected. Thus, nowadays, less than 2‰of the direct gas energy use at extraction goes to gas extraction, i.e., less than $\sim$ 0.01EJ/yr (a generous overestimate of the actual limit). This is totally negligible, in comparison to both oil and gas direct energy use for extraction, in the present and in the future.

These two lines of argument imply that the direct energy invested for oil and gas extraction can in fact be assumed to be used solely for oil extraction, to a very good level of approximation.

[23] This does not include the energy required to produce biofuels and CTL. This energy is small, less than 3% of the energy needed for all liquids production in the case of CTL, and less than 6% for biofuels. Neglecting them in the direct energy use will result in an underestimation of direct energy use for oil liquids production, exactly compensated by an overestimation at the cumulative boundary between the indirect and auxiliary boundaries. This has no influence on our conclusions. The same remark holds at the refinery point.

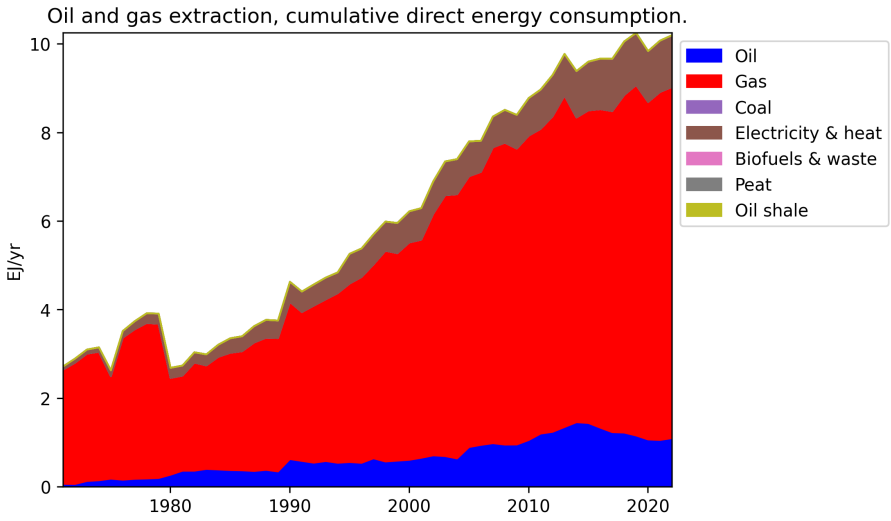


FIGURE 3.A1: Origin of the direct energy invested for oil and gas extraction (from IEA's World Energy Balances database).

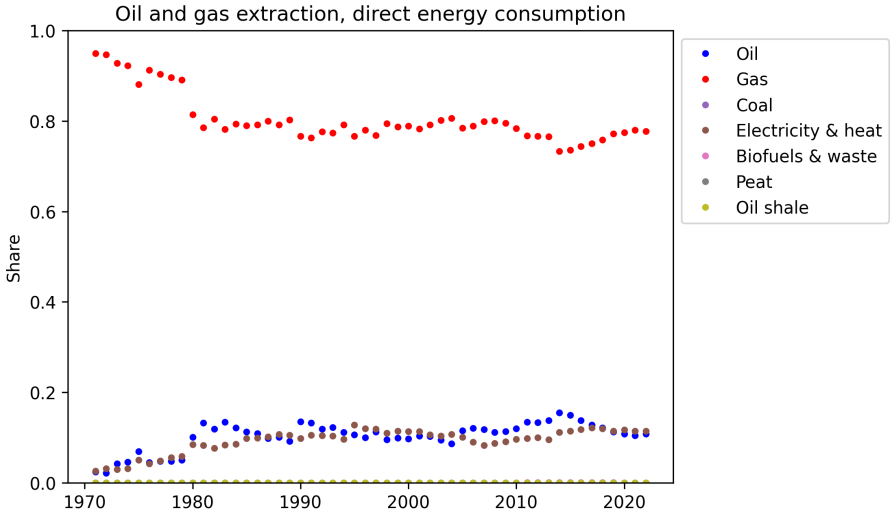


FIGURE 3.A2: Origin of the direct energy invested for oil and gas extraction, in relative values (from IEA's World Energy Balances database).

3.A.1.1. DIRECT OIL AND GAS ENERGY USE AT THE OIL POINT OF EXTRACTION

Next, we find from Fig. 3.A1 that between 1980 to 2020, this direct energy use in oil extraction has increased from $\simeq 2.6$ to $\simeq 10$ EJ/yr, i.e., by a factor of 3.8. This can be explained with the help of Eqs. (3.3) and (3.5) which give the total energy cost of oil extraction as

$$E_{r,o}^{ex,tot} = \frac{E_{G,o}}{\xi_o^{ex,tot}}, \tag{3.A1}$$

where $\xi_o^{ex,tot}$ is the EROI used in figure 3 of Delannoy et al. (2021a). $E_{G,o}$ is obtained from GlobalShift's data as explained in section 3.2.2.1. In this relation, $\xi_o^{ex,tot}$ is the EROI of all oil liquids including their non-energy uses, counted in energy unit[24].

It is shown in Appendix 3.D that $\xi_o^{ex,tot}$ defined by Eq.(3.5) is also the EROI of all liquids excluding non-energy uses. More precisely, if $E_{G,o}^{\dagger}$ designates the gross all oil liquids energy, excluding non-energy uses, and $\xi_o^{\dagger,ex,tot}$ the energy invested to produce $E_{G,o}^{\dagger}$, one also has

$$E_{r,o}^{\dagger,ex,tot} = \frac{E\dagger_{G,o}}{\xi_o^{ex,tot}}. \tag{3.A2}$$

Note that Eq. (3.A1) leads to estimate the contributions of all forms of oil liquids to the total energy invested in their production from the mean EROI $\xi_o^{ex,tot}$. The correctness of this procedure is guaranteed by Eq. (3.5), and this mean EROI includes oil liquids not coming from oil (i.e., CTL, GTL, NGLs and biofuels).

We use Eq. (3.A1) to quantify $E_{r,o}^{ex,tot}$. From Fig. 1 and 3 of Delannoy et al. (2021a), one can estimate that in 1980, $E_{G,o} \simeq 120$ EJ/yr and $\xi_o^{ex,tot} \simeq 24$ while in 2020, $E_{G,o} \simeq 170$ EJ/yr and $\xi_o^{ex,tot} \simeq 6$. With these data one obtains that $E_{r,o}^{ex,tot}$ increases from 5 EJ/yr to 28 EJ/yr between 1980 and 2020, i.e. by a factor of about 5.6. From these numbers and figure 3.A1, one sees that the fraction of direct energy in the energy cost, γ_{ex}, varies from $E_{r,o}^{ex,d}/E_{r,o}^{ex,tot} = 2.6/5.6 = 0.46$ in 1980 to $10/30.6 = 0.33$ in 2020.

Thus, the direct energy needed for oil extraction $E_{r,o}^{ex,d}$ represents a decreasing fraction of $E_{r,o}^{ex,tot}$. This is not quite expected as the fraction of non-conventional oil in oil production, in particular offshore oil, has increased from less than 1/3 to nearly 1/2 over the same period. This suggests that technological progress has more than compensated this trend.

These back-of-an-envelope estimates guided us in our more precise calculations: we evaluated the $E_{r,o}^{ex,d}/E_{r,o}^{ex,tot}$ ratio in the same way annually from 1980 to 2020 and using our more precise quantification of $E_{G,o}$. The results are shown on Fig. 3.A3. This indicates that one may extrapolate linearly the later trend up to 2050. This assumption is made in what follows, i.e.:

$$E_{r,o}^{ex,d} = \gamma_{ex} E_{r,o}^{ex,tot}, \tag{3.A3}$$

$$\gamma_{ex} = a_{ex}(t - t_0) + b_{ex}, \tag{3.A4}$$

with $a_{ex} = -6.6 \times 10^{-3}\,\mathrm{yr}^{-1}$, $b_{ex} = 0.33$, and $t_0 = 2020$ is the reference year. This predictor is used to project the direct use of oil in oil extraction to 2050.

The next step is to find the quantity of oil and gas in $E_{r,o}^{ex,d}$. Fig. 3.A2 shows that the fraction $f_{ex,o}$ of oil in this direct energy use has been stable at

$$f_{ex,o} = 0.12, \tag{3.A5}$$

[24] All oil products can be characterized by their heat energy content, whether or not they are used as an energy source.

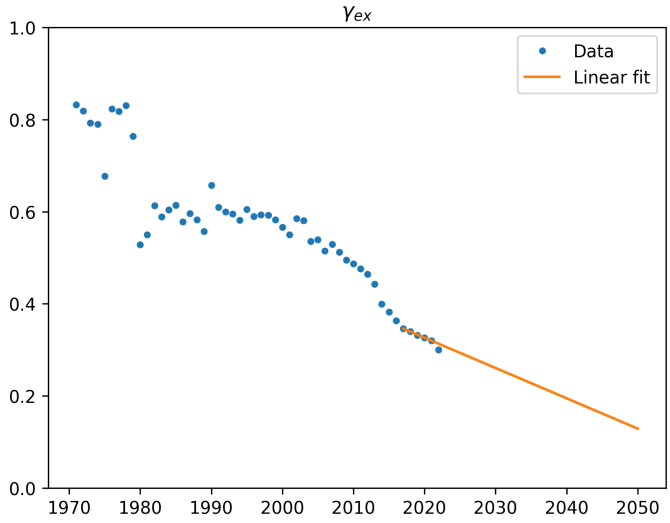


FIGURE 3.A3: Ratio of direct oil energy use on the total energy used at the extraction point.

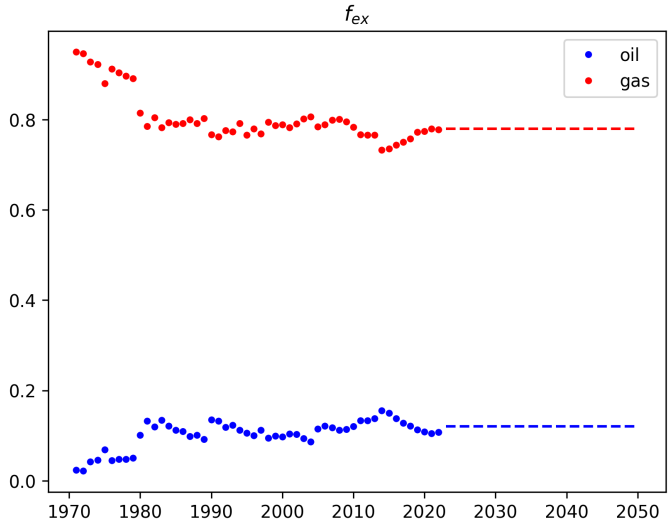


FIGURE 3.A4: Relative fractions of the direct oil and gas energy invested at the extraction point. The points represent data, while the dashed line represents projections.

since $\sim$ 1980 and we assume this will remain the case in the future. Note that the use of electricity is at the same level. The same constancy is observed the fraction of gas in oil extraction, $f_{ex,g}$, but at a different level:

$$f_{ex,g} = 0.78, \tag{3.A6}$$

This is shown on figure 3.A4.

Putting all these results together, we find that the direct oil, gas and other sources of energy

invested in oil extraction, $E_{r,o}^{ex,d,o}$, $E_{r,o}^{ex,d,g}$ and $E_{r,o}^{ex,d,e}$ are given by

$$E_{r,o}^{ex,d,o} = g_{ex,d,o} E_{r,o}^{ex,tot} = g_{ex,d,o} \frac{E_{G,o}}{\xi_o^{ex,tot}}, \tag{3.A7}$$

$$E_{r,o}^{ex,d,g} = g_{ex,d,g} E_{r,o}^{ex,tot} = g_{ex,d,g} \frac{E_{G,o}}{\xi_o^{ex,tot}}, \tag{3.A8}$$

$$E_{r,o}^{ex,d,e} = g_{ex,d,e} E_{r,o}^{ex,tot} = g_{ex,d,e} \frac{E_{G,o}}{\xi_o^{ex,tot}}, \tag{3.A9}$$

where

$$g_{ex,d,o} \equiv f_{ex,o} \gamma_{ex}, \tag{3.A10}$$

$$g_{ex,d,g} \equiv f_{ex,g} \gamma_{ex}, \tag{3.A11}$$

$$g_{ex,d,e} \equiv f_{ex,e} \gamma_{ex} = \gamma_{ex} - g_{ex,d,o} - g_{ex,d,g}. \tag{3.A12}$$

γ_{ex} and f_{ex} are given above, $E_{G,o}$ is extracted from GlobalShift's data, and $\xi_o^{ex,tot}$ are extracted from the data used to produced Figs. 1 and 3 of Delannoy et al. (2021a). The last relation follows because, by definition, $E_{r,o}^{ex,d,o} + E_{r,o}^{ex,d,g} + E_{r,o}^{ex,d,e} = E_{r,o}^{ex,d}$ (see Eq. 3.9) or equivalently because $f_{ex,o} + f_{ex,g} + f_{ex,e} = 1$.

3.A.1.2. Oil, gas and other energy use beyond the direct boundary at the oil point of extraction

Let us define $E_{r,o}^{ex,tot-d} = E_{r,o}^{ex,tot} - E_{r,o}^{ex,d}$. We wish to quantify $E_{r,o}^{ex,tot-d,o}$, $E_{r,o}^{ex,tot,o}$, $E_{r,o}^{ex,tot-d,g}$,$E_{r,o}^{ex,tot,g}$, $E_{r,o}^{ex,tot-d,e}$ and $E_{r,o}^{ex,tot,e}$. Again $E_{r,o}^{ex,tot-d} = E_{r,o}^{ex,tot-d,o} + E_{r,o}^{ex,tot-d,g} + E_{r,o}^{ex,tot-d,e}$, following Eq. (3.9).

These various sources of energy represent a multiplicity of goods and services used in the oil supply chain, so that we assume that their shares of $E_{r,o}^{ex,tot-d,x}$ ($x \in \{o, g, e\}$) in $E_{r,o}^{ex,tot-d,x}$ is the same as the shares h_o, h_g and h_e of oil, gas and other energies in the global economy — thus in the global energy mix — in the absence of more precise information. This energy mix is known historically, and the remaining task is therefore to project it to 2050. This is performed in Appendix 3.E, from which h_o, h_g and h_e are directly obtained (see figure 3.E4).

Thus, we have

$$E_{r,o}^{ex,tot-d,o} = h_o E_{r,o}^{ex,tot-d} = h_o \left(1 - \gamma_{ex}\right) E_{r,o}^{ex,tot}, \tag{3.A13}$$

$$E_{r,o}^{ex,tot-d,g} = h_g E_{r,o}^{ex,tot-d} = h_g \left(1 - \gamma_{ex}\right) E_{r,o}^{ex,tot}, \tag{3.A14}$$

$$E_{r,o}^{ex,tot-d,e} = h_e E_{r,o}^{ex,tot-d} = h_e \left(1 - \gamma_{ex}\right) E_{r,o}^{ex,tot}, \tag{3.A15}$$

so that

$$E_{r,o}^{ex,tot,o} = g_{ex,tot,o} E_{r,o}^{ex,tot}, \tag{3.A16}$$

$$E_{r,o}^{ex,tot,g} = g_{ex,tot,g} E_{r,o}^{ex,tot}, \tag{3.A17}$$

$$E_{r,o}^{ex,tot,e} = g_{ex,tot,e} E_{r,o}^{ex,tot}, \tag{3.A18}$$

where

$$g_{ex,tot,o} \equiv \left[h_o(1-\gamma_{ex}) + g_{ex,d,o}\right], \tag{3.A19}$$

$$g_{ex,tot,g} \equiv \left[h_g(1-\gamma_{ex}) + g_{ex,d,g}\right], \tag{3.A20}$$

$$\begin{aligned} g_{ex,tot,e} &= \left[h_e(1-\gamma_{ex}) + g_{ex,d,e}\right] \\ &= 1 - g_{ex,tot,o} - g_{ex,tot,g}. \end{aligned} \tag{3.A21}$$

Note that this satisfies $E^{ex,tot,o}_{r,o} + E^{ex,tot,g}_{r,o} + E^{ex,tot,e}_{r,o} = E^{ex,tot}_{r,o}$, as required.

3.A.2. FROM THE POINT OF EXTRACTION TO THE POINT OF USE

Table 2 of Murphy et al. (2022) indicates that the energy investment at the refining (ref) and distribution ($dist$) points account together for 11.5% of the output flow of oil products. The boundary of the energy investments is the standard one. As explained in the methodological outline section 3.2, we add a conservative +50% increase factor k_{tot} on these estimates as a lower estimate of the energy investment at the cumulative (tot) boundary (thus $k_{tot} = 1.5$). The distribution of energy investments between oil, gas and other sources of the boundary extension (standard to $\{lab+aux\}$) is again assumed to be proportional to their share in the global energy mix.

From Murphy et al. (2022), refining constitutes $\nu_{ref} = 8.9\%$ of $E_{G,o}$. Transmission and distribution account for 1.5% and 1.1% respectively. The Supplementary Material of Murphy et al. (2022) specifies that "transmission" is the concatenation of all types of freight transport, of which oil is expected to represent the vast majority of energy investments at least in the next decade (in 2022, oil represented 91% of all energy investment in transport; IEA 2024b). Similarly, freight transport constitutes a significant proportion of the investments in "distribution", the remaining types of energy used being heat and electricity. It is not possible to accurately quantify the associated respective shares due to the absence of conversion coefficients between metric ton×km to MJ for different types of transport. However based on other data provided in the same Supplementary Material, we conservatively assume that oil represent 1.5% and gas 0.3% of these $1.5 + 1.1 = 2.6\%$, the remaining percentage being attributed other sources of energy.

We define the following fractions of energy investments to account for this information, $\nu_{dist} = \nu_{dist,o} + \nu_{dist,g} + \nu_{dist,e}$, with $\nu_{dist,o} = 0.015$, $\nu_{dist,g} = 0.003$ and $\nu_{dist,e} = 0.008$.

The numbers quoted in the Table 2 of Murphy et al. (2022) are given as shares of the output flow of the products. At the refinery stage for oil, these are diesel, gasoline, etc. At the level of precision aimed at in this work, the energy density of oil products can be assumed to be identical to the crude oil one (less than 2% of error on average)[25].

[25] For example, the energy density of crude oil and gasoline differ by 1%. All refined oil products display the same $\sim$ 1% difference, except for heavy fuel oil and LPGs, but their energy density is within 10% of the mean, and they collectively represent less than 12% of the mass of refined products. The production of naphtha (which represents approximately 7% of refined oil products) and other oil products (less than 10%) seem to be neglected in the data used in Murphy et al. (2022), however naphtha has a similar energy density to gasoline (3% lower), and the same is expected to hold for all non-energy uses products. Energy densities can be found on the engineering toolbox website. `https://www.engineeringtoolbox.com/fuels-higher-calorific-values-d_169.html`.

In the case of gas, the energy density of the gas "in ground" is 5% larger than sales gas energy in the data of Murphy et al. (2022). This difference is due to the extraction of NGLs, which are counted in the oil supply by GlobalShift, a common accounting convention for oil liquids.

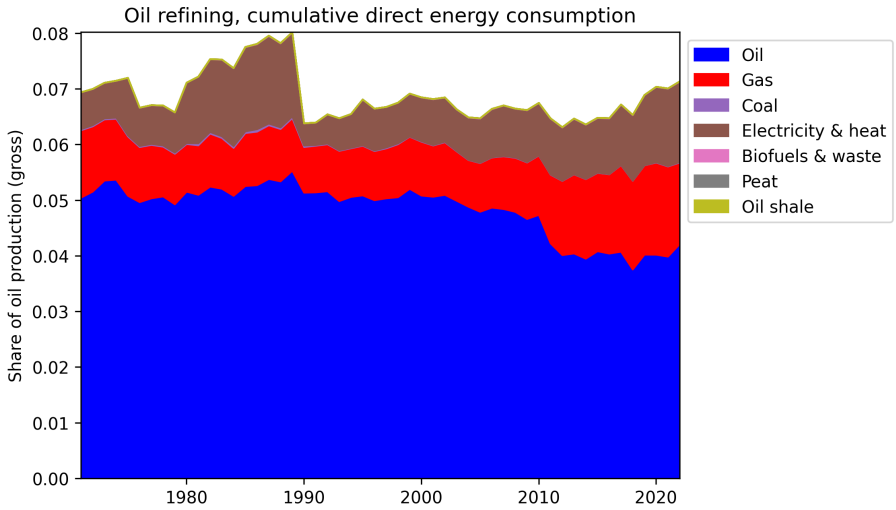


FIGURE 3.A5: Ratio of energy invested for refining to oil gross production (oil refining data from IEA's World Energy Balances database).

We summarize this series of arguments and data in the following two relations

$$E_{r,o}^{ref,tot} = k_{tot}\nu_{ref}E_{G,o}, \tag{3.A22}$$

$$E_{r,o}^{dist,tot} = k_{tot}\nu_{dist}E_{G,o}, \tag{3.A23}$$

where $k_{tot} = 1.5$ stands for our estimate the factor of increase (+50%) of energy investments applied to account for the extension of the standard boundary to the cumulative one.

The disaggregation problem addressed in this work is now reduced to analyzing energy investments in the refining process, which we address next.

3.A.2.1. DIRECT USE OF OIL, GAS AND OTHER ENERGY AT THE OIL REFINING POINT

To estimate the oil used in the refining process, $E_{r,o}^{ref,d,o}$, we proceed as previously for extraction, but somewhat more straightforwardly. First, it is natural to assume that the energy required for refining is proportional to the quantity of gross oil refined. To test this hypothesis, we show on Fig. 3.A5 the direct energy invested for refining by energy source as a fraction of the gross oil energy production. The ratio of energy used over oil gross energy is roughly constant at $\gamma_{ref} = 0.07$ from 1970 to 2020. We assume this will remain constant in the future.

Thus, the direct energy needed for oil refining $E_{r,o}^{ref,d}$ is directly proportional to $E_{G,o}$

$$E_{r,o}^{ref,d} = \gamma_{ref}E_{G,o}, \tag{3.A24}$$

$$\gamma_{ref} = 0.07, \tag{3.A25}$$

This extrapolation fit is shown on figure 3.A6.

Second, the same data allows us to represent the various types of energy invested for refining, relatively to the total energy invested in the process, Fig. 3.A7.

There is an overall decline of the share of oil in the refining process and a correlative increase of the share of gas and electricity. From a linear regression fit of this decline one finds that the

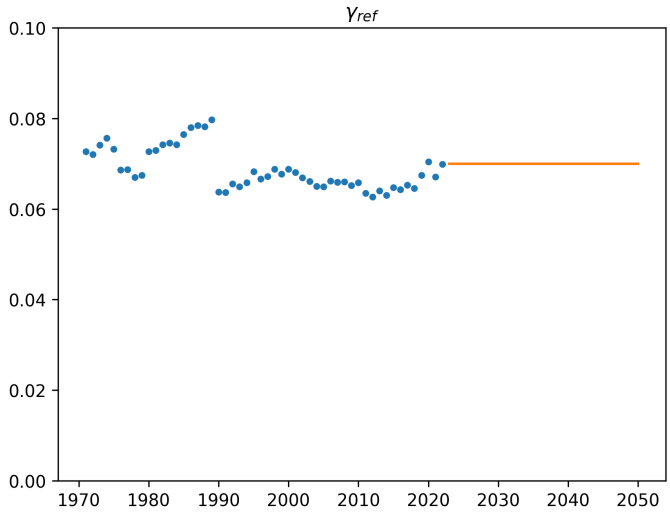


FIGURE 3.A6: Ratio of direct energy use in the refining process to gross oil energy. The points represent data, while the dashed line represents projections.

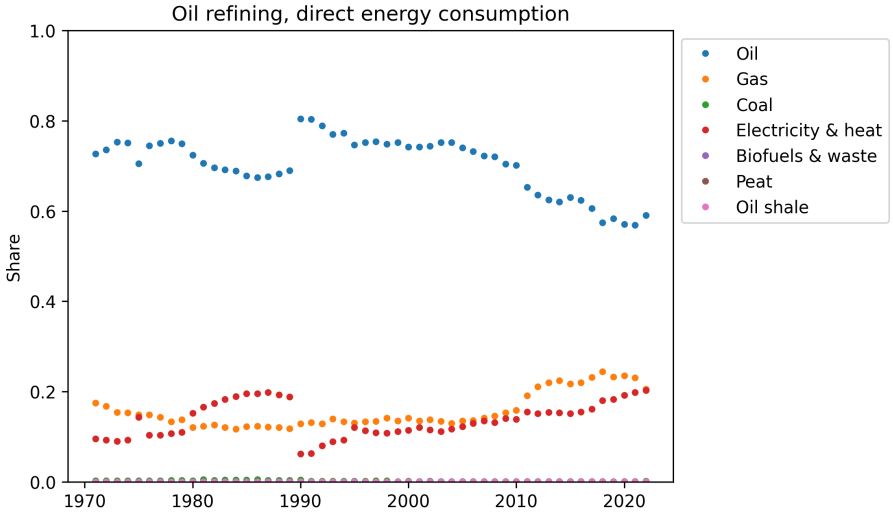


FIGURE 3.A7: Sources of energy invested for oil refining, in relative values (data from IEA's World Energy Balances database).

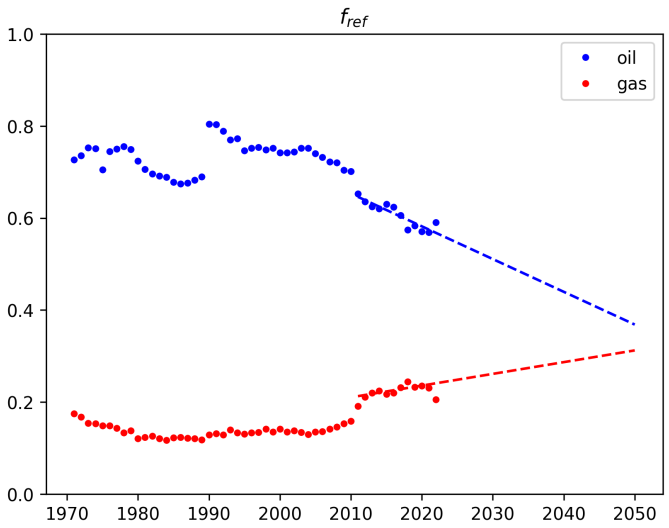


FIGURE 3.A8: Relative fractions of the direct oil and gas energy invested at in the refining process. The points represent data, while the dashed line represents projections.

fraction of oil in the refining energy is

$$f_{ref,o} = a_{ref,o}(t - t_0) + b_{ref,o}, \tag{3.A26}$$

where t is the date (in years), $t_0 = 2020$ the reference year, $a_{ref,o} = -7.12 \times 10^{-3}$/yr and $b_{ref,o} = 0.58$ (dimensionless). The same exercise for gas leads to

$$f_{ref,g} = a_{ref,g}(t - t_0) + b_{ref,g}, \tag{3.A27}$$

where $a_{ref,g} = 2.55 \times 10^{-3}$/yr and $b_{ref,g} = 0.24$ (dimensionless).

This is shown on figure 3.A8.

Putting everything together, one finds that the direct oil and gas energy invested in the refinement process are given by

$$E_{r,o}^{ref,d,o} = g_{ref,d,o} E_{G,o}, \tag{3.A28}$$
$$E_{r,o}^{ref,d,g} = g_{ref,d,g} E_{G,o}, \tag{3.A29}$$
$$E_{r,o}^{ref,d,e} = g_{ref,d,e} E_{G,o}, \tag{3.A30}$$

where

$$g_{ref,d,o} \equiv f_{ref,o}\gamma_{ref}, \tag{3.A31}$$
$$g_{ref,d,g} \equiv f_{ref,g}\gamma_{ref}, \tag{3.A32}$$
$$g_{ref,d,e} \equiv f_{ref,e}\gamma_{ref} = \gamma_{ref} - g_{ref,d,o} - g_{ref,d,g}. \tag{3.A33}$$

γ_{ref}, $f_{ref,o}$ and $f_{ref,g}$ are given above and $E_{G,o}$ and $\xi_o^{ex,tot}$ are extracted from the data used to produced Figs. 1 and 3 of Delannoy et al. (2021a). As before, the last relation follows because, by definition, $E_{r,o}^{ref,d,o} + E_{r,o}^{ref,d,g} + E_{r,o}^{ref,d,e} = E_{r,o}^{ref,d}$ (Eq. 3.9) or equivalently because $f_{ref,o} + f_{ref,g} + f_{ref,e} = 1$.

3.A.2.2. Oil, gas and other energy use beyond the direct boundary at the oil refining point

Proceeding again as before (extraction point), one may write (with the same meaning of subscripts and superscripts):

$$\begin{aligned} E_{r,o}^{ref,tot-d} &= E_{r,o}^{ref,tot} - E_{r,o}^{ref,d} \\ &= \left(k_{tot}\nu_{ref} - \gamma_{ref}\right) E_{G,o}. \end{aligned} \tag{3.A34}$$

As before and with the same rationale, we assume that the oil, gas and other energy shares is given by the share of oil, gas and other energy in the global energy mix:

$$E_{r,o}^{ref,tot-d,o} = h_o \left(k_{tot}\nu_{ref} - \gamma_{ref}\right) E_{G,o}, \tag{3.A35}$$

$$E_{r,o}^{ref,tot-d,g} = h_g \left(k_{tot}\nu_{ref} - \gamma_{ref}\right) E_{G,o}, \tag{3.A36}$$

$$E_{r,o}^{ref,tot-d,e} = h_e \left(k_{tot}\nu_{ref} - \gamma_{ref}\right) E_{G,o}, \tag{3.A37}$$

so that

$$\begin{aligned} E_{r,o}^{ref,tot,o} &= E_{r,o}^{ref,tot-d,o} + E_{r,o}^{ref,d,o} \\ &= \left(g_{ref,d,o} + h_o \left(k_{tot}\nu_{ref} - \gamma_{ref}\right)\right) E_{G,o}, \end{aligned} \tag{3.A38}$$

$$\begin{aligned} E_{r,o}^{ref,tot,g} &= E_{r,o}^{ref,tot-d,g} + E_{r,o}^{ref,d,g} \\ &= \left(g_{ref,d,g} + h_g \left(k_{tot}\nu_{ref} - \gamma_{ref}\right)\right) E_{G,o}, \end{aligned} \tag{3.A39}$$

$$\begin{aligned} E_{r,o}^{ref,tot,e} &= E_{r,o}^{ref,tot-d,e} + E_{r,o}^{ref,d,e} \\ &= \left(g_{ref,d,g} + h_g \left(k_{tot}\nu_{ref} - \gamma_{ref}\right)\right) E_{G,o}. \end{aligned} \tag{3.A40}$$

3.A.2.3. Oil distribution

The direct energy investments in the distribution of oil does not appear explicitly in the IEA World Energy Balances. The cumulative energy investments in the distribution of oil thus follows from the investments data of Murphy et al. (2022) and of the factor introduced to account for the standard to cumulative boundary extension (see the definitions of the quantities in the introduction of this Appendix 3.A.2):

$$E_{r,o}^{dist,tot,o} = \left(\nu_{dist,o} + (k_{tot} - 1)\nu_{dist} h_o\right) E_{G,o}, \tag{3.A41}$$

$$E_{r,o}^{dist,tot,g} = \left(\nu_{dist,g} + (k_{tot} - 1)\nu_{dist} h_g\right) E_{G,o}, \tag{3.A42}$$

$$E_{r,o}^{dist,tot,e} = \left(\nu_{dist,e} + (k_{tot} - 1)\nu_{dist} h_e\right) E_{G,o}. \tag{3.A43}$$

In these relations, the first term represent the investment at the standard point, and the second the $k_{tot} - 1$ excess beyond the standard point, distributed in accordance to the global energy mix among the various sources of energy.

3.A.2.4. Oil net energy

In the end, the EROI-based net energy of oil follows from

$$\begin{aligned} E_{N,o}^{pou,tot} &= E_{G,o} - E_{r,o}^{ex,tot} - E_{r,o}^{ref,tot} - E_{r,o}^{dist,tot} \\ &= E_{G,o}\left(1 - \frac{1}{\xi_o^{ex,tot}} - k_{tot}\nu_{ref} - k_{tot}\nu_{dist}\right) \\ &\equiv E_{G,o}\left(1 - \frac{1}{\xi_o^{pou,tot}}\right). \end{aligned} \tag{3.A44}$$

3.B. Energy investments in the gas supply chain

We proceed as described in the previous subsection for the oil supply chain and use the same notations, *mutatis mutandis*.

A small fraction of the world gas production is devoted to non-energy uses (mostly for fertilizer production). It represents 5-6% of the total gas energy and non-energy supply since 1990[26]. The only product in gas supply is methane, so that non-energy uses do not come from a particular source of gas.

Delannoy et al. (2021b) have implicitly ignored non energy uses in the total gas production. As the argument of Appendix 3.D for oil applies much more straightforwardly for gas, we are justified to deduce the energy invested in the extraction of gas $E_{r,g}^{ex,tot}$ from Delannoy et al. (2021b).

3.B.1. Gas extraction

It has already been shown that the direct gas energy invested for gas extraction is negligible (see the end of Appendix 3.A.1.1). Consequently, the energy invested beyond the direct boundary represents all the energy invested by the gas supply chain at the point of extraction. As in Appendix 3.A and for the same reason, it is assumed that the fraction of gas (and other energies) in $E_{r,g}^{ex,tot}$ is given by the global fraction of gas, oil and other energies in the global energy mix, h_o, h_g and g_e (see Appendices 3.A.1.2 and 3.E). Thus:

$$E_{r,g}^{ex,tot,g} = h_g E_{r,g}^{ex,tot}, \tag{3.B1}$$

$$E_{r,g}^{ex,tot,o} = h_o E_{r,g}^{ex,tot}, \tag{3.B2}$$

$$E_{r,g}^{ex,tot,e} = h_e E_{r,g}^{ex,tot}, \tag{3.B3}$$

with

$$E_{r,g}^{ex,tot} = \frac{E_{G,g}}{\xi_{r,g}^{ex,tot}}. \tag{3.B4}$$

In this last relation, $E_{G,g}$ comes from GlobalShift gas data and $\xi_{r,g}^{ex,tot}$ is the quantity used in figure 3 of Delannoy et al. (2021b), and retrieved from this earlier work.

[26] Demand is mainly driven by the production of fertilizers, in which gas is used to produce the dihydrogen needed in the Habber-Bosch process.

In principle, one should subtract the share of energy invested at extraction corresponding to the fraction of NGLs in raw gas. However, NGLs represent less than 10% of the natural gas energy production, and their EROI (~ 6) ensures that this share of energy is between 1 and 2% of the total gas gross energy. Therefore, we neglect this small subtraction, as this will not affect our conclusions on gas net energy in any relevant way. The same argument holds for GTL, whose share of energy invested at extraction represent an even smaller fraction.

3.B.2. Gas transmission

The energy invested in the remainder of the gas supply chain is primarily due to the processes of liquefaction and regasification, transport by LNG (Liquefied Natural Gas) carriers and pipelines, and associated losses. From IEA (2024b) WEB database, the direct energy invested by the liquefaction and regasification processes comes almost exclusively (at 99%) from gas, and we therefore neglect oil and other energy sources in this process. The losses in distribution, transportation and transmission, representing slightly more than 1 EJ in 2022, are taken into account for the sake of presenting a general methodology, although they can be neglected at the level of approximation adopted in this work. We have grouped all these forms of energy use into the "transmission" category.

The energy invested in pipelines — which accounted for 3.0 EJ in 2022 — is mainly provided by gas (95% in 2022), the remainder being electricity. However, the "pipeline" category of IEA (2024b) does not exclusively represent pipelines dedicated to gas transport but rather all pipelines used for gas, oil and other fluids. Consequently, the proportion of energy allocated to gas pipelines remains uncertain. Nevertheless, as gas pipelines constitute majority of pipelines[27], and in the absence of more precise information, we allocate all the energy invested in pipelines to the gas supply chain.

Based on historical data, we assume, as for oil refining, that the energy invested in each of these processes is proportional to the gross gas supply. Consequently, the total energy invested in the transmission of gas $E_{r,g}^{trans,d}$ can be expressed as:

$$E_{r,g}^{trans,d} = \gamma_{lng} E_{G,g} + \gamma_{pip} E_{G,g} + \gamma_{los} E_{G,g}, \tag{3.B5}$$

where γ_{lng} (liquefaction/regasification) and γ_{los} (losses) are projected as $\gamma_{lng} = 0.011$ and $\gamma_{los} = 0.008$. These parameters are found empirically by projecting the historical data, as illustrated in figures 3.B1, and 3.B2. γ_{pip} (pipelines) is projected by a linear fit on the historical data between 1991 and 2022 which results in $\gamma_{pip} = a_{pip}(t - t_0) + b_{pip}$ with $a_{pip} = -5.2e \times 10^{-4}$/yr and $b_{pip} = 0.019$ for $t_0 = 2020$. This is shown in figure 3.B3.

The total gas invested in gas transmission is again modeled following the procedure adopted for the oil supply chain. This leads to:

$$E_{r,g}^{trans,d,g} = \gamma_{lng} E_{G,g} + f_{pip} \gamma_{pip} E_{G,g} + \gamma_{los} E_{G,g}, \tag{3.B6}$$

where f_{pip} represents the fraction of gas in the share of gas energy in pipelines. This relation is also used for projections, as explained in this section.

Following the classification adopted for the oil supply chain, we recast these relations in the

[27] https://www.aljazeera.com/news/2021/12/16/mapping-world-oil-gas-pipelines-interactive

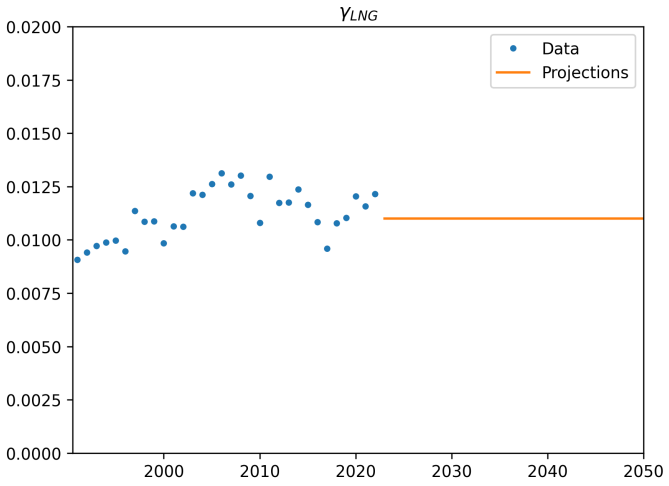


FIGURE 3.B1: γ_{lng}, share of the energy invested in liquefaction/regasification on gross gas supply.

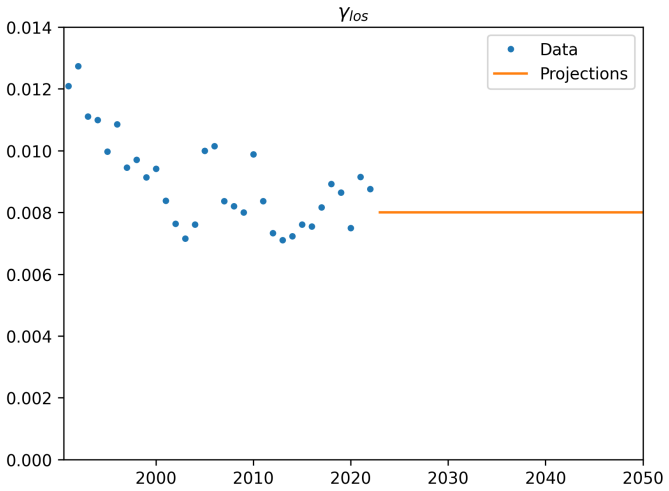


FIGURE 3.B2: γ_{los}, share of the gas lost in transmission on gross gas supply.

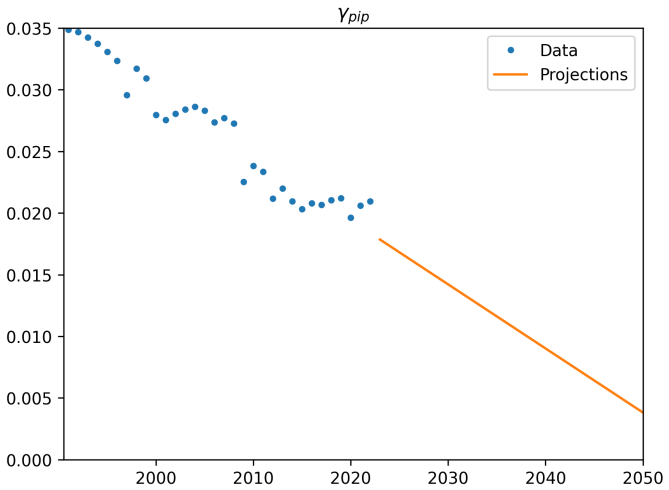


FIGURE 3.B3: γ_{pip}, share of the energy invested in pipelines on gross gas supply.

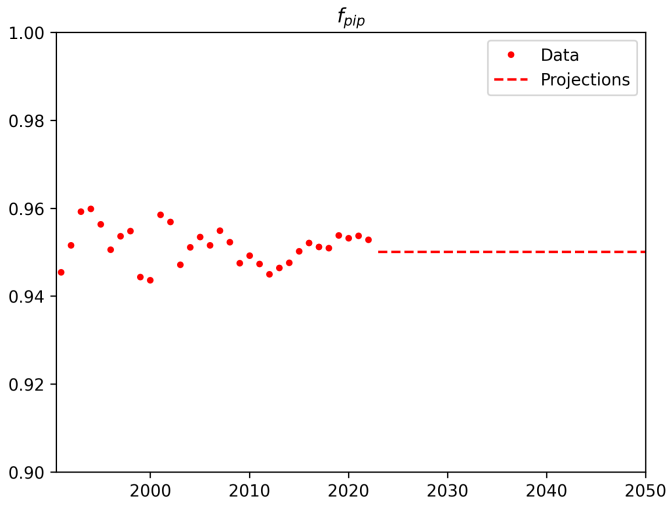


FIGURE 3.B4: f_{pip}, share of gas in the energy invested in pipelines.

following way:

$$E_{r,g}^{trans,d,o} = 0, \tag{3.B7}$$

$$E_{r,g}^{trans,d,e} = (1 - f_{pip})\gamma_{pip} E_{G,g}. \tag{3.B8}$$

Based on Murphy et al. (2022), the energy invested at the cumulative boundary of the entire transmission chain is given by:

$$E_{r,g}^{trans,tot} = k_{tot}\nu_{trans} E_{G,g}, \tag{3.B9}$$

where $\nu_{trans} = 0.179$ is deduced from Table 2 of this earlier work.

The share of oil, gas and other energies in the $\{tot - d\}$ processes are then deduced based on their share in the energy mix,

$$\begin{aligned} E_{r,g}^{trans,tot-d,x} =& h_x (E_{r,g}^{trans,tot} - E_{r,g}^{trans,d}) \\ =& h_x E_{G,g} \left[k_{tot}\nu_{trans} \right. \\ & \left. - (\gamma_{lng} + f_{pip}\gamma_{pip} + \gamma_{los}) \right], \end{aligned} \tag{3.B10}$$

with $x \in \{o, g, e\}$ being the energy source (oil, gas or other sources) used, and h_x the share of the energy x in the energy mix.

Finally, the EROI-based net gas energy can be written:

$$\begin{aligned} E_{N,g}^{pou,tot} &= E_{G,g} - (E_{r,g}^{ex,tot} + E_{r,g}^{trans,tot}) \\ &= E_{G,g} \left(1 - \frac{1}{\xi_g^{ex,tot}} - k_{tot}\nu_{trans} \right) \\ &\equiv E_{G,g} \left(1 - \frac{1}{\xi_g^{pou,tot}} \right). \end{aligned} \tag{3.B11}$$

3.C. Commentary on the proportion of direct energy in energy investments

Figure 3.A3 shows that the share of the direct energy in the cumulative energy invested at the oil extraction point has decreased from $\sim$ 60% in 1980—2000 to 31% in 2022, and is projected to reach 13% in 2050. This reflects the increase in capital investment due to decreasing EROI, while direct operational investments (pumping oil, essentially) increases less rapidly.

At the refining point, direct energy has been shown to constitute a stable share of cumulative energy investments at $\sim$50% from 1991 to 2022 and projected to remain at this level in the future. Indeed, the decrease in the accessibility of oil does not result in an significant change in oil types. Consequently, the energy needed for refining oil (see Karras 2010) as well as the infrastructures required remain almost unchanged.

IEA' WEB data do not provide information on the direct energy invested in the distribution of oil and gas as this is included in the overall consumption of transport in the WEB categories. This prevents the estimation of the share of the direct energy investments in the cumulative ones at this point. Similarly, the direct energy investments for gas extraction are not accounted for, as discussed in Appendix 3.A.1.

This short appendix highlights the importance of the $\{tot - d\}$ energy investments, which represent around half of the total energy investments. Nevertheless their estimation is somewhat less robust than direct energy investments'.

3.D. Relation between gross energy, used energy, and the definition of EROI for all oil liquids

In this Appendix, we show *a posteriori* that Delannoy et al. (2021a) were justified to use an EROI defined for all oil liquids including their non energy uses to estimate the energy invested for oil production excluding their energy uses, although they did not think of the issue. This is fortunate, as these authors did not identify the issue discussed here.

To this effect, one must in principle distinguish the mean EROI for all liquids, including their non-energy uses, $\xi_{r,o}^{ex,tot}$, from the mean EROI of all oil liquids excluding energy uses, $\xi_{o}^{\dagger,ex,tot}$. These are specified by

$$\xi_{o}^{ex,tot} = \frac{E_{G,o}}{E_{r,o}^{ex,tot}}, \tag{3.D1}$$

where the numerator and denominator on right-hand side are respectively the gross and used energy of all oil liquids, including their non-energy uses, for the first, and

$$\xi_{o}^{\dagger,ex,tot} = \frac{E_{G,o}^{\dagger}}{E_{r,o}^{\dagger,ex,tot}}, \tag{3.D2}$$

for the second, where the numerator and denominator now exclude non-energy uses. These mean EROIs are obtained from Eq. (3.5) (*mutatis mutandis* for non-energy uses).

For these two EROIs to be equal, one must have, at least to some high level of precision

$$\frac{E^{\dagger}_{G,o}}{E^{\dagger,ex,tot}_{r,o}} = \frac{E_{G,o}}{E^{ex,tot}_{r,o}}. \tag{3.D3}$$

First note, that this equality holds exactly if the same proportion of non-energy uses is applied uniformly to all types of oil liquids. This follows because in this case, one may affect the energy invested for their production also uniformly, at the same prorata, in the mean (i.e., with the definition of mean EROI recalled above). For the same reason, the EROIs of each oil liquid type, including and excluding non-energy uses, are equal.

Delannoy et al. (2021a) apply such a uniform proportion, chosen at 8%, except for NGLs (40% for non-energy uses). However one can check that this leads only to minor differences with respect to a uniform rate of 8%. From Delannoy et al. (2021a) gross energy data by oil liquids types, one finds that the difference between the two rules of computation of the fraction of oil liquids devoted to non-energy uses leads to a difference of energy invested for production of oil liquids of a few percents of the total energy production, both in 2020 and in 2050. This difference is totally negligible, both in itself, and in comparison with the uncertainties in the determination of the EROIs of the various oil liquids types.

This justifies the statement made at the beginning of this Appendix.

3.E. Projection of the energy mix

The first subsection of this Appendix is reproduced from Chapter 2. This very short self-plagiarism is done in order for each paper to be independent from the other.

3.E.1. Total energy demand

Modeling the $\{tot - d\}$ energy invested in the oil and gas supply chains requires the knowledge of the share of oil and gas in the energy mix. This is obtained from a projection of the total energy demand, based on the empirically observed GDP/energy correlation.

First, the global GDP is projected. This consists just of a linear extrapolation of the linear fit on the historical data performed between 1990 and 2020. The resulting global GDP is shown in figure 3.E1.

This is by design somewhat less optimistic than OECD's (OECD, 2023), which expects a small exponential growth rate in the next decades. The difference however is small, even in 2050. Similarly, it is less optimistic than IEA's 2.7% average annual growth rate to 2050[28]. This reflects our slight bias towards a moderate growth paradigm, due to the new area of world turmoil and uncertainties on resources (including energy resources) that started with the peak of conventional oil around 2006, and that has been observed through the accelerated pace of crises of various sources since then. As explained in introduction this bias makes future energy demand easier to satisfy and therefore, our conclusions on potential future tensions between demand and supply more robust.

[28] IEA uses a purchasing power parity (PPP) GDP whereas we simply use a deflated one. Therefore, our projections cannot be directly compared to theirs. OECD's projections are in PPP unit, and they provide a PPP conversion factor that allows us to convert PPP units into non-PPP ones. The GDP projections from OECD (OECD, 2023) are slightly more optimistic than ours, but less than the IEA's 2.7%/yr growth. We conclude that our deflated GDP projections are somewhat more moderate than IEA's equivalent deflated non-PPP projections.

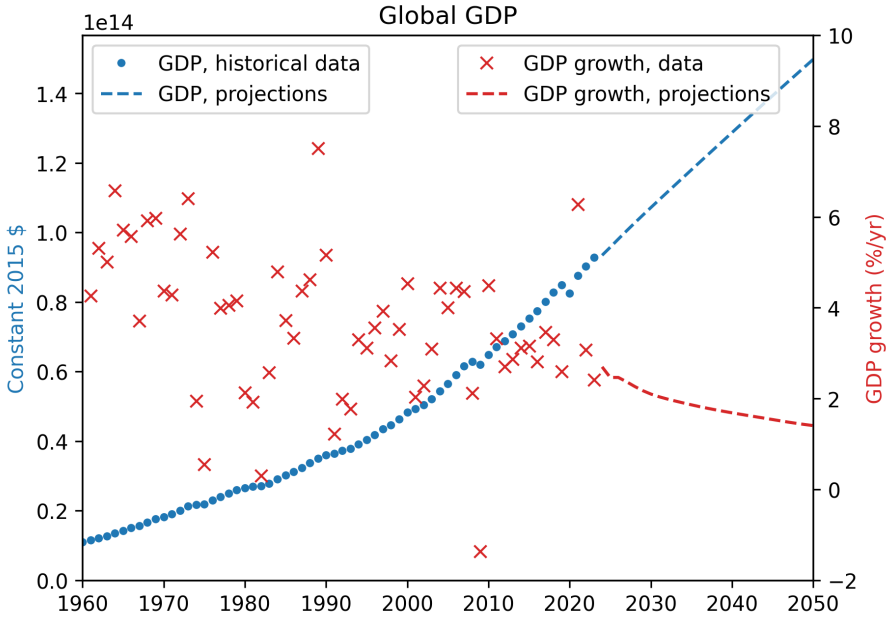


FIGURE 3.E1: Evolution of the global GDP (blue, left axis) and its growth rate (red, right axis).

Second, a projection of the total energy demand is made based on the well-known GDP/energy correlation. The correlation between GDP and the primary energy consumption has been extensively studied in many countries in the literature (see, e.g., Haberl et al. 2020). However, projecting the future trend is not straightforward due to the deployment of renewable energies. Indeed, Haberl et al. (2020) point out that the relevant correlation is between GDP and useful energy rather than primary energy. This difference become an issue when the penetration of renewable energies in the energy mix increase, in which case the GDP/energy correlation would not follow linearly. This is due to the fact that the primary to useful energy conversion has a far better efficiency in the case of renewable energies than for fossil fuels (Brockway et al., 2024).

In order to account for this effect while keeping the model quite simple, we first projected the GDP/energy correlation linearly, extrapolating historical trends between 1991 and 2022, and assuming no further renewable energy deployment. Next, we correct this projections by taking into account the wind and photovoltaic power projected contribution to the energy mix, and assuming, following Aramendia et al. (2024) and Brockway et al. (2024), that, on average, 1 EJ of wind and PV replaces 2 EJ of primary energy from fossil fuels. This allows us to compute how much primary energy is not needed in the earlier, simple linear extrapolation. For this exercise, the wind and PV energy supply projection is taken from Appendix 3.H. The resulting GDP/energy correlation projections are shown in Fig. 3.E2.

The energy demand is then derived from the previous GDP and GDP/energy correlation projections, and shown in Fig. 3.E3.

The total energy demand thus found is ∼10% larger than in IEA's STEPS (IEA, 2024d) scenario under a similar correction to the energy demand due to renewable deployment has been performed. As IEA's GDP projections are higher than in our adopted growth scenario, the GDP/energy correlation from IEA increases slower than ours.

In any case, the uncertainty on the energy mix remains are of minor importance compared to other sources of uncertainty in our analysis.

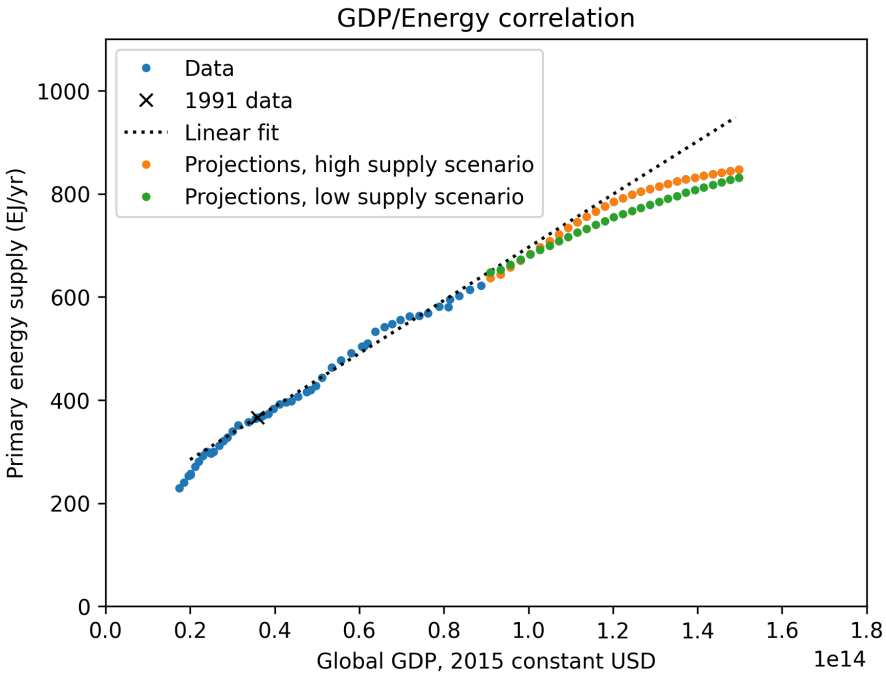


FIGURE 3.E2: GDP/Energy correlation from 1970 onward and our BAU projections

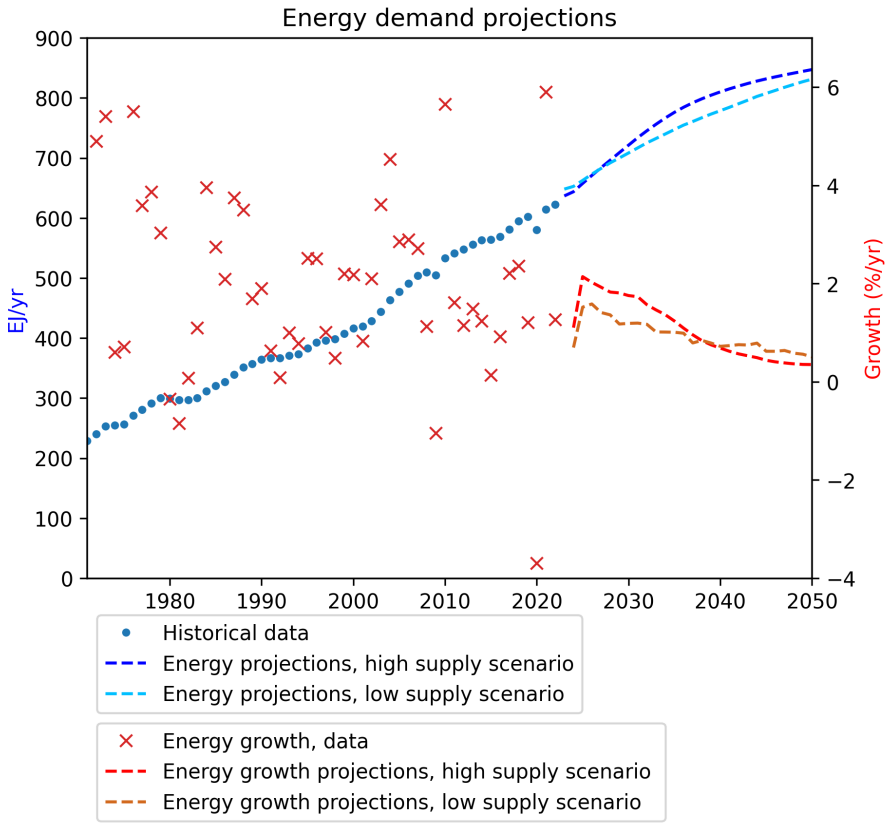


FIGURE 3.E3: Total primary energy demand projections (blue, left axis) and the associated growth rates (red, right axis).

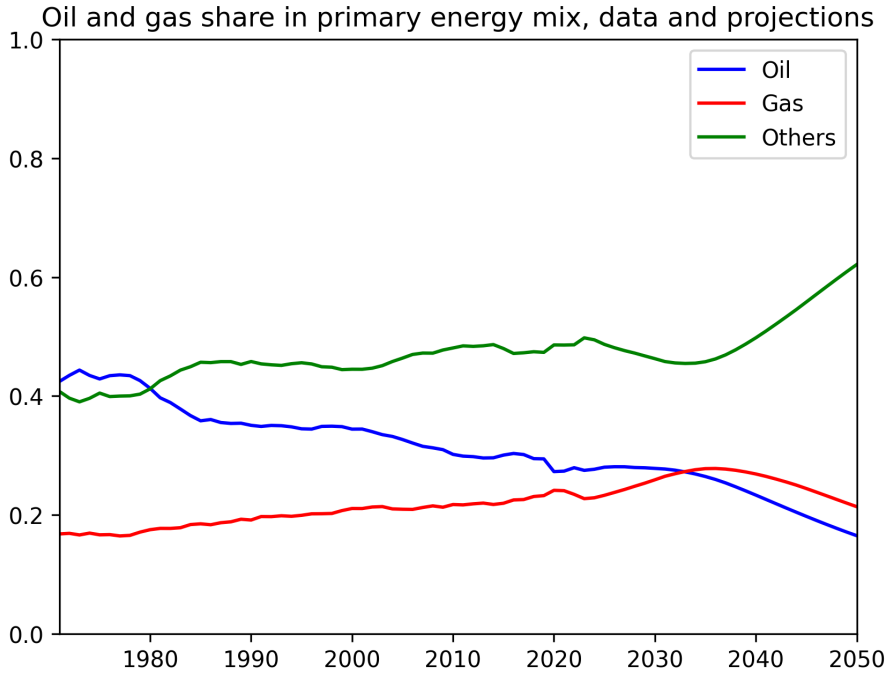


FIGURE 3.E4: Evolution of the energy mix within our modelling.

3.E.2. RESULTING ENERGY MIX

We now have, on the one hand, the total energy projection in our growth scenario, and, on the other hand, the projection of oil and gas gross supply. We are therefore in position to project project the oil / gas / other sources energy mix needed in previous Appendices. The projections of the oil and gas gross energy production are directly taken from the oil and gas gross supply of GlobalShift, but corrected for oil and gas non-energy uses (this is evaluated in Appendix 3.F), while all other energies are derived from the subtraction of the oil and gas energy supplies to the total energy projection demand just obtained. The evolution of this energy mix is illustrated on Fig. 3.E4.

The fast growth of other energy sources in the energy mix after 2035 is the consequence of the decline of oil and gas supply while the total energy demand is still growing steadily under the mild BAU growth scenario adopted above.

The energy demand on other sources of energy in this scenario increases significantly, as illustrated in figure 3.E5 (absolute energy instead of energy share)[29]. The energy demand for other energies rises slightly from 310EJ in 2023 to 336EJ in 2032 and then increases strongly to 478EJ in 2050 because of the deployment of wind and PV power required for compensating for the decline in oil and gas supplies.

We stress again that our energy projections reflect a mild business-as-usual (BAU) scenario, the aim being to study net energy and EROI issues in such scenarios. By design, this BAU scenario ignores some of the limits to the possibility of BAU scenarios themselves. In terms of energy, this scenario thus ignores some possible barriers to the deployment of wind and PV such as the deployment of electric grids and end-use electric technologies(Cherp et al., 2021; Greig et al., 2025; Nemet et al., 2023; Papagianni et al., 2020; IEA, 2023; Grimault, 2021; Gorman

[29] The increase observed between 2022 and 2023 (22EJ) is a consequence of the concatenation of data and projections: the value of the total energy demand in 2022 is lower than the trend projected by the GDP/energy correlation of figure 3.E2. This small inconsistency has no effect on our results.

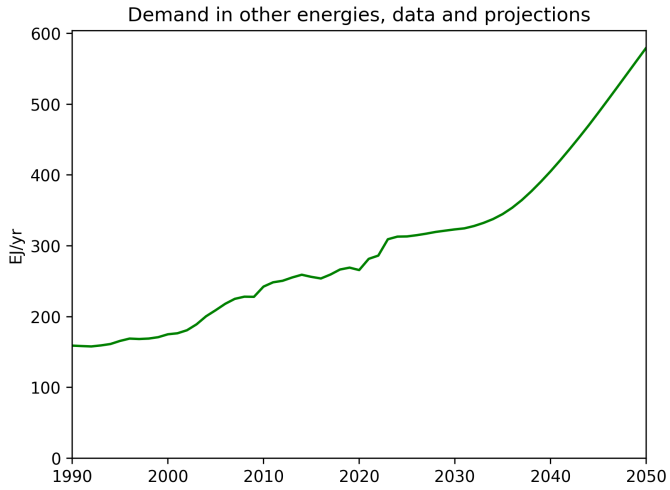


FIGURE 3.E5: Evolution of the energy demand in the "other" energy sector (i.e., other than oil and gas) and its growth rate (right axis).

et al., 2025; Obuseh et al., 2025; IEA, 2025a; Jacques et al., 2023; Černý et al., 2024; Capellán-Pérez et al., 2019; Sgouridis et al., 2016).

3.E.3. NOTE: IMPACT OF RENEWABLE ENERGIES ON QUANTITATIVE RESULTS

The current article focuses on primary energy and net energy. However, the substitution of fossil fuels by renewable energies (mostly wind and PV) brings in accounting biases, due to the fact mentioned above that the primary to useful energy conversion generally has a higher efficiency in the case of the energy produced by wind or PV than for fossil fuels (Aramendia et al., 2024): less wind and PV energy than fossil energy would be required on average, at the same level and mix of economic activities.

Consequently, the EROI of the global energy system is expected increase with the gradual substitution of wind and PV to fossil fuels. In our scenario, the amount of energy required to achieve the same demand decreases by 3.5% in 2035 and 10% by 2050 (compared 2022). Self-consistency would thus require that we reduce by the same quantity the projections of wind and PV of Appendix 3.H, in a first step and in fact iterate the process until convergence is achieved. We have not implemented this self-consistent bootstrap requirement in our modeling. The difference is small enough to be neglected in quantitative results of our paper (in particular, energy demand projection, final energy mix, and the results where the energy mix is used in the previous Appendices).

3.F. OIL AND GAS NON ENERGY USES SUPPLY PROJECTIONS

Projections of the non-energy uses of oil and gas are needed in our modeling for two purposes. First, non-energy uses have to be subtracted from gross supply in the computation of the final EROI as the EROI is defined as a ratio between actual energy quantities (i.e., intended for energy uses). Second, this quantity has also to be subtracted from the energy quantities when computing the energy mix.

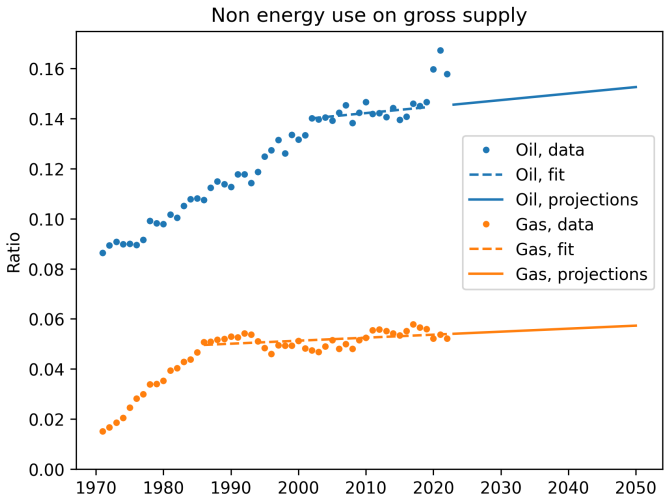


FIGURE 3.F1: Data and projections of the share of the non-energy uses of oil and gas in their gross supply. The linear fit are performed between 2002 and 2020 for oil, and 1986 and 2022 for gas. In the case of oil, the share has increased in 2020-2022 because of the impact of the COVID crisis on oil consumption in the transportation sector, while the use of oil for non-energy purposes remained nearly unaffected.

To this effect, we base ourselves on historical trends of the share of non-energy uses for oil and gas in their respective gross production, depicted on Fig. 3.F1. We fit these and extrapolate these shares linearly, from 2002 for oil and 1986 for gas. The resulting final non-energy use projections are shown on Fig. 3.F2.

3.G. REVISITING THE COURT AND FIZAINE (2017) ESTIMATE OF THE EROI OF CONVENTIONAL OIL AND GAS

Court and Fizaine (2017) state in the last paragraph of their section 2.2.1 that their EROI perimeter should be $(1, lab)$ in the classification of Murphy et al. (2011). Furthermore their analysis uses annual gross money generated and annual operational expenditures (OPEX) as proxies to annual energy produced and invested at the extraction point, in order to estimate the conventional oil EROI from monetary quantities and energy intensities (EJ/$).

This approach is relevant in the absence of more direct historical information, but raises two different issues:

- Their price of oil comes from various sources, e.g., BP 2015. This price includes by construction the direct, indirect, labor and auxiliary costs[30]. Thus the actual boundary is the cumulative auxiliary one instead of the cumulative labor one. This is more a remark than an issue in itself, as this does not affect Court and Fizaine (2017) methodology.
- More critically, oil spot prices also cover by necessity the (mean) conventional oil breakeven over the lifetime of oil extraction facilities, as well as the producing companies margins and speculation gains on oil markets. One must therefore retrieve actual annual operational expenditures from oil prices for their method to work through.

[30] Environmental costs are excluded from historical price data as this is accounted for through a carbon price, which is recent and anyway almost negligible up to now.

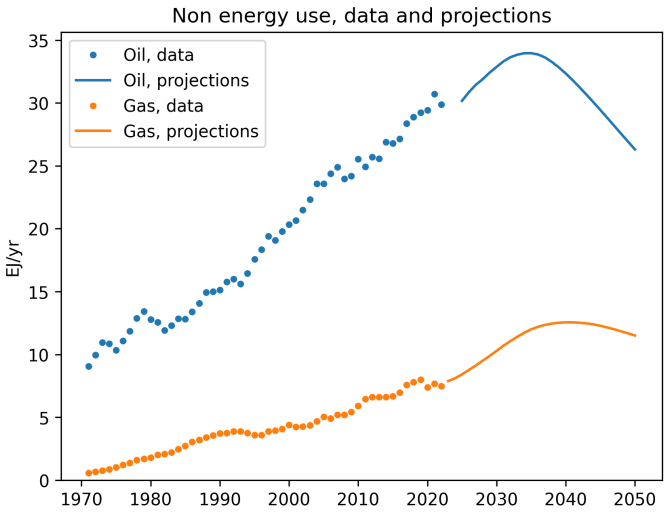


FIGURE 3.F2: Data and supply projections of the non-energy uses of oil and gas.

On this second point, Court and Fizaine (2017) considered only the producers' operational margins. Correcting their analysis to include speculation and capital expenditures (CAPEX) is a more involved task to which this Appendix is devoted. We also correct the analysis of Delannoy et al. (2021a) on this issue at the end of the Appendix, as the results of the latter authors have been used at various points in the present work.

To this effect, it is useful to reproduce here the relevant part of the analysis of Court and Fizaine (2017). Denoting M the various annual money amounts (with various indices), and in analogy with Eq. (3.1), Court and Fizaine (2017) define the money return over investment (MROI), denoted χ here, as

$$\chi \equiv \frac{M_G}{M_r}, \tag{3.G1}$$

where M_G is the annual gross money generated from oil sales and M_r the annual oil money expenditure (in deflated dollars; Court and Fizaine 2017 use 1990 as base year). We designate by χ_{CF} the Court and Fizaine (2017) estimate of this quantity.

M_r is related to E_r in Eq. (3.1) through

$$E_r = M_r E_I, \tag{3.G2}$$

where E_I is an energy intensity (annual energy investment at the $\{tot\}$ perimeter per unit of invested dollar). The whole problem is reduced to determining E_I and this is the main objective of the Court and Fizaine (2017) article.

Court and Fizaine (2017) furthermore define a production cost C_p per unit of energy produced ($/EJ), so that

$$M_r = C_p E_G. \tag{3.G3}$$

This production cost should include only annual operational costs in order to reflect the fact that M_r represents annual operational expenditures (consistently with the fact that Court and Fizaine 2017 mention that this is a non levelized cost).

Finally, they introduce the market price of oil energy P (\$/EJ) and state that

$$M_G = PE_G. \tag{3.G4}$$

Combined with Eq. (3.G1), the last two equations lead to

$$C_p = \frac{P}{\chi}. \tag{3.G5}$$

Finally, from Eqs. (3.G3) and (3.G2), one can express the looked for EROI in terms of the various quantities introduced so far:

$$\xi^{ex,tot} = \frac{E_G}{E_r} = \frac{M_r/C_p}{M_r E_I} = \frac{\chi}{PE_I}. \tag{3.G6}$$

In this last equation, P is historically known, E_I is deduced by the method explained in Court and Fizaine (2017) (which is not at issue in this discussion[31]), and χ is estimated by these authors as explained now.

In the past, there were three different periods. A high volatility one in the 19th century due to bursts of discoveries, followed by a more sedate one until the two oil shocks of the 70s (Energy Institute 2025, p. 30). Since then, volatility has progressively increased due to the emergence of financial oil derivatives in the 1980s and their ever increasing weight, in particular since the turn of the century (Bouchouev, 2023). Throughout these different periods, Court and Fizaine (2017) assume a gross production margin of 10%, leading to $\chi_{CF} \simeq 1.1$; in fact, Court and Fizaine (2017) also use different methods to estimate this ratio and obtain similar results, from which they conclude that this assumption is probably not critical. This allows them to recover M_r from M_G over time.

This reasoning is incorrect in two different places:

- As pointed out earlier, the assumption leading to Eq. (3.G4) is not valid. The current oil price P (in \$/bbl converted to \$/EJ using the barrel energy content) must, on average over the lifetime of producing fields, cover not only operational costs but capital investments as well (and producers and speculators margins), whereas M_G includes only annual operational expenditures by definition.
- The implicit assumption leading to the evaluation of χ is incorrect as well: for the cost C_p to be meaningful, the scope of P and χ in Eq. (3.G5) must be identical. For example, if P includes both the producers and speculators margins plus operational expenditures, so must χ and C_p. In the analysis presented above, the scopes of χ_{CF} (producers margin expressed as a fraction of the sum of this margin and operational expenditures) is inconsistent with the scope of P (producers *and* speculators margin plus *capital* expenditures instead of operational expenditures) so that the scope of C_p is not well-defined and its resulting value meaningless.

These shortcomings make us question the conclusion that the assumption on χ may not be critical, and prompt us to revisit the issue. This is done in several steps: first, we provide an estimate of the relation of the spot price P to breakeven P_B. Next we align all relevant quantities to the relevant scope, chosen here to cover operational expenditures (a requirement of the analysis) and the producers' and speculators' margins (as we were unable to evaluate each

[31] This method involves some approximations to relate this energy intensity to the energy intensity of reconstructed historical GDP.

one independently), in order to remove these margins from the final result and find an EROI based only on operational expenditures. Finally we assess the effect of these corrections on the EROI of conventional oil in the analysis of Delannoy et al. (2021a).

One may evaluate the difference between breakeven and oil prices nowadays, which equals the sum of the producers and speculators margins. For example, current crude oil prices ($\sim$ 75$/bbl on average over the last six months at the time of writing) are substantially higher than the current mean breakeven of conventional oil ($\sim$ 25$/bbl from the most recently available Rystad Energy data release[32]) or, e.g., current light tight oil mean breakeven ($\sim$ 45$/bbl, from the same Rystad Energy data). From this we conclude that the added margins between mean price and mean breakeven account for a factor of 1.5 (to be on the safe side) to a factor of 3. We retain a factor of $\sim$ 2 as a characteristic number. This factor may seem large at first sight, but one must keep in mind the major increase of activity on the oil derivatives market, especially since the 2008 economic crisis, which increases oil price volatility, and therefore the need for a large enough producer margin to hedge against this volatility combined with hedging on oil markets derivatives, on top of the profit made by speculators[33].

Our assumption on the ratio of oil price to oil breakeven is realistic for recent prices, but it is unclear that it applies over the whole period of historical prices that was used by Court and Fizaine (2017) in their analysis. As we were unable to find any estimate of breakeven vs price for oil in the past, we just assume that the current estimate of a factor of $\sim$ 2 is valid in the past as well. We are aware this may be an overestimate due to the present role of oil derivatives; on the other hand, the Court and Fizaine (2017) estimate of 10% is most probably underestimating the actual margins of historical actors in the oil market (mostly producers and carry traders in the historical period). On the other hand, there is little prospect of this ratio decreasing in the future, especially in a BAU scenario where constraining regulations on financial markets are not in order.

Under the simple (and most likely reasonable) assumption that all such margins constitute a (more or less constant) fraction of oil prices, and denoting oil unit prices ($/bbl) by P_b, the breakeven P_B can be estimated from the oil market price by

$$P_b = \alpha \times P_B, \tag{3.G7}$$

where $\alpha \in [1.1, 2]$ is the (assumed) constant factor between the two, as using prices per barrel or per energy unit does not affect this relationship. P_b and P are related through $P \times E_B = P_b$ where $E_B = 6.1$ GJ/bbl is the barrel of oil equivalent. This factor E_B arises from the fact that breakeven is usually given in $/bbl whereas P as defined above is in $/GJ.

The breakeven is rid of margins but includes both operational and capital expenditures. However, from Figure 4 of Wachtmeister and Höök (2020), we deduce that operational expenditures largely dominate capital expenditures for conventional oil (in the sense of Court and Fizaine 2017), so that in practice, breakeven P_B can be related to C_p (which reflects only operational expenditures) through

$$C_p \times E_B = P_B, \tag{3.G8}$$

[32] `https://www.rystadenergy.com/news/upstream-breakeven-shale-oil-inflation`.

[33] Daily "virtual" barrels exchanges on oil derivatives markets nowadays amount to $\sim$ 50 times the actual daily sales of oil (Bouchouev, 2023)

With all these corrections, the relevant previous equations become

$$E_r = M_r E_I, \tag{3.G9}$$

$$M_r = (P_B/E_B)E_G, \tag{3.G10}$$

so that

$$\xi^{ex,tot} = \frac{E_G}{E_r} = \frac{1}{(P_B/E_B)E_i}, \tag{3.G11}$$

Finally, Eq. (4) of Court and Fizaine (2017) leads us to

$$\xi^{CF} = \frac{\chi_{CF}}{P \times E_i} = \frac{\chi_{CF}}{\alpha \times (P_B/E_B)E_i} \equiv \frac{\chi_{CF}}{\alpha}\xi^{ex,tot}. \tag{3.G12}$$

Thus, the EROI of interest, $\xi^{ex,tot}$, is in the end about twice as large as the evaluations ξ^{CF} obtained by Court and Fizaine (2017), once all needed corrections are taken into account.

One last question must be addressed before concluding this Appendix. In their own Appendix, Delannoy et al. (2021a) point out that the URR (Ultimate Recoverable Reserves) used in Court and Fizaine (2017) is overestimated as it covers both conventional and unconventional oil and not simply conventional oil. This correction leads these authors to use a lower conventional oil URR estimate of 15,000 EJ and a high estimate of 25,000 EJ (this corrects a misprint in energy unit in this earlier paper). This leads them to use an EROI differing from the one obtained by Court and Fizaine (2017), ξ^{CF}, that we designate here by ξ^D (the superscript D now standing for Delannoy *et al.*).

Conventional oil supply URR (in the meaning used by Court and Fizaine 2017, which covers onshore and offshore oil) is in principle more constrained than assumed in Delannoy et al. (2021a), as most if not all of its oil sub-categories have peaked in the last twenty years or so. Laherrère et al. (2022) provide an estimate of 2500 Gbbl, in the 2300-2700 range of most recent estimates (see table in the Appendix of this article, which summarizes these various estimates). There is little doubt that the Hubbert linearization method used by Laherrère et al. (2022) is reliable for this category of oil[34], and this expectation can be directly checked on the quality of the very precise fit seen on their Fig. 7 for conventional oil. This brings us to consider that the lower URR estimate of Delannoy et al. (2021a) is in fact the correct URR.

Consequently, Eq. (3.G12) applies as such to the minimum estimate of ξ^D, i.e., $\min(\xi^D) = (\chi^{CF}/\alpha)\xi^{ex,tot}$. Taking $\alpha \sim 2$ into account brings the EROI estimate back in the vicinity of the mean EROI assumed by Delannoy et al. (2021a): $\xi^{ex,tot} \simeq \xi^D$ (this last result is obtained from an analysis of the data used to produce Fig. A.1 of Delannoy et al. 2021a). A lower α would keep the conventional oil EROI in between the mean and lower EROI estimates of these authors.

In light of this discussion, and consistently with our bias towards overestimating within reason the net oil supply when in doubt (i.e., overestimating $\xi^{ex,tot}$), we finally adopt Delannoy et al. (2021a) mean EROI as our EROI estimate for conventional oil, keeping in mind that it may be overestimated by a factor of order unity. This result is welcome, but fortuitous considering the complexity of the reanalysis performed in this Appendix.

[34] It always is when production is close to its peak. The only caveat is when a new source of oil becomes available or old sources can be exploited further with more efficient technologies, but this is highly unlikely for conventional oil. We provide elsewhere a much more precise critical discussion of the URRs of the various categories of oil. See Chapter 2.

3.H. WIND AND PHOTOVOLTAIC ENERGY PRODUCTION PROJECTIONS

The energy supply from wind and photovoltaic (PV) sources is projected using a logistic (S-shaped) function, following a common practice in the literature (Grübler et al., 1999; Hansen et al., 2017),

$$f(t) = \frac{L}{1 + \exp\left[-k(t - t_0)\right]}, \tag{3.H13}$$

where $f(t)$ is the logistic function over time t. L is the saturation parameter, k the shape parameter and t_0 the x-axis value of the inflection point of the logistic function.

It is currently impossible to extrapolate correctly the deployment of wind and PV based on past history, as they are still in the very first stages of deployment; as a consequence, a direct fit to the data would be very imprecise. Instead, we constrain the saturation and shape parameters, combined with existing deployment data, to find a reliable projection of wind and PV deployment, as explained right next.

To this effect, we rely on the analyses of Dupont et al. (2018) and Dupont et al. (2020) for the wind and PV energy potentials worldwide. These two studies are the most extensive and careful to date in their methodology, and the potential estimates obtained in this way are largely considered reliable. They find a maximum of $\sim$ 760 EJ/yr for wind, and $\sim$ 1200 EJ/yr for photovoltaic panels (PV). However, as the suitability factor of various locations (measuring the fraction of area suitable for generating electricity) is taken from the literature and is unrealistically high in some locations (such as, e.g., deep deserts), we conservatively estimate that the potential of both is overestimated by $\sim$ 20%. The saturation of the logistic functions is thus defined as 80% of the maximum potential just quoted.

Finally, we constrained the deployment of wind and PV required in order for the energy supply to meet demand in a BAU scenario (see Appendix 3.E.1). We concluded that the required normalized growth rates of wind and PV deployment — i.e., the growth rate at the point of inflection — should be around 3%/yr for wind and 5%/yr for PV. These values seem plausible when compared to historical examples found in Nemet et al. (2023). The normalized growth rate (at the point of inflection) is equal to $k/2$ for a logistic function, half of the shape parameter in the case of a logistic function. This is used to define the shape parameter of the logistic functions to $k = 0.06$ yr^{-1} for wind and $k = 0.10$ yr^{-1} for PV. The last parameter of the logistic function, t_0, is finally deduced based on a logistic fit on historical data with the other parameters defined as described.

Figure 3.H1 shows our projections of wind and PV supply up to 2050. The discontinuity between the data and the projections is due to the saturation and shape parameters being defined independently of the historical data. However, this discontinuity is not a major issue as the aim is to determine the order of magnitude of the energy investments in the wind and PV supply chain. Note that in all cases where logistic fits can be used (including fossil fuels past and future production), early stages of deployment/production/etc are usually poorly fitted by a logistic function, due to many real world effect that influence the early trends, before the related industrial sectors reach a stable regime.

In this exercise, some potential barriers to the deployment of wind and PV have been ignored, such as the deployment of electric grids and end-use electric technologies. Finally, as pointed out earlier, the normalized growth rates obtained for our mild BAU growth scenario are characteristic of quite a few past light and heavy industry deployments. Larger growth rates may be reached, but would probably require dedicated, sustained efforts in the long run.

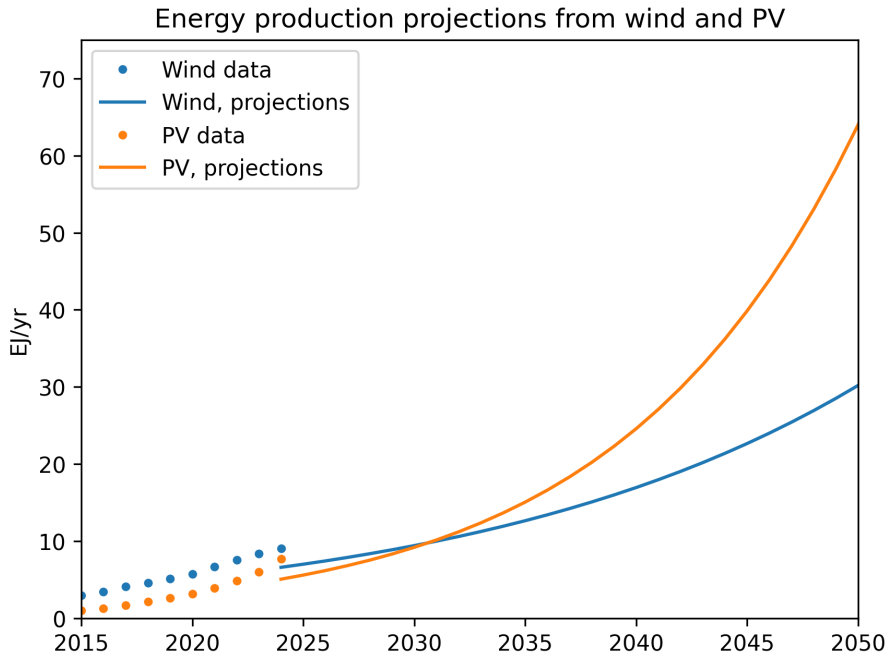


FIGURE 3.H1: Energy supply projections of wind and PV, based on a logistic function.

CHAPTER 4 | Road Transport Electrification is the Arbiter between Increasing and Peaking Oil Demand

Chapter 1 points out that oil cannot easily be substituted by other energy sources in many of its applications, while Chapter 2 highlights that the peak in oil supply is expected to occur around 2030. This raises concerns on whether oil supply would be able to match oil demand in a BAU scenario. Chapter 3 additionally finds that the oil demand of the oil and gas supply chains is expected to increase between 2022 and 2035.

Chapter 5 therefore seeks to find if and when oil supply would be unable to match a BAU demand, while the present chapter models the oil demand of a BAU scenario.

This material is intended for submission to Energy and Environmental Science, after the publication of Chapter 3.

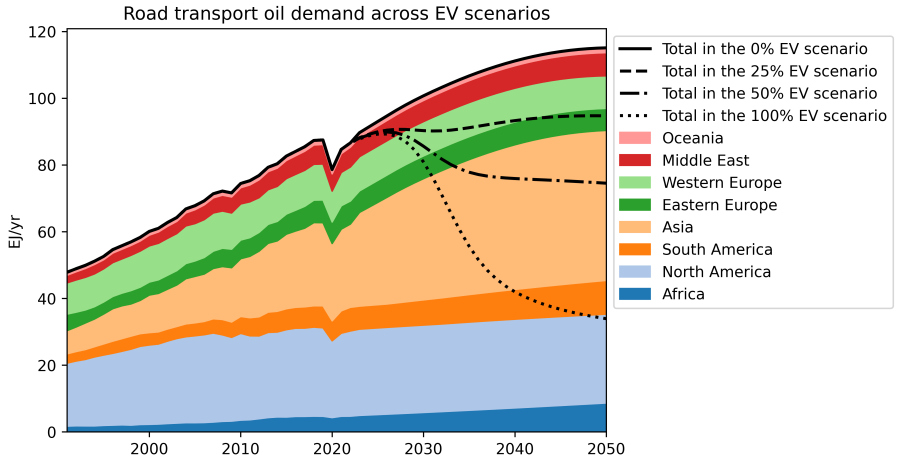
Abstract

Forecasting global oil demand is crucial for anticipating potential future tensions in gross oil supply, which is expected to peak and decline in the next decade. This article models the evolution of the oil demand in a business-as-usual (BAU) scenario. In particular, the transport sector (by far the largest oil consumer) is analyzed in detail with a focus on oil demand by private vehicles, and is disaggregated by country

The analysis reveals that the evolution of the oil demand primarily relies on the pace of the deployment of electric vehicles (EVs). In the absence of EVs, total oil demand would steadily increase and reach +25% in 2050 compared to the 2024 value. Conversely, pursuing EV deployment towards the electrification of all private vehicles would result in a decrease of 18%. It is also found that the model uncertainties are relatively low, and that the oil demand in sector others than road transport is almost consensual across institutional reports.

This study calls for further research into the barriers to EV deployment, and for a comparison of BAU oil demand scenarios against oil supply ones.

Graphical abstract



4.1. Introduction

A peak in gross oil supply is anticipated around 2035 (Delannoy et al. 2021b; Laherrère et al. 2022; Rabas 2024; GlobalShift[1]), due to geological and economic factors. It is thus relevant to inquire whether oil consumption would follow this decline by a voluntary decrease in demand or by constraint, which has vastly different consequences on society and its economy.

Oil demand is expected to be driven by antagonistic trends. From a geographic perspective, it is first anticipated that OECD (Organisation for Economic Co-operation and Development) countries will experience a stable or slow decline of their oil consumption, while a strong and steady growth of oil demand in non-OECD countries is expected due to their projected economic growth.

From a sectorial perspective, the economic development of China and India is expected to perpetuate the significant growth of the vehicles stock in these countries (Giannopoulos Balos, 2022; Gan et al., 2020; Wan et al., 2025), the aggregated population of which reaches 2.9 billion people in 2024. The growth in their vehicle stock fleet could lead to a substantial increase in road transport oil consumption. The road transport sector accounted for 44% of the global oil consumption in 2022 (IEA, 2024b), while oil constitutes $\sim$ 90% of the energy source of the transport sector.

On the other side, the deployment of electric vehicles (EVs) has the potential to mitigate or even reverse this increase in oil demand if implemented massively. Indeed, the deployment of the EV stock is still exponential in 2024 (IEA, 2025b). However, their stock only represent approximately 4% of the global vehicles stock in 2024. In addition, it is expected that the higher purchasing cost of EVs, along with other barriers such as the deployment of charging points, supply in critical raw materials or technical constraint in their use, would hinder the widespread adoption of EVs (Virmani et al., 2023; Muratori et al., 2021; Rajper and Albrecht, 2020; Zhuge and Shao, 2019; Fevang et al., 2021; Purwanto and Irawan, 2024; Naseri et al., 2024; Soszynska et al., 2024; Pulido-Sánchez et al., 2022; IEA, 2022, 2023b, 2024d). Furthermore, the deploy-

[1] https://www.globalshift.co.uk/glooprcharts.html

ment of electric trucks[2] is still under experimentation and faces techno-economic challenges (IEA, 2024d). Consequently, the pace of the future deployment of EVs and the limit in their penetration in the world vehicle fleet remain uncertain.

A body of literature modeling vehicle ownership (as presented in section 4.2.2.1) has been established, but few articles or reports model the evolution of the oil demand in the vehicle fleet or road transport (Huo and Wang, 2012; Lu et al., 2018; Gan et al., 2020; Keshavarzian et al., 2012; IEA, 2024d; BP, 2024; US EIA, 2023; OPEC, 2025). When addressed, the purpose is generally to compute the carbon emissions associated with this sector. In the case of oil consumption in other sectors, the academic literature is scarce, although some reports provide various scenarios (IEA, 2023a; IRENA, 2021; IEA, 2024d,a; BP, 2024; US EIA, 2023; OPEC, 2025).

Outside road transport, historical trends in oil demand do not indicate any sign of decline, and it is anticipated that it will keep growing in the main sectors outside road transport (IEA, 2024a; BP, 2024; US EIA, 2023; OPEC, 2025).

Moreover, a sizable increase in oil demand of the oil and gas own supply chains can be anticipated due to the gradual decrease of the energy return on investment (EROI) of oil and gas, either at extraction, processing or distribution (Aramendia et al., 2024; Brockway et al., 2019; Slameršak et al., 2022; Feng et al., 2018a). We analyze oil and gas supply in Chapter 3 and conclude that, although stocks are plentiful, annual net energy flows will be limited much faster than usually expected, as also pointed out in Delannoy et al. (2021a) and Delannoy et al. (2021b). The fact that oil annual supply may be limited may seem counterintuitive precisely because of the large stocks but one must keep in mind that a large fraction of these stocks cannot be economically or even technically exploited. This is not only true of resources but of parts of what is counted as reserves, as discussed in Chapter 2 (see also Laherrère et al. 2022).

More generally, we did not find any article comparing possibles futures on oil supply against those of oil demand. Major institutional reports (IEA, 2024d; OPEC, 2025; BP, 2024) operate under the basic assumption that supply would always meet demand, which prevent them to account the inner constraints of oil supply.

In the present article, a Business-As-Usual (BAU) approach is used to model the oil demand of all sectors, with a special focus on road transport, which represents 44% of oil demand in 2022. This BAU demand will be compared to oil supply in a future article in order to quantify possible future tensions between oil supply and demand. The approach initiated in the present article is not normative, but rather aims to discuss in the end the feasibility of BAU scenarios themselves, as these constitute the point of focus of policies worldwide in terms of GDP growth. In this respect, the maximum oil demand (in the absence of energy transition) quantified in this article is virtual, and the actual future oil demand will fall below this maximum. The issue is by how much.

Section 4.2 describes the methods and assumptions of this study. Section 4.3 presents our findings, section 4.4 discusses sources of uncertainties, and section 4.5 concludes the article. A set of appendices provides further details on the methods used. Our Supplementary Materials primarily contains additional figures.

[2] Trucks represent at least 30% of the oil consumption in road transport (IEA, 2024d; US EIA, 2023).

4.2. METHODS AND MODELS

Our modeling assumptions are consistent with a BAU approach. Indeed, an important ultimate aim of this study is to compare BAU oil demand and supply projections, in order to quantify potential tensions oil supply. This aim will be fulfilled in another paper, as mentioned in the introduction.

When some uncertainty arises in our assumptions, we choose to err on the side of lowering demand in a moderate and reasoned way. This will lead to a mildly optimistic view on possibly oil tension.

In order to quantify demand projections, we first need to address GDP and population projections. This is done at the country level in section 4.2.1.

Next, vehicle ownership by country is modeled as a Gompertz function of GDP per capita in section 4.2.2.1. Section 4.2.2.2 quantifies the evolution of annual oil consumption per vehicle. Sections 4.2.2.4 and 4.2.2.5 present the equations of the problem. Scenarios of the deployment of electric vehicles (EVs) are described in section 4.2.2.3. This allows us to establish oil demand projections for the road transport sector.

Finally, section 4.2.3 outlines how the oil demand in the oil and gas supply chains is modeled, while section 4.2.4 is devoted to oil demand in other sectors.

The data on oil sectoral consumption as well as more general energy data is taken from IEA's *World Energy Balances* database (IEA, 2024b). Appendix 4.J explains in detail the categories of the database used for the present work.

Finally, and consistently with a simplification made in earlier work, the differences in energy density of all oil products is neglected; this approximation leads to small and rather negligible errors, see Chapter 3. More details on the difference between gross oil demand and final oil products demand are given in Appendix 4.K.

4.2.1. GDP AND POPULATION ASSUMPTIONS

4.2.1.1. GDP DATA AND PROJECTIONS

In order to model vehicle ownership trends, one first needs to obtain historical data on and make projections of Gross Domestic Product (GDP) per capita (see section 4.2.2.

Our GDP data come from the World Bank (World Bank, 2024b) in constant 2015 dollar money unit (i.e., adjusted for inflation). Another common source of GDP projections is OECD (OECD, 2023). However, only OECD countries only are represented, and for a number of countries, the projections do not appear to align with historical trends in a consistent manner. This motivated us the compute our own GDP projections (in constant 2015 US dollars) for the specific needs of the present study.

To this effect, we extrapolate the growth rates of recent decades by an exponential decrease, down to some low asymptotic bound (specified below), as part of our BAU scenario. This follows because no institution anticipates zero or negative GDP growth rates in BAU scenarios, but some kind of convergence to a small GDP growth rate. The time period for the fit is chosen to be representative of the economic characteristics of the country at the year at which the projection begins. A detailed description of these time periods can be found in the Supplementary Materials.

This procedure leads to the following GDP growth projection model:

$$Y^c_{g,R,\$}(t,t_0) = \frac{Y'^c_{R,\$}(t,t_0)}{Y^c_{R,\$}(t,t_0)} = Ae^{\lambda(t-t_a)} + B. \tag{4.1}$$

In these relations, Y denotes GPD and Y' denotes the derivative of the GDP, with the subscript c denoting the country. The various subscripts are defined as follows: g denotes the growth rate, R indicates that the money is in constant unit (inflation adjusted), \$ the currency (2015 dollars). The current year is denoted t, the year at which extrapolation begins $t_a = 2019$ and the reference year for inflation correction $t_0 = 2015$. The coefficients A and B have a unit of yr^{-1}. Projections start in 2019 to avoid the wild fluctuations induced by the COVID, but actual projections the are shown from 2023 onwards, and GDP is continuous at this date.

One has:

$$A = Y^c_{g,R,\$}(t_a,t_0) - B, \tag{4.2a}$$

$$A\lambda = Y'^c_{g,R,\$}(t_a,t_0) \equiv C, \tag{4.2b}$$

with $Y'^c_{g,R,\$}(t_a,t_0)$ being the derivative of the growth rate, at year 2020. The exponential tangent at the origin is made equal to the slope C of the linear regression performed on historical data, giving us $\lambda = C/A$.

Most countries have experienced a decrease in growth rates, so that $\lambda < 0$. The coefficient B is arbitrarily set to 0.01 for India and China, 0.005 for other countries, in order to ensure that growth continue at as stabilized, low, constant growth rate in the future.

When available, OECD projections will also be presented for comparative analysis. These are not original OECD data, but were obtained by converting the Purchasing Power Parity (PPP) constant GDP data in unit to non-PPP constant ones with the help of the following relation:

$$Y^c_{R,\$}(t,t_0) = Y^{c,p}_{R,\$}(t,t_0)\frac{\overline{k}^c_{OECD}(t_1)}{e_{OECD}(t_0)}, \tag{4.3}$$

where $\overline{k}^c_{OECD}(t_1)$ represents the PPP conversion factor for GDP at year $t_1 = 2017$ and $e_{OECD}(t_0)$ is the exchange rate of the local currency to the US dollar at year $t_0 = 2015$. The "p" exponent denotes the PPP nature of GDP, and the somewhat convoluted notation $\overline{k}$ is adopted to conform to our generic notations for conversions used in our different papers. Finally the subscript $OECD$ refers to the fact that these conversion factors are provided for OECD specifically[3].

The GDP projections of major countries are presented in section 4.3.1.1.

4.2.1.2. Population data and projections

Demographic data are also required to compute country vehicle stocks from the modeling of vehicle ownership, as well as for converting GDP into GDP per capita.

In this work, we use the World Bank population data (World Bank, 2024a). Details about method and uncertainties are available whithin the World Bank's .xls or .csv data files. Long time series are not available for all countries. These data encompass population data for over 200 regions from 1960 to 2022, with projections extending from 2023 to 2050. Estimates are

[3]Generically speaking, one should not mix data series from one organization/program with another, as this leads to inconsistencies more often than not.

derived from countries census, interpolation and extrapolation by a demographic model, and considerations on international migration. The projections are conservative, formulated based on "assumptions of mortality, fertility, and migration by age and sex through 2050, based on the UN Population Division's World Population Prospects database medium variant". These projections estimates are the most widely used and probably the most robust available worldwide.

GDP per capita data and projections are then directly obtained for each country by dividing the country GDP $Y^c_{R,\$}(t, t_0)$ by its population $P^c(t)$.

4.2.2. Modeling gross oil demand in the road transport sector

We have categorized road transport vehicles (subscript r for road) into two main groups: motorcycles (2W) and vehicles that are at least four-wheeled (4W). More precisely, the category "motorcycles" encompasses all motorized two-wheeled and three-wheeled vehicles, including mopeds. The four-wheeled vehicles category encompasses private vehicles (PV) and commercial vehicles (CV). Private vehicles are used for private purposes (cars and private pick-ups), while commercial vehicles group together heavy-duty trucks, buses, and light commercial vehicles. In other words:

$$v^c_{x,r} = v^c_{x,4W} + v^c_{x,2W} \tag{4.4}$$

$$= v^c_{x,PV} + v^c_{x,CV} + v^c_{x,2W} \, , \tag{4.5}$$

$v^c_{x,y}$ denoting the number of vehicles (in-use vehicles) of the 'y' category with 'x' as its energy source, in country c. The time dependence of each parameter has not been indicated for simplicity.

CVs constitute only approximately 10% of the vehicles stock (see Appendix 4.E), although it is assumed that their oil use represents approximately 40% of the consumption of 4Ws (see Appendix 4.M).

4.2.2.1. Country level vehicle fleet modeling

Vehicle ownership is defined as the number of vehicles per inhabitant within a country. The common term "Vehicle in use" is used to refer to the stock of vehicles that are used in a country. Wrecked vehicles or vehicles that are not used as vehicles anymore are excluded from this count. The data used in this study is mainly the database compiled by Freyssenet (2016), completed by other official sources. Appendix 4.F gives a precise list of all sources of data used for this purpose.

11 countries represent 65% of the global vehicle fleet: China, the United States, Japan, Russia, Germany, Brazil, India, France, Mexico, the United Kingdom and Indonesia (sorted by their vehicle stock in 2020). These countries are therefore of particular interest and are referred to as "major" countries. 11 other countries account for a further 15% of the global vehicle fleet. Theses countries gathered with the major countries, are referred to as "important" countries. This is discussed in more detail in Appendix 4.S

Dargay et al. (2007) is probably the most influential article in the vehicle ownership literature. It builds on Dargay and Gately (1999) and Dargay (2001). The authors model vehicle ownership as a Gompertz function of GDP per capita, Eq. (4.6) below; time is indirectly taken into account through GDP and population growth. Some authors proposed other types of models (Lian et al., 2018; Lu et al., 2017; Lescaroux, 2010), However, most authors use Gom-

pertz functions to represent past and future vehicle ownership (Felis Rota et al., 2016; Wu et al., 2014; Poi et al., 2023; Silva et al., 2022; Huo and Wang, 2012; Li et al., 2019; Singh et al., 2020; Keshavarzian et al., 2012; Gan et al., 2020; Ma et al., 2019; Lu et al., 2018).

One may debate the scope of the type of vehicles that need to be included in such modeling. This is relevant as ownership of commercial vehicles is not subject to the same rationale as private vehicles. However the cited literature most frequently includes all types of 4W vehicles in the same model (passenger cars, pick-ups, light trucks, buses, medium and heavy trucks). This follows because the availability and the quality of in-use vehicle data is critical for the quality of the model (see Appendix 4.F), and data sources often provide data only for the total of 4Ws. Nevertheless, some articles model passenger cars instead of all four-wheeled vehicles, and some others do not clearly define the scope of their data. In line with most of the existing literature and the data used, we have chosen to model the ownership of the total number of four-wheeled vehicles. The next most important issue bears on vehicle ownership saturation levels and its determinants, among which urbanization and population density are most prominent.

The Gompertz function itself is given by:

$$V^c_{4W}(y^c_{R,\$}) = \gamma^c \exp[-\alpha^c exp(-\beta^c y^c_{R,\$})]. \tag{4.6}$$

In this relation, V is the average number of vehicles per capita; c refers to the modeled country and $4W$ for four-wheeled vehicles; $y^c_{R,\$} = Y^c_{R,\$}/P^c$ is the country's GDP per capita in constant (inflation adjusted) US dollars[4] (Y being GDP and P^c_t the country population, both for the same given year). γ^c designates the saturation level of vehicle ownership, while α^c and β^c control the shape of the Gompertz function (see Appendix 4.D). These three parameters are positive by assumption; α^c and γ^c are dimensionless while β is measured in yr.cap/(2015$). Dargay et al. (2007) add a parameter taking into account the delay between income increase and car purchase. We ignore this refinement here, in line with a common habit in the literature.

The Gompertz fit parameters of vehicles ownership for different countries are discussed and compared to the literature in Appendix 4.G. The saturation level γ^c is of particular importance. Its values are discussed in Appendix 4.H and its impact in section 4.4.2.

Section 4.3.1.2 shows the results of our Gompertz fits for major countries.

This allows us — combined with the projections of GDP and population of sections 4.2.1.1 and 4.2.1.2 — to quantify the vehicle stock at the country level, which can be written:

$$v^c_{f,4W}(t) = P^c(t) V^c_{f,4W}\left(y^c_{R,\$}(t)\right), \tag{4.7}$$

the f subscript designating the type of fuel used by the car, and the subscript F referring the total of all fuel types (mostly oil and electricity); t is time.

At the world level, the total vehicle fleet is directly obtained from $v^{wld}_{F,4W}(t) = \sum_c P^c(t) V^c_{F,4W}\left(y^c_{R,\$}(t)\right)$. The results are presented in section 4.3.3

4.2.2.2. Annual oil use of a vehicle

As vehicle stocks by country are known, the annual consumption of oil of PVs and CVs are projected in order to quantify the oil consumption of road transport sector by country.

As discussed in Appendix 4.P, the annual consumption of a passenger vehicle within a country can be expressed as the product of the consumption per kilometer (MJ/km or L/100km) and the annual mileage. The evolution of fuel consumption per kilometer is the consequence

[4] The reference year for inflation adjustment is 2015 in this work.

of a combination of factors, including the increased efficiency of engines due to technological progress on the long term, as well as changes in vehicle characteristics, including alterations in weight, engine power and the amount of equipment. Variations in annual mileage are contingent upon a multitude of factors, including urban planning and the number of individuals using a given vehicle. One may assume that an increase in wealth (GDP/cap) results a reduction in vehicle sharing, which would in turn result in a reduction in annual consumption of each vehicle (GJ/PV). Furthermore, it is conceivable that the increase of urban population in countries where vehicle ownership has reached a plateau will result in a decline in annual consumption of PVs (GJ/PV), as vehicles become less frequently used.

More precisely, and based on the information and arguments discussed in Appendix 4.P, the annual consumption of oil PVs $C^c_{o,PV}(t)$ can be modeled on the basis of an annual decline rate as:

$$C^c_{o,PV}(t) = Ak^{t-t_0}, \tag{4.8}$$

with $A = C^c_{o,PV}(t_0)$ a constant, k the annual factor of decline and t_0 the reference year.

Data and projections for several important countries are shown in section 4.3.1.3.

4.2.2.3. Electric vehicle deployment assumptions

In 2024, electric vehicles (EVs) represented only 4% of the total vehicle stock (IEA, 2025b). However, their deployment is in an exponential phase, and it is difficult to predict the evolution of their stock. On the one hand, many countries have embarked on strong development trajectories for these technologies (IEA, 2024b), but on the other, barriers to their deployment are to be expected.

Firstly, the electric cars' higher cost ranges from 10% to 80%[5] compared to ICVs (Internal combustion engines vehicles) (IEA, 2024d), due to the cost of batteries. This could be expected to decline over time due to technological progress and scale economies on the cost of batteries and following a learning curve (Wright's law), but the annual cost reductions are getting smaller over time (IEA, 2025b) and — most importantly — are subject to variation of the price of raw materials (IEA, 2022; Bernhart, 2022), that represent around 70% of the costs of batteries (Pillot and Renard, 2022; Bernhart, 2022). Although this higher upfront cost can be compensated to some extent by a lower fuel cost, this is still expected to represent the main barrier to the deployment of electric cars (Virmani et al., 2023; Muratori et al., 2021; Rajper and Albrecht, 2020; Zhuge and Shao, 2019; Fevang et al., 2021; Purwanto and Irawan, 2024; Naseri et al., 2024; Soszynska et al., 2024; IEA, 2022, 2023b, 2024d). It is possible that the deployment of charging stations, the supply of raw materials for these batteries, the growth capacity of power generation to supply them or social choices may also act as barriers. The lithium supply chain in particular is considered critical (Pulido-Sánchez et al., 2022; IEA, 2024d). In our "25% EV" and "100% EV" scenarios, defined below, EV sales are assumed to decrease logistically from 50% annual increase in 2025 to respectively 10% in 2032 or 2035. As EVs batteries represent 85% of the world lithium consumption in 2023 IEA, 2024d, the growth of the lithium supply chain would have to follow the growth of the EV sales.

In first approximation, the deployment of electric cars may be modeled by a logistic function. Indeed, an exponential growth fits very well the historical evolution of the electric vehicle stock ($R^2 = 0.999$ from 2011 to 2023 included), and a logistic function is usually accurate for the

[5] China is an exception, with a lower price premium. Moreover, the MiniEV model is available for well under $10,000 and has been the best-selling electric car in China. This is the result of China's decade-long policy of developing electric cars for geostrategic reasons (notably energy and industry considerations) and because it controls a large part of the supply chain for these vehicles. China is also suspected of large subsidies to this industry, and even dumping for exportation.

deployment of new technologies (Grübler et al., 1999; Hansen et al., 2017; Cherp et al., 2021). For these reasons, the logistic model is adopted in this work.

The saturation level of the electric car stock is defined as a share of the total stock of cars. The different scenarios are named according to these saturation values. We present mostly results for four scenarios: "0% EV" (or rather negligible), "25% EV", "50% EV" and "100% EV"; however we occasionally refer to scenarios corresponding to other saturation values, in particular when comparing our results with the literature on EV deployment. The remaining parameters (slope and inflection point) are determined by a fit on historical data. The model can be written:

$$v_{e,PV} = \frac{l_{e,PV} v_{F,PV}}{1 + \exp[-k_{e,PV}(t - t_{0,PV})]}, \tag{4.9}$$

with $l_{EV} v_{F,PV}$ being the actual saturation level ($l_{e,PV} \in \{0, 0.25, 0.50, 1.00\}$ the fraction of the total $v_{F,PV}$), $k_{e,PV}$ the slope and $t_{0,PV}$ the year of inflection in EV deployment.

The real deployment of EVs may be slower than a logistic function at some point, due to the barriers mentioned above and to the fact that the lifetime of ICVs (about 15-20 years following Held et al. 2021; Oguchi and Fuse 2015) could extend the amount of time needed to replace the entire vehicle fleet. Nevertheless, in this modeling, the time dynamics at the initial phase of the curve is of less importance compared to the uncertainty surrounding the saturation of EVs in PV stocks. Consequently, the initial rate speed of EV deployment in this modeling may be overestimated, which tends to reduce the oil demand, in line with the reasoned bias adopted in this work.

The "25%" scenario best matches the 2035 IEA projections IEA (IEA, 2024d). Moreover, the 2023 U.S. EIA International Energy Outlook (US EIA, 2023) reference case projects a 33% deployment of electric vehicles in the global stocks of vehicles in 2050. Considering the above barriers and these indications, we believe that a range of 10-50% for the saturation of the EV stock by 2050 is realistic.

In this study, the "electrical vehicle" (EV) category encompasses plug-in hybrid electric vehicles (PHEV) which represent 30% of the EV stocks in 2023 (IEA, 2024d), declining over time. This study assumes that EVs consume exclusively electricity, thus neglecting the oil consumption of PHEVs. This appears to be a reasonable assumption, as Battery Electric Vehicles (BEVs, defined as 100% electric vehicles) are expected to deploy much faster than PHEVs (IEA, 2024d), thus making the error in oil demand due to PHEVs negligible.

Finally, it is assumed that the deployment of electrical commercial vehicles (CV) can also be modeled by a logistic function, but with a late deployment and lower saturation levels (40%) than for electric PVs, as explained in Appendix 4.N.

4.2.2.4. Equations system

The IEA's World Energy Balances (IEA, 2024b) provides data on the energy consumed by the road transport sector. In 2022, this energy use was divided between oil (93%), biofuels (5%), natural gas (3%) and electricity (0.5%). The categorization of oil and biofuels (liquid fuels) as a single entity, designated as "oil", is employed for the sake of simplicity, aligning with oil supply conventions. The consumption of natural gas is neglected as its share in energy consumption is expected to decrease over time (see Appendix 4.O).

The oil energy consumption by road transport is denoted $E^c_{o,r}(t)$, for year t between 1960 and 2022 and country c. To alleviate notations, the superscript "c" and the "t" variable will be dropped in the remainder of this section. $E_{o,r}$ aggregates the total amount of oil consumed by

all types of road vehicles. Data on disaggregation between Private Vehicles (PV), Commercial Vehicles (CV) and motorcycles (2W) (see Appendix 4.E) are not directly available. To proceed further in spite of this limitation, we start with the two following conservation equations:

$$\begin{aligned} E_{o,r} =& E_{o,PV} + E_{o,CV} + E_{o,2W}, \\ =& E_{o,4W} + E_{o,2W}, \end{aligned} \tag{4.10}$$

$$v_{F,4W} = v_{o,PV} + v_{o,CV} + v_{e,PV} + v_{e,CV}, \tag{4.11}$$

where $E_{o,PV}$, $E_{o,CV}$, $E_{o,2W}$, $E_{o,4W}$ stand for the oil energy consumption of PV, CV, 2W and 4W respectively; $v_{F,4W}$ is the total vehicle stock 4-wheeled vehicles, disaggregated in the sum of the stock of oil PV $v_{o,PV}$ and CV $v_{o,CV}$ vehicles and electric PV $v_{e,PV}$ and CV $v_{e,CV}$ vehicles.

In order to solve the system, a number of assumptions are made, which are detailed in specific sections and Appendices that will be mentioned along the way. The annual energy consumption per vehicle is defined as follows:

$$C_{x,y} = \frac{E_{x,y}}{v_{x,y}}, \tag{4.12}$$

where $x \in \{o, e, F\}$ represents the energy source (fuel) used by the vehicle and $y \in \{r, 4W, PV, CV, 2W\}$ the type of vehicle.

For most countries, the modeling of motorcycles is not performed. This is equivalent to assuming implicitly that the oil demand from motorcycles is proportional to 4-Wheelers'. The oil demand of motorcycles is only modeled in India and Indonesia, which account for the half of the global motorcycle stock, and the stock of 2W in these countries exceeds that of 4W. In all other countries, the stock of 2W is much lower than 4Ws'. Combined with the lower annual oil consumption of 2W compared to 4Ws (and also to the lack of available data), their neglect is reasonable and has little impact on the results. Further arguments and details about the modeling of motorcycles can be found in Appendix 4.L.

For India and Indonesia, we assume that the annual consumption of oil per motorcycle is proportional to PVs' (see Appendix 4.L). This yields the following equations:

$$C_{o,2W} = K_{2W} C_{o,PV}, \tag{4.13}$$

or equivalently

$$\frac{E_{o,2W}}{v_{o,2W}} = K_{2W} \frac{E_{o,PV}}{v_{o,PV}}, \tag{4.14}$$

where the second equality follows from Eq. (4.12). K_{2W} is a constant, evaluated in Appendix 4.L from historical data. The data for motorcycle stocks $v_{o,2W}$ are retrieved from official sources, and future projections are given by a Gompertz fit, as explained in Appendix 4.L.

The effect of the deployment of electric vehicles is only modeled modeled as oil demand reduction, and not as electricity demand, as we are not interested in electricity use per se in this work

With $C_{o,y}$ the annual oil consumption of a y-type vehicle ($y \in \{r, 4W, PV, CV, 2W\}$), and $C_{e,y}$ the annual electricity consumption of a vehicle of type y, we assume that:

$$C_{e,y} = C_{o,y}/\kappa, \tag{4.15}$$

or equivalently

$$\frac{\kappa E_{e,PV}}{v_{e,PV}} = \frac{E_{o,PV}}{v_{o,PV}}, \tag{4.16}$$

$$\frac{\kappa E_{e,CV}}{v_{e,CV}} = \frac{E_{o,CV}}{v_{o,CV}}. \tag{4.17}$$

with κ a constant.[6] However, this constant has no influence on the computation of oil consumption of the vehicles, as shown in Appendix 4.Q. Consequently, we do not need to estimate it in this work.

As described in Appendix 4.M, we postulate that the energy used by CVs and 4Ws are proportional. Thus:

$$\begin{aligned} E_{o,PV} + \kappa E_{e,PV} =& K_E \left(E_{o,PV} + \kappa E_{e,PV}\right. \\ &\left. + E_{o,CV} + \kappa E_{e,CV}\right), \end{aligned} \tag{4.18}$$

where K_E is a constant determined from historical data as explained in Appendix 4.M; $E_{o,PV}$ and $E_{o,CV}$ are the oil used by PV and CV respectively, while $E_{e,PV}$ and $E_{e,CV}$ are the electricity used by PV and CV respectively. Similarly, we assume that the stocks of CVs and 4Ws are proportional, as described in Appendix 4.E. Thus:

$$v_{o,PV} + v_{e,PV} = K_v \left(v_{o,PV} + v_{o,CV} + v_{e,PV} + v_{e,CV}\right), \tag{4.19}$$

where K_v is a constant determined from historical data as explained in Appendix 4.E.

In principle, Eqs. (4.10), (4.11), (4.14), (4.16), (4.17), (4.18) and (4.19) allow us to find $E_{o,PV}$, $E_{o,CV}$, $E_{e,PV}$, $E_{e,CV}$, $E_{o,2W}$, $v_{o,PV}$ and $v_{o,CV}$, from the know quantities $E_{o,r}$ (see below), $v_{F,4W}$ (section 4.2.2.1), $v_{e,PV}$ (see Appendix 4.N), $v_{o,2W}$ (Appendix 4.L), and know constants K_v (Appendix 4.E), K_E (Appendix 4.M) and K_{2W} (Appendix 4.L). However, no information on the future behavior of $E_{o,r}$ was found in the literature. Instead, we established projections of the annual oil consumption per vehicle $C_{o,PV}$ as described in section 4.2.2.2. This allows us to obtain $E_{o,PV}$ alternatively from Eqs. (4.8) and (4.12) and $E_{o,r}$ from Eq. (4.11). Algebraic details are given in Appendix 4.Q.

4.2.2.5. Multi-regional computation

The preceding system, Eqs. (4.10) – (4.19), is solved independently for each of our 62 main countries, which are referred to as modeled countries and specified in Appendix 4.S. In each of the eight regions defined in the same Appendix, the remaining countries (dubbed other countries) are aggregated. It is then assumed that the fraction of vehicle stocks and of energy used by vehicles in these other countries is constant over time. This parameter is determined from historical data, as described in Appendix 4.R. The evolution of all parameters over time for these other countries is thus directly deduced from modeled countries.

The global (world-wide) evolution of all quantities of interest is obtained by aggregation of regional results.

[6] It is assumed that the behaviors of drivers of EVs and ICVs are identical. Consequently, κ primarily accounts for the differences in energy efficiency of electric engines compared to thermal ones.

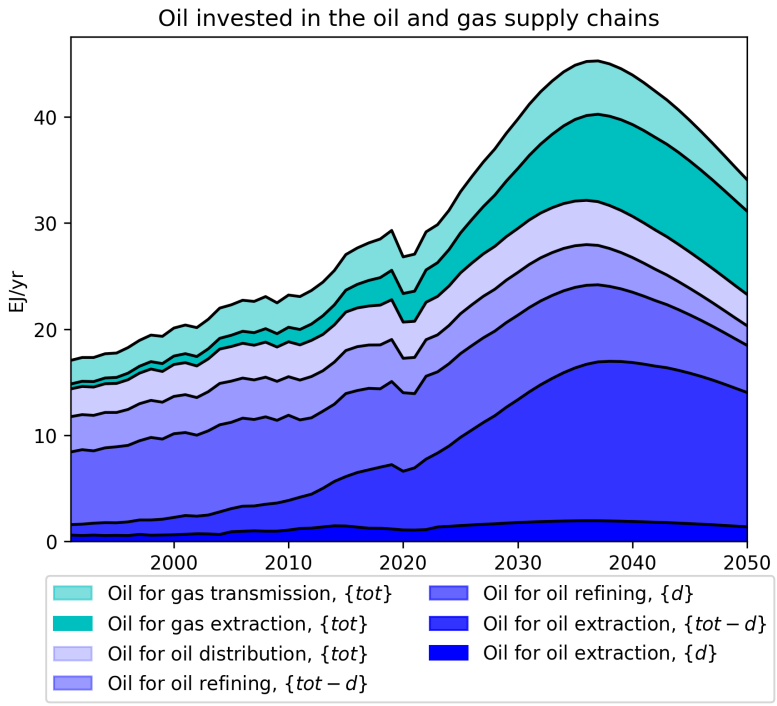


FIGURE 4.1: Oil cumulative demand in the oil and gas supply chains. The legend describes the various processes, and the boundary: direct ($\{d\}$), embodied ($\{tot - d\}$) or cumulative ($\{tot\}$) investments. See Chapter 3.

4.2.3. GROSS OIL INVESTMENTS IN SUPPLY CHAINS

Gross oil demand in the oil and gas supply chains is directly derived from our previous study (see Chapter 3, where we quantified the different energy investments required in the oil and gas supply chain up to point of use and to the cumulative boundary. It should be noted that these investments include direct ($\{d\}$) energy investments as well as the embodied energy ($\{tot - d\}$) covering the indirect, labor and auxiliary energy investments (Murphy and Hall, 2011).

The cumulative oil investments in the oil and gas supply chain obtained in this previous work are shown in Fig. 4.1. The oil investments increase until 2036 mostly due to the decrease in the accessibility of oil and gas. The post-2036 decline in the oil requirements is mainly due to the decline in the gross supply of oil, meaning that there is less oil to extract, refine and distribute.

By definition, the $\{tot - d\}$ oil demand is already accounted for in historical data within the different sectors consuming oil. In order to represent the evolution of this $\{tot - d\}$ oil demand, we extracted only the additional $\{tot - d\}$ energy investment compared to the last data point in the additional demand:

$$E_{o,OG}(t) = \sum_{x} \sum_{p} E_{r,x}^{a,d,o}(t) + \left(E_{r,x}^{a,tot-d,o}(t) - E_{r,x}^{a,tot-d,o}(t_0) \right), \tag{4.20}$$

where $E_{o,OG}(t)$ is the additional oil demand due to the oil investments in the oil and gas supply chains, over time t. $E_{r,x}^{a,b,o}$ is the direct ($b = d$) or embodied ($b = tot - d$) oil invested in the process $a \in \{ex, ref, dist, trans\}$ — extraction of oil or gas, refining of oil, distribution of oil, transmission of gas — of the oil or gas supply chain $x \in \{o, g\}$. $t_0 = 2022$ is the last year for which data is available.

This approach ensures that the increase in $E_{o,OGSC}(t)$ energy is accounted for and double-counting is avoided. However, trends in the evolution of the different sectors of oil demand

(section 4.2.4) are affected by the evolution of $E_{o,OGSC}(t)$. In this regard, we point out that $E_{o,OGSC}(t)$ constituted 10% of the gross oil supply in 2022. Evolutions due to these 10% should have a limited impact on the evolution of oil demand in the different sectors, and are neglected.

4.2.4. Gross oil demand in other sectors

The evolution of gross oil demand in other sectors is modeled by extrapolation of historical trends. Total oil use amounted to 171 Exajoules (EJ) in 2019, of which 58% came from the transport sector (see Fig. 4.17), itself divided into 6 sub-sectors (see figure 4.I1), including the road transport sector (the lion share), modeled in <detail in section 4.2.2.

Following a sharp reduction in aviation activity in 2020 caused by the Covid-19 pandemic, a sharp increase in energy consumption by the aviation sector is forecast until 2050 (IEA, 2023a,c; BP, 2024; US EIA, 2023; OPEC, 2025), with IEA, BP, EIA and OPEC projecting it to reach 22-24EJ in 2050 for "Business as usual" (BAU) scenarios[7]. Projections for alternative fuels (biofuel, synthetic kerosene) — which are not yet used on a large scale — differ between these scenarios. We projected oil consumption linearly in the aviation sector (see Fig. 4.I1) consistently with the trend observed between 1990 and 2015, which results in rather conservative a projection reaching 20 EJ in 2050, a little lower than the projections of the aforementioned institutions.

The maritime sector (shipping) is expected to experience an increase in energy demand by 2050 (+45% according to the IEA's STEPS scenario, +70% according to BP's "Current trajectory", +30% according to IRENA's "Base Energy Scenario", which forecasts an effect of energy efficiency; see IEA 2023a,c; BP 2024; IRENA 2021). Furthermore, alternative fuels (liquefied natural gas, biofuels, ammonia, methanol) are expected to emerge in the energy mix with a variable role (4% in 2030 in IEA's STEPS, 35% in BP's current trajectory). Based on this information, oil demand is projected linearly to zeroth order on the basis of recent years' data, with the addition of an annual decline rate of 0.5% to first order to account for energy efficiency gains and the partial penetration of alternative fuels. The projections then indicate an oil consumption of 13.3 EJ in 2050, which is in line with IEA, BP and OPEC projections[8].

The oil consumption of the other transport sectors (rail, pipelines and the other category which gathers the rest) represents less than 2 EJ. In line with historical trends over the last few years, they are projected to remain constant.

Oil consumption outside the transport sector is also projected (see Fig.4.I2). 2/3 of non-energy oil consumption is dominated by products used as chemical feedstocks and non-energy products in the petrochemical industry (IEA, 2024b). It is expected that this trend will continue to grow strongly by 2050, in a linear extension of historical trends. Oil consumption is then projected to reach 45EJ in 2050 (compared with 30EJ in 2020), which is consistent with the projections of IEA, BP and OPEC (IEA, 2024a,d; BP, 2024; OPEC, 2023)[9]. IEA forecasts an increase in energy consumption of around +1EJ/year for all energy sources combined, which can reasonably be expected to translate into projections similar to these of this model, given that oil accounted for 3/4 of the energy consumed in the non-energy products sector in 2020 and that this share is declining slowly (about 10% in 20 years).

[7] BAU scenarios are IEA's STEPS scenario (Stated Policies Scenarios), BP's "current trajectories" and EIA's "Reference case".

[8] Assuming a 15% penetration of alternative fuels in 2050 in IEA STEPS scenario amounts to expecting an oil consumption of 13.6 EJ. BP assumes an increase in energy demand of 70% and a penetration of alternative fuels of 35% in 2050, which results in an oil consumption of 13 EJ in 2050.

[9] BP forecasts a non-linear increase, but reaching the equivalent of +20EJ in 2050 compared with 2020. OPEC forecasts an increase of $\sim$ 10EJ in petrochemicals oil consumption over the same period. IEA forecasts an increase in energy consumption of $\sim$ 1EJ/year for all energy sources combined, which can reasonably be expected to translate into projections similar to ours, given that oil accounted for 3/4 of the energy consumed in the non-energy products sector in 2020 and that this quantity is declining slowly (about 10% in 20 years according to IEA 2024b). The projections from OPEC (2025) are $\sim$ 10% lower than ours.

We assume that direct oil consumption by commercial/public services will fall by 1% per year, thereby continuing the downward trend observed over the long term. Conversely, the consumption in agriculture and forestry, fishing, industry, residential and the other such sectors is projected to remain constant. OPEC (2025) projects a 16—19% increase of these quantities between 2024 and 2050.

The oil demand of the energy industry sector (excluding the oil and gas supply chains) and of the "electricity and transformations" sector are projected linearly. Actually, each flow constituting these categories (provided by IEA's World Energy Balances) are projected individually, and then aggregated. These aggregated projections are shown in the Appendix 4.I.

The direct oil consumption of armed forces is not quantified in the WEB database[10] thus not modeled in the present study. This would represent approximately 2EJ/yr (Transform Defence, 2020), which is unlikely to decrease in the post-2020 context of growing regional tension. Ignoring it results in a slight underestimation of the future oil demand, in line with the reasoned bias adopted in this work.

In the comparisons mentioned above, one may note that OPEC and BP may have economic interest in forecasting rather high values of oil demand. However, if the projections from OPEC are indeed higher than those of the other reports, this is not the case for BP. On the other side, we may possibly expect IEA and BP to be optimistic on the energy transition, but each institution has an interest in maintaining credibility. In the end, the projections from STEPS (IEA WEO 2024), the reference case of EIA IEO 2023 and the "current trajectory" of the BP EO are quite close. The main differences in these scenarios lie in the projections on the deployment of EVs.

The resulting oil demand is shown in section 4.3.1.5

4.3. Results

4.3.1. Intermediate results

4.3.1.1. GDP projections

The BAU (Business-As-Usual) GDP projections of major countries are presented in Figures 4.2 and 4.3. Additional figures representing global and regional GDP growth projections, and concerning the aggregated GDPs at the regional level can be found in the Supplementary Materials. In general, the projections in this study are less optimistic than OECD's. This is consistent with the tendency of OECD projections to be optimistic compared to historical trends, and with the approach of this paper which tends to minimize GDP growth within the BAU assumptions as explained earlier. Generically, lowering GDP results in a lower vehicle ownership thus in a lower overall oil consumption.

In any case, the uncertainty analysis of section 4.4.1 tends to show that the results are little sensitive to these assumptions on GDP growth, at least on the time horizon of our study.

4.3.1.2. Gompertz fits

Figs. 4.4 and 4.5 show the results of our Gompertz fits for major countries up to 2050 (i.e., we use GDP per capita up to this date). Developing countries display earlier and steeper depen-

[10] This largest consumption is due to aircraft(Albert, 2022). The oil consumption of the defense industry is included in the "industry" category of the IEA's WEB.

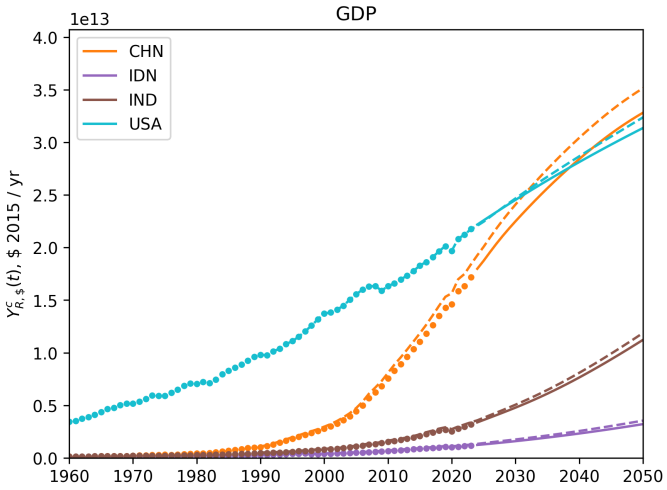


FIGURE 4.2: GDP projections for China, Indonesia, India and United States. Historical data taken from the World Bank are shown with dots, while the line represent our projections and the dashed line represent OECD data and long term baseline projections.

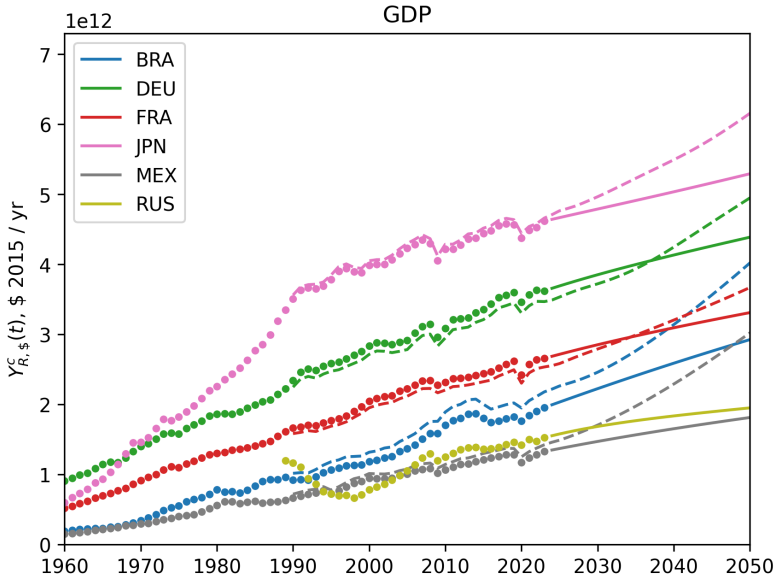


FIGURE 4.3: GDP projections for Brazil, Germany, France, Japan, Brazil, Mexico and Russia. Historical data taken from the World Bank are shown with dots, while the line represent our projections and the dashed line represent OECD data and long term baseline projections.

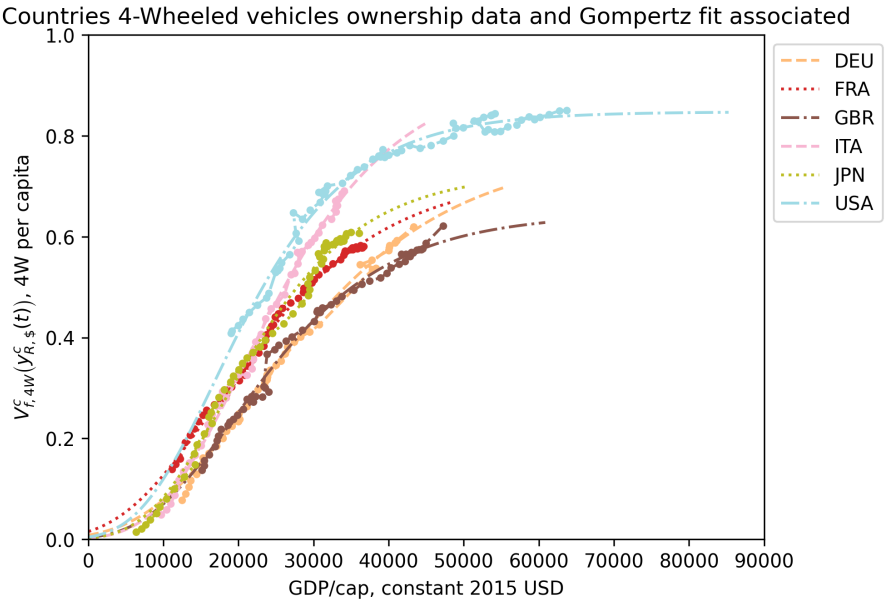


FIGURE 4.4: Gompertz fits of 4W ownership for some important countries. Points represent historical data and lines (dashed and/or dotted) show their fits and projections until 2050. Countries are identified by their alpha-3 code, see Appendix 4.A.

dencies on GDP per capita than advanced economies. This may be due to automobile industrial technological progress which has led to substantial global price reductions (at constant quality) over time, or, alternatively, to the effects of the major role of cars in advanced economies, leading to earlier car deployment in the developing economies. Moreover, it is observed that prices (in constant $) of equivalent cars are lower in developing economies than in advanced ones.

The same observations led Vidal et al. (2022) to include the 2015 GDP of a country as a control parameter of this country's vehicle ownership projection in the DyMEMDS model.

4.3.1.3. ANNUAL OIL USE OF A PV

Based on section 4.2.2.2 and Appendix 4.P, data and projections for several important countries are illustrated in Figs. 4.6 and 4.7. We note that the annual oil consumption of a vehicle and its trends are similar in countries belonging to the same region. This has not been shown in the figures, as the resulting curves would have been too cluttered.

Individual figures for major countries are available in the Supplementary Materials.

4.3.1.4. PROJECTIONS OF THE GLOBAL STOCK OF PRIVATE ELECTRIC VEHICLES ACROSS SCENARIOS

The time projections of the global stock of private electric vehicles are shown on Fig. 4.8, as modeled in section 4.2.2.3. The projections of the stock of electric commercial vehicles are presented in Appendix 4.N.

4.3.1.5. OIL DEMAND IN OTHER SECTORS

The oil demand of all sectors except road transport are finally displayed on Fig. 4.9. Appendix 4.I provides non-cumulative figures, clarifying the trends in each sector.

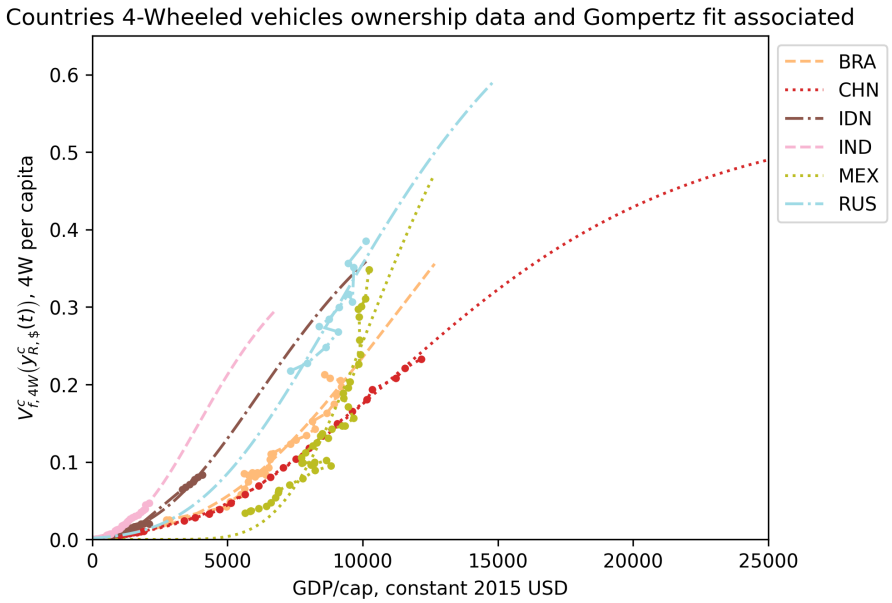


FIGURE 4.5: Gompertz fits of 4W ownership for some important countries. Points represent historical data and lines show their fits and projections up to 2050. Countries are identified by their alpha-3 code, see Appendix 4.A. It should be noted that the scales of the axis are different than those of the previous figure 4.4

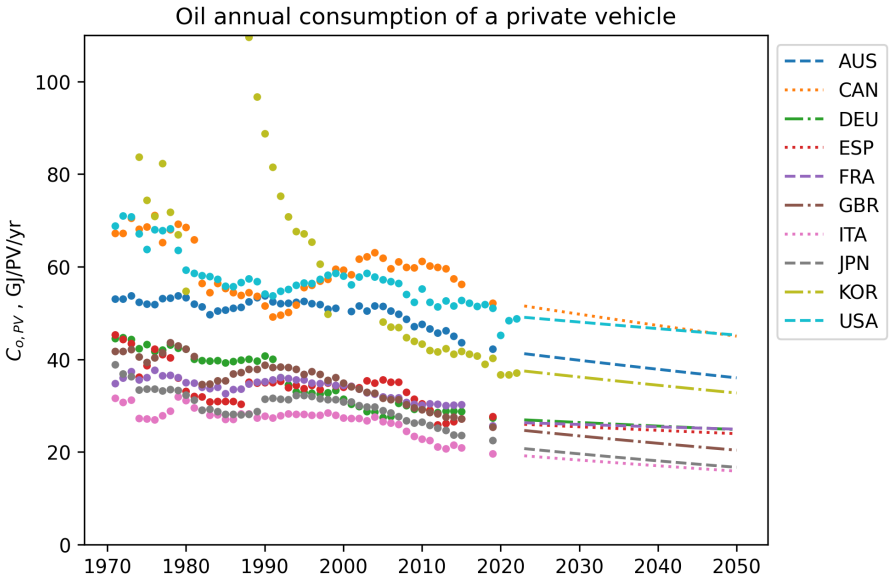


FIGURE 4.6: Data and projections on the annual oil consumption of private vehicles for some western countries. Countries are chosen to illustrate the observed variability.

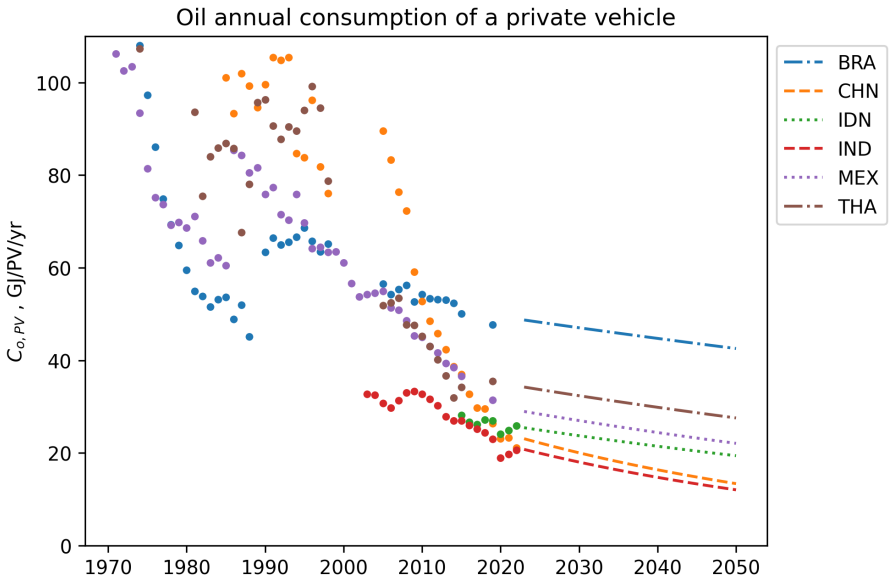


FIGURE 4.7: Data and projections on annual oil consumption of private vehicles for some developing countries.

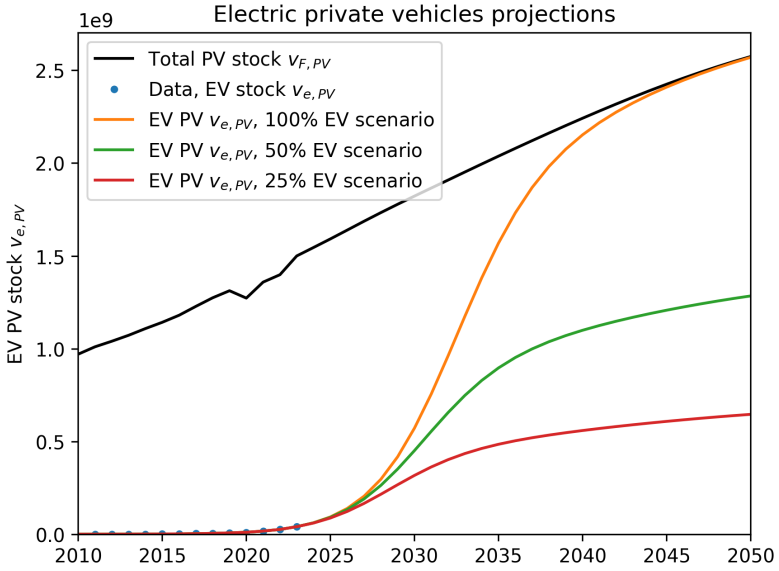


FIGURE 4.8: Projections of the stock of the private electric vehicles at the global level. The three colored curves represent the evolution of the stock in the "100% EV" (orange), "50% EV" (green) and "25% EV" (red) scenarios. The percentage value designates the $l_{e,PV}$ saturation value of equation 4.9.

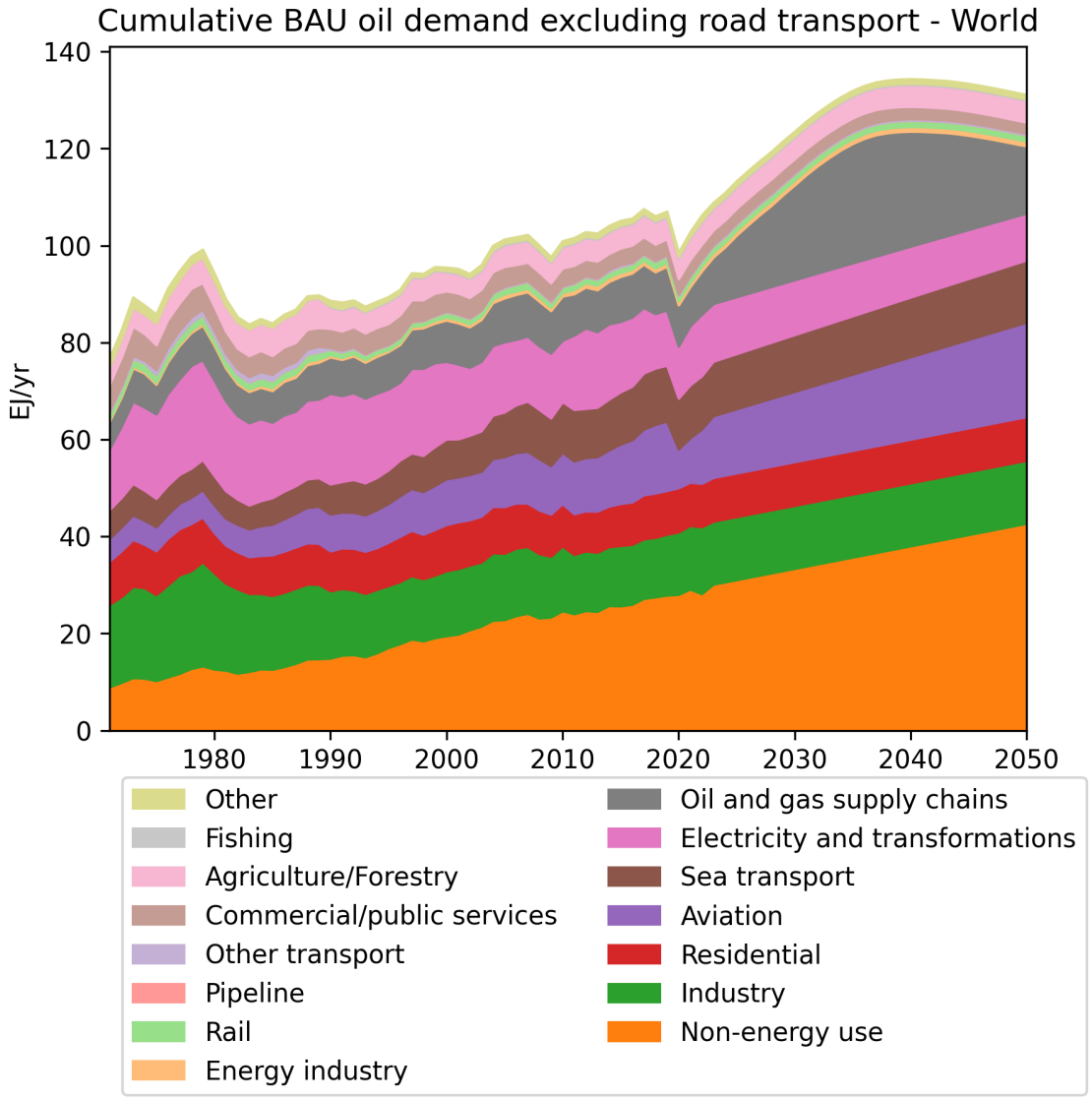


FIGURE 4.9: Cumulative consumption of oil in all sectors excluding demand in road transport. The figure shows historical data, and projections from 2023 onward.

4.3.2. Regional disaggregation

We present below a number of figures showing the regional distribution of quantities of interest in this work. The various regions are labeled by 3 letters. "afr" designates Africa, "amn" North America, "ams" South America, "asi" Asia, "euw" Western Europe, "eue" Eastern Europe, "mde" Middle East, "oce" Oceania. Countries are referenced in figures by 3 letters corresponding to their ISO 3166-1 alpha-3 code, see Appendix 4.A.

This regional disaggregation has been chosen in order to constitute groups of countries with similar economies. The rationale behind this choice is that countries within a given region are expected to exhibit comparable GDP per capita and GDP per capita growth so that vehicle ownership should be at similar stages in their evolution, but also similar geographical characteristics (leading to similar saturation levels in ownership and similar annual mileage of PVs). This should lead to similar trends in the annual oil consumption of PVs.

This approach allows us to derive the evolution of PVs stocks and oil demand by the road transport sector of countries that are not modeled within a region, on the basis of the global trend due to the aggregated modeled countries within the same region. A suffix "_o" added to the region name (e.g. "asi_o") designates the aggregation of these other, not modeled countries. The countries modeled in each region are listed in Supplementary Materials.

4.3.3. Vehicle stocks

The evolution of the stock of 4-wheeled vehicles (4Ws) by region is illustrated in Figs. 4.10 and 4.11. The world fleet reaches 2.9 billion vehicles in 2050, compared to 1.7 billion in 2024. The data of OICA (2022) estimated the global stock of 4Ws to be 1.59 billion vehicles in 2020. A large part of this stock and of this evolution is due to China and India, which experience a huge growth in vehicle ownership (see Fig. 4.5). The vehicle stock of China and India represent 1.1 billion vehicles in 2050, compared to 450 million in 2024, as shown in Fig. 4.12. Another part of the increase is due to other Asian countries, whose stock of vehicles increases from 230 million in 2024 to 450 million in 2050.

Figures showing the evolution of the vehicle stocks in other regions can be found in Supplementary Materials.

This dominance of India and China is critically dependent on the saturation parameter of the Gompertz function of vehicle ownership. Indeed, saturation is reached before 2050 in the case of China. Consequently, the transitory stage has a low influence on the vehicle stock in China after 2030. Nonetheless, this saturation parameter is quite uncertain as discussed in Appendix 4.H for China and India. The related uncertainty is quantified in section 4.4.2. Still, our projections for China are in line with Huo and Wang (2012); Lu et al. (2018); Gan et al. (2020).

We also compared our results and DyMEMDS'. This latter model which was developed by one of the authors of the present study. The assumptions made in DyMEMDS differ somewhat from ours, and this comparison is carried out in Appendix 4.B. Our global vehicle stock is found to be 400 million vehicles lower in 2050. This difference is entirely explained by the difference in the adopted saturation value for China (which amounts 0.74 PV/cap in DyMEMDS). The difference in saturation values in the case of India does not have a significant impact as the vehicle ownership is not projected to reach saturation in 2050 in both models.

On the other hand, EIA (US EIA, 2023) forecasts a vehicle fleet with half a billion fewer vehicles than the projections of the present study. If the GDP/cap projections cannot be compared due to differences in the units (EIA uses PPP constant $), it is quite clear from the data

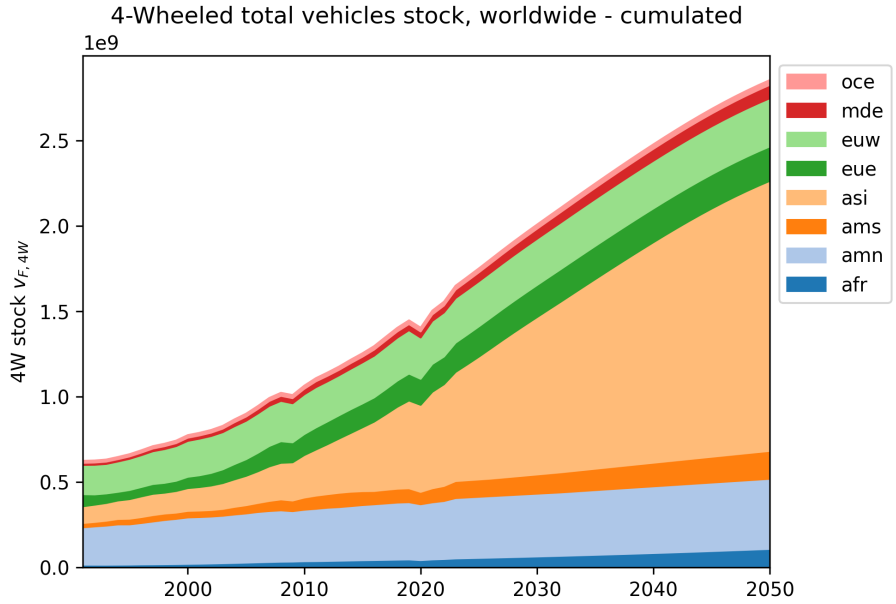


FIGURE 4.10: Evolution of the stocks of 4-Wheeled vehicles (4W), by world region. "oce" stand for Oceania, "mde" for Middle East, "euw" for Western Europe, "eue" for Eastern Europe, "asi" for Asia, "ams" for South America, "amn" for North America, "afr" for Africa (see section 4.3).

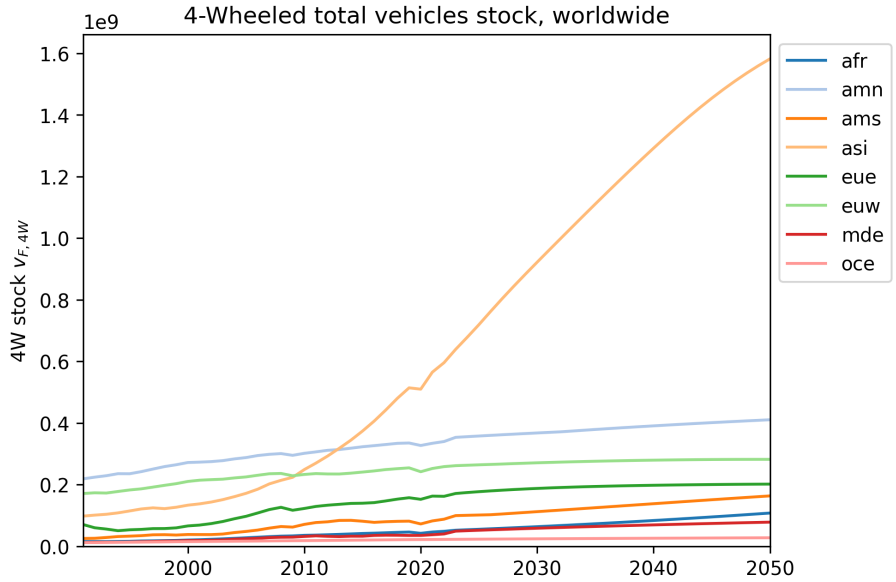


FIGURE 4.11: Evolution of the stocks of 4-Wheeled vehicles (4W) in each region of the world. Region codes as in Fig. 4.10.

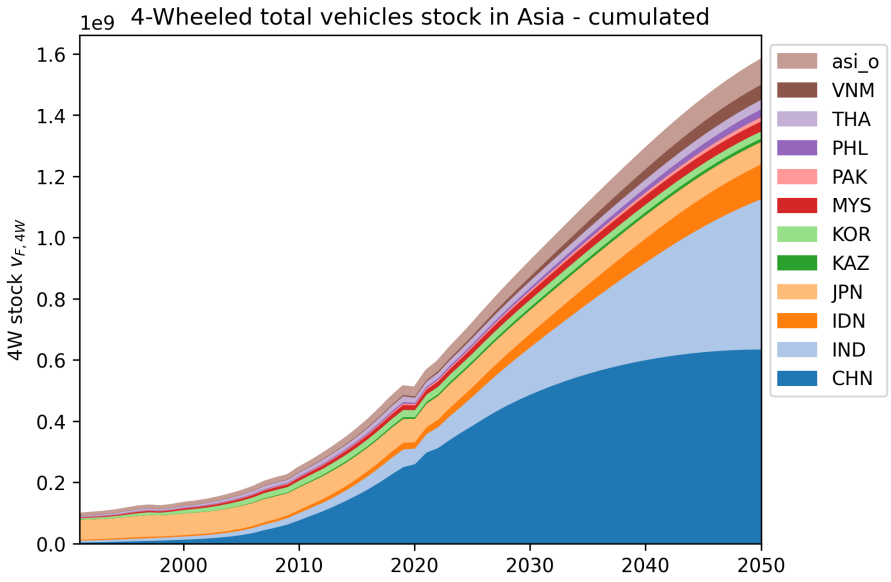


FIGURE 4.12: Evolution of the stocks of 4-Wheeled vehicles (4W) in countries of Asia.Region codes as in Fig. 4.10.

that the saturation of vehicle ownership in China is assumed to be lower in IEA's model, at around 0.32 4W/cap in their case. This is very optimistic in terms of oil demand moderation given the current trend of continuous growth of vehicle ownership, reaching 0.23 4W/cap in 2023 and because of the arguments presented in Appendix 4.H. In the case of India, their modeling results in 200 million less vehicles, which could be due either to different GDP growth assumptions or different assumptions on the saturation level.

The projections of the vehicle stock from the OPEC (2025) are consistent with the present study, at the global and regional levels.

4.3.4. GROSS OIL DEMAND IN THE ROAD TRANSPORT SECTOR

The evolution of oil use in road transport in the different regions defined above, and for the no EV deployment scenario, is illustrated in Fig. 4.13. This demand increases from 91EJ in 2024 to 115EJ in 2050. While China and India drive again the global trend, their influence is more limited than on vehicles stock. This is explained by their lower annual oil consumption (GJ/yr/PV) compared to the other major countries, which furthermore decreases at a faster rate.

Generally speaking, the rise in the vehicle stocks due to the growth in GDP per capita and the associated rise in vehicle ownership is partly (or fully in some regions) offset by a decline in the annual oil consumption per vehicles (see Fig. 4.14). In the case of China, this makes oil use in the transport sector peak in 2034 and decrease afterwards (see Fig. 4.15).

Demography also plays a role, though its impact is limited (-9% for China between 2024 and 2050), and because it leads to two contradictory effects. On the one hand a population decline directly plays against the vehicle stock (the product of vehicle ownership and population). On the other hand it has a favorable effect on GDP per capita as GDP per capita is calculated by GDP projections divided by population projections, which has a positive effect on vehicle stock.

More figures on the evolution of the oil consumption in other regions can be found in Supplementary Materials.

Fig. 4.16 shows the demand in the road transport sector for our four scenarios.

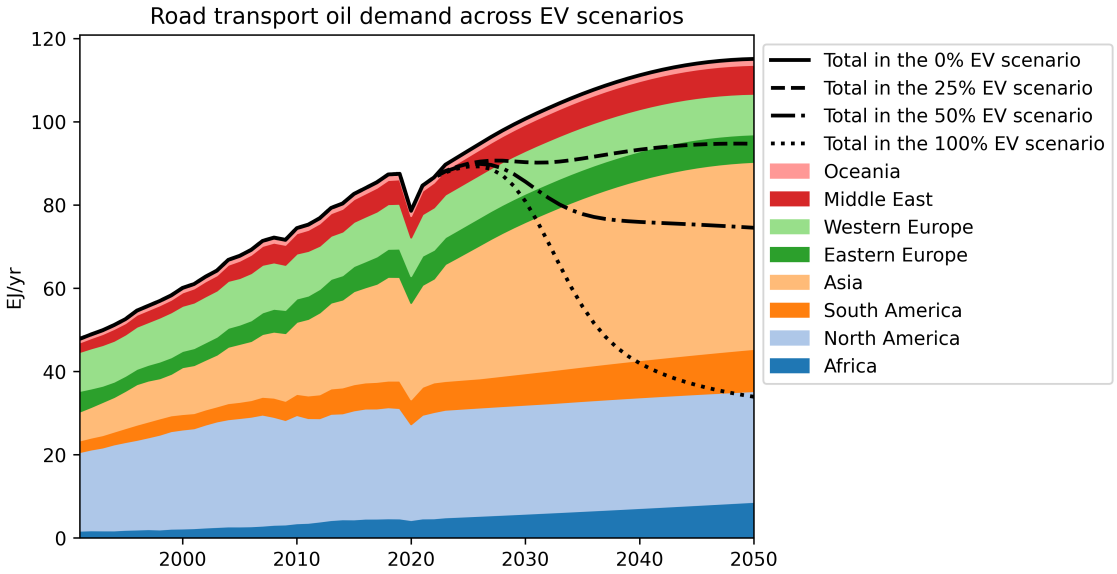


FIGURE 4.13: Cumulative evolution of the oil demand in the road transport sector across regions, in the case of no EV deployment. The black lines also show the total cumulative demand in the 25%, 50% and 100% EV scenarios.

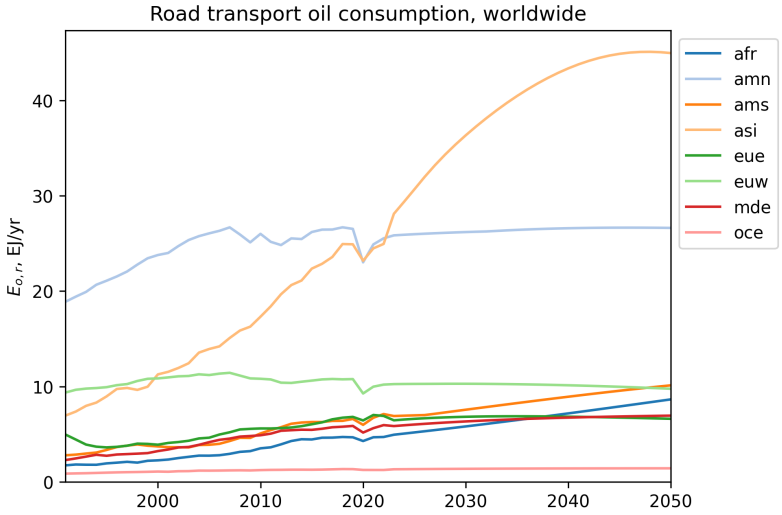


FIGURE 4.14: Evolution of oil demand in the road transport sector for the no EV deployment scenario, by region. Codes for the regions are specified in Fig. 4.10 and in section 4.3.

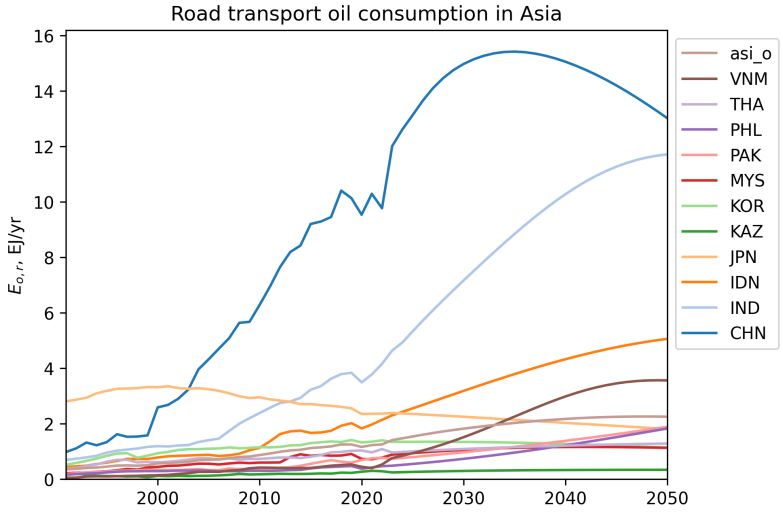


FIGURE 4.15: Evolution of oil demand in the road transport sector for the no EV deployment scenario in Asian countries. Codes for the regions are specified in Fig. 4.10 and in section 4.3.

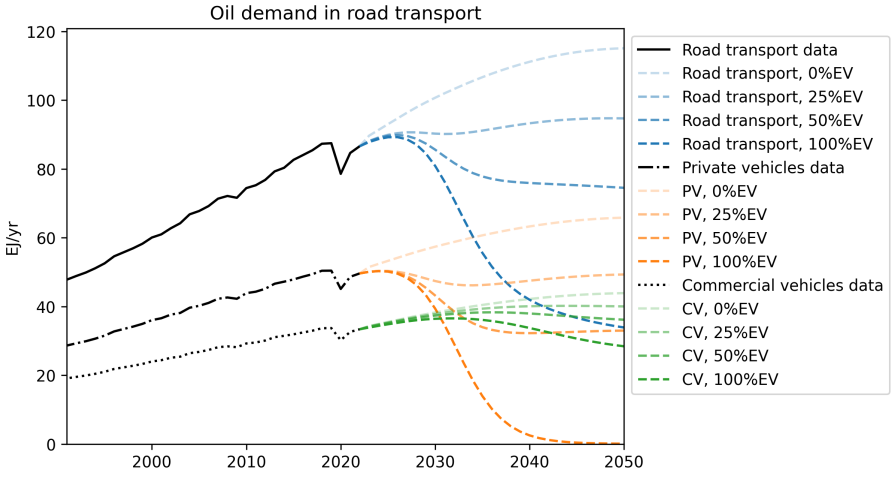


FIGURE 4.16: Oil demand in road transport and its disaggregation in PVs and CVs. The various curves of the same color with different shades represent oil demand under different scenarios of EV deployment. Motorcycle oil demand is not represented, and amounts to a maximum of 5 EJ/yr.

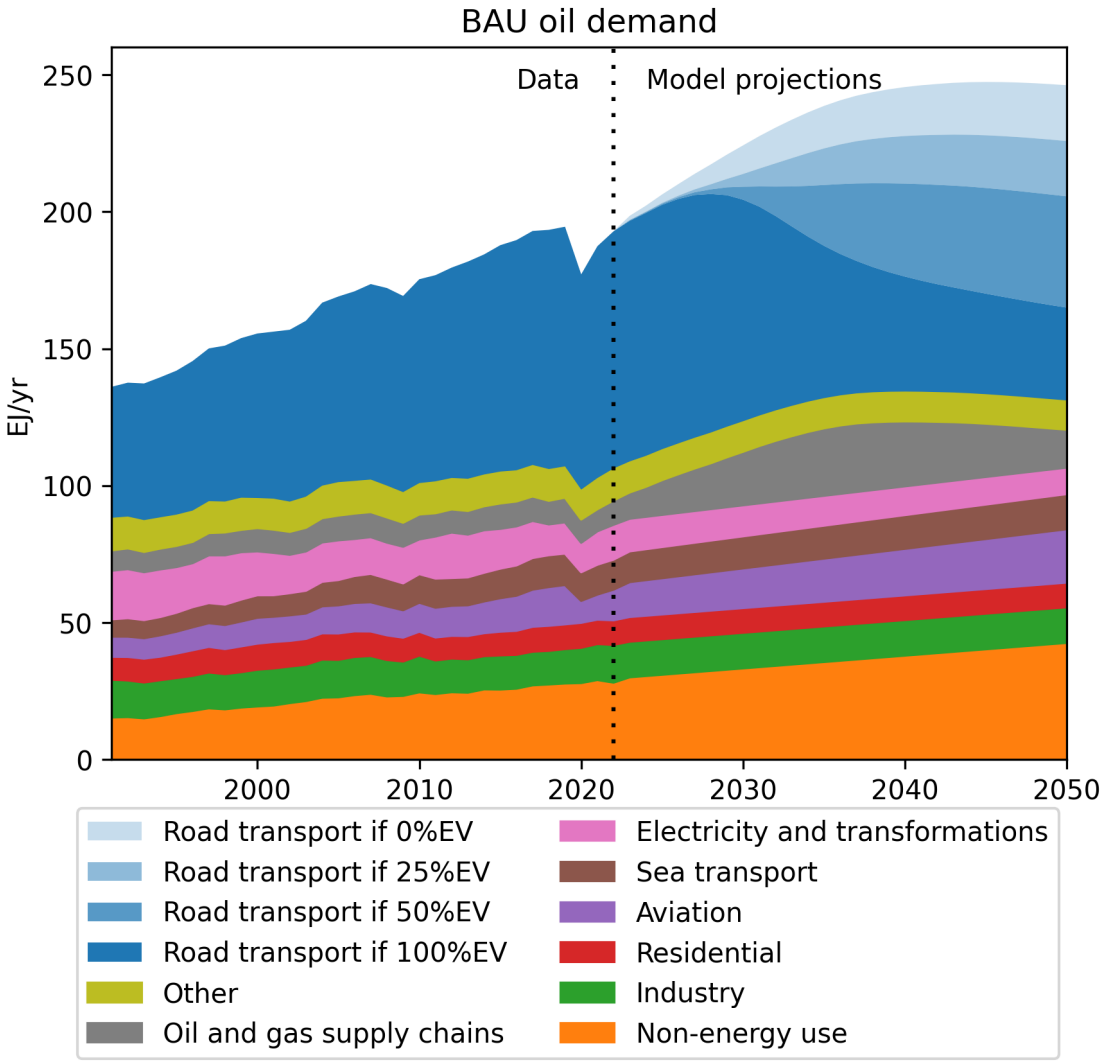


FIGURE 4.17: Cumulative oil demand in all sectors. The total oil demand in each scenario of EV deployment corresponds to the upper limit of the associated colored zone.

4.3.5. OIL DEMAND IN A BAU SCENARIO

In all scenarios on the deployment of EVs, oil demand grows at least up to 2028 at 206—210EJ/yr. At this point, the 50% EV scenario reaches a plateau until 2050, between 205 and 210 EJ/yr. Oil demand in the 100% EV scenario decreases significantly and reaches 165 EJ/yr in 2050. On the other end, the 25% EVs scenario reaches 225 EJ/yr in 2036 and then levels out between 225—228EJ/yr. Oil demand of the 0% EVs scenario increases until 2041 and then remains constant at 246—247EJ/yr.

The plateaus observed in 2035—2040 are explained by the combination of the penetration of EVs in the world fleet which reaches saturation as seen in Fig. 4.8, and the plateau of the cumulative oil demand from the other economic sectors from 2037 onward, at 131—134 EJ/yr.

4.4. Discussion

4.4.1. Uncertainty analysis

Our analysis was performed within a BAU scenario, in which our model parameters follow the historical trends. The model uncertainties within this BAU assumption are here discussed.

The main uncertainty regarding modeling future oil demand comes from the expected level of deployment of electric PVs (see also section 4.2.2.3), which is highly speculative, as illustrated by the diversity of EV deployment scenarios proposed in institutional/oil companies reports (10% to 80% EV.

The assumed indexation of the deployment of electric CVs on electric PVs is also uncertain. However, this uncertainty is of second order in comparison to the diversity of scenarios on EV deployment and by comparison to the uncertainty on saturation levels.

Then, the modeling of the road transport sector, and more specifically of vehicle ownership by a Gompertz function is uncertain. The most critical parameter in vehicle ownership modeling is the saturation level. Indeed, the uncertainty due to the α and β parameters is limited as data on the early and mid-stage evolution provide constraints on these parameters. Consequently, remaining uncertainties on these parameters produce final uncertainties that are significantly lower compared to the effect of the saturation level. The uncertainty surrounding saturation — stemming from the absence of empirically good predictors of this saturation — have been studied in section 4.4.2.1 for China and India which are projected to account for 40% of the global vehicle stock in 2050. Furthermore, these two countries are projected to witness the most important stock evolution and display the uncertain saturation levels of vehicle ownership. Other countries also have large saturation level uncertainties, but their projected vehicle stock is smaller. Advanced countries show a limited uncertainty on the saturation level of their vehicle ownership.

PV annual oil consumption projections (GJ/PV/yr) are uncertain due to the absence of clear trends in historical data on fuel consumption per kilometer (GJ/km) and on annual mileage (km/PV/yr). In particular, historical data on fuel consumption display various trends due to the competition between technological progress (which decreases fuel consumption) and increase in the weight and power of cars (which increase it). Annual mileage data are scarce, which makes projections difficult. Section 4.2.2.2 and Appendix 4.P study the regional disparities of these two parameters and propose projections of annual oil consumption. The final uncertainties associated with these projections in China and India are discussed in section 4.4.2.2. The final uncertainty is lower for other countries. There are two reasons for this: first China and India account for a significant part of oil consumption, and second the fast evolution of annual oil consumption in China and India dominates uncertainties.

The modeling of CVs is uncertain, primarily due to the scarcity of lack of data on their stock and oil consumption. These have been quantified in the uncertainty analysis of section 4.4.2.3.

Projections of oil demand in other sectors have been made by extrapolating historical trends. Uncertainties on oil consumption in aviation, sea transport and non-energy sectors have been discussed in section 4.2.4 and are primarily limited by the low substituability of oil in a BAU scenario. Indeed, it is highly unlikely that oil use in aviation and shipping will be substituted by other solutions before 2050. The costs of biofuels and di-hydrogen-based solutions are expected to remain higher than those of conventional jet fuel and fuel oil, the scalability of biofuel solutions is limited and the di-hydrogen based solutions are not yet technologically mature. Finally, LNG could be used in shipping, however this solution is of little interest regarding climate is-

sues, and it is anticipated that gross gas supply will peak around 2040 as pointed in the article of Chapter 2 (Bergero et al., 2023; Detsios et al., 2023; Balcombe et al., 2019; Ansell, 2023; Bauen et al., 2020; Cabrera and de Sousa, 2022; Afonso et al., 2023; Islam Rony et al., 2023; Prussi et al., 2021; Foretich et al., 2021).

The GDP projections made in this study are generally more conservative than OECD projections (when available). This tends to minimize oil demand with respect to OECD. However, we point out that our model is not very sensitive to uncertainties in the GDP projections of China and India (the two countries dominating the growth of PVs ownership and oil consumption in the road transport sector).

4.4.2. Uncertainty from the most critical parameters

The major source of uncertainty in our model bears on the deployment of electric PVs and CVs and this is addressed through the use of scenarios.

Apart from this, five parameters turn out to be particularly critical. They are naturally grouped into three categories: 1/ the levels of saturation of vehicle ownership in China and India (which collectively accounts for approximately 35% of vehicles and 25% of road transport oil consumption in 2035 in the reference case); 2/ the annual oil consumption of vehicles in China and India; 3/ the oil demand of the road transport sector due to trucks, discussed in Appendix 4.M.

4.4.2.1. China and India level of ownership saturation

As discussed in Appendix 4.H, these parameters are subject to substantial uncertainty ($\lesssim \pm 30\%$). Predictors, in particular population density do not perform very well. From this Appendix discussion, the bounds for the saturation of China and India are respectively is set to $[0.4, 0.8]$ and $[0.25, 0.6]$. These bounds lead oil demand to deviate by 2.5% at maximum compared to the reference case, decreasing with the increase of EVs deployment in scenarios. The associated uncertainty range is illustrated on Fig. 4.C1 (see Appendix 4.C).

4.4.2.2. Vehicle annual oil consumption

As discussed in Appendix 4.P, the data for India and China exhibit a pronounced decreasing trend while these values are already below those of advanced economies. The future trajectory of this decline remains uncertain, and it is conceivable that it may plateau due to increase of vehicles weight or stabilization of annual mileage. For both countries, the bounds of the annual decrease in their annual oil consumption per vehicle are set at $[0, 3]\%/yr$, based on this Appendix. The total oil demand for the highest bound deviates by 8% at maximum from the reference scenario, but only 3% for the lowest bound . The range of uncertainty associated with these bounds are illustrated on Fig. 4.C2 (see Appendix 4.C).

4.4.2.3. Trucks oil use share

The assumption of Appendix 4.M is uncertain due the paucity of data available. Also, this share should evolve over time because of economic evolutions in the various countries. The proportion of commercial vehicles (CV) in the consumption of 4-wheeled vehicles (4W) is set within the range of $[0.35, 0.45]$ from this Appendix discussion. The total oil demand of for the highest and lowest truck shares deviates from 2% at maximum compared to the reference case,

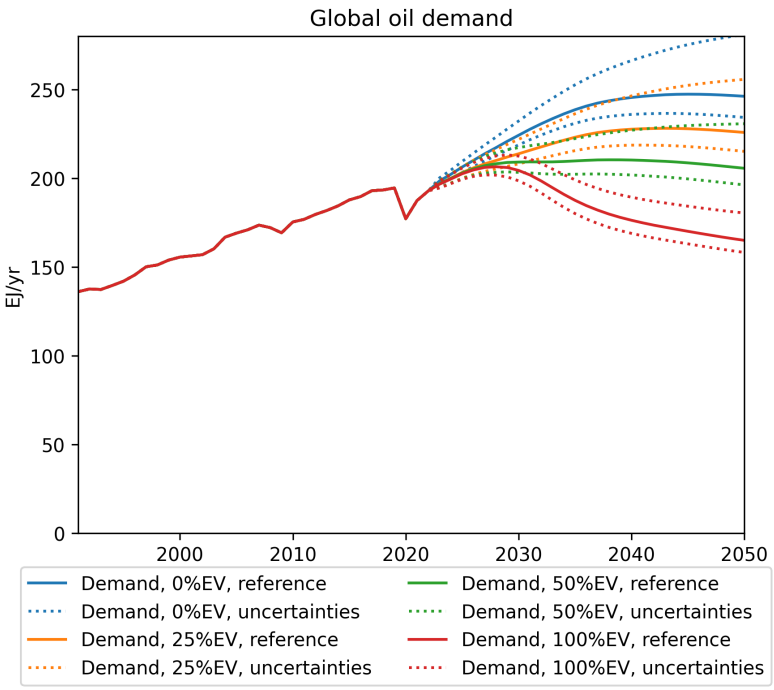


Figure 4.18: Effect of the combination of the uncertainties on the three main parameters. The bounds for the oil demand of each EV scenario is represented by dotted lines.

increasing with the increase of EVs deployment. The bounds of the uncertainty is illustrated on Fig. 4.C3 (see Appendix 4.C).

4.4.2.4. Overall uncertainty

Finally, the uncertainties on these parameters are combined. The highest scenario results in a deviation on total oil demand of +14% at maximum compared to the reference scenario. However, the lowest scenario only deviates by -5%. The bounds on the uncertainty computed by combining the bounds values of each parameter are shown on Fig. 4.18.

Uncertainties on the total oil demand are therefore contained, particularly at the lower end. This is consistent with our approach which tends to moderate oil demand.

4.4.3. Demand underestimation due to the neglect of oil investments in renewable energies

In Chapter 3, we estimated oil and gas energy investments in the deployment of solar and wind energy at a level designed to meet energy demand up to 2050 under the mild BAU growth scenario adopted in this work. This has not been included in oil demand, as these estimates are quite limited, representing 1.5 – 3 EJ in 2035.

4.4.4. Comparison with existing scenarios

The results obtained with the DyMEMDS' model are quite similar to ours when the EV deployment scenarios of this model and its hypothesis on the annual decline rate of the annual oil consumption of vehicles (GJ/vehicle/yr) — parameters defined by the user — are chosen to

align with the present study. This is discussed in Appendix 4.B.

Interestingly, the reference case scenario of US EIA (2023) gives trends in the oil demand of light-duty vehicles that are quite consistent with those of the present study when compared to our 25% EV deployment scenario. More importantly, this observation is still valid when disaggregated by regions: the regional projections of IEO (International Energy Outlook) are quite consistent with this 25% EV scenario. Indeed, both the reference case scenario of IEO from EIA and our 25% EV scenario predict a modest decline in oil demand of PVs until approximately 2035-2040, followed by a period of growth reaching in 2050 values close those observed in 2022. In our model, the initial decline is attributed to the rapid deployment of EVs, while the subsequent increase is attributed to the slowdown in the EV deployment reaching saturation, concurrent with the continued increase in the vehicle stock in China and India. However, as IEO predicts lower vehicles stocks for China and India, we deduce that their assumption on the annual decline of oil use per vehicle is less steep than the present study's for China and India.

On the total oil demand side, the reference case of EIA's International Energy Outlook forecasts a more or less linear increase, with its 2050 value also falling within the range of our 0%—25% EV scenarios.

Similar to the projections from the U.S. EIA, the World Oil Outlook of OPEC (2025) forecasts a growth of oil demand is the road transport sector closely resembling a 20% EVs deployment scenario from our model between 2024 and 2050, which is lower than the projections of the last two sources. On the total oil demand side, it forecasts a stable increase which within the range of our 0%—25% EV scenarios.

The STEPS scenario of IEA (2024d) anticipates a plateau and subsequent decline in road transport oil demand. The projected level of oil use in 2050 corresponds to our 50% EV deployment scenario. However, this decline is slower than ours, which implies that their deployment of EVs is not modeled by a logistic function. On the total oil demand side, projections from IEA's World Energy Outlook[11] are lower than those of the present study until 2030, at which point they align with the 75% EV scenario of the present study.

BP (2024) also envisions substantial reductions in total oil demand. BP anticipates a bell-shaped decline reaching the 2000 level in 2050. This corresponds to the level reached in 2050 in our 80% EV scenario, a drastic reduction.

In summary, the total oil demand forecasts by OPEC and EIA are aligned with the 0—25%EV scenarios of the present study, while those of BP and the IEA depict a significant decline, which makes their projections closer to our 75% EV scenario.

Our analysis shows that the discrepancies observed between the results obtained for our scenarios and the literature quoted above almost entirely stems from the assumptions concerning the electrification of road vehicles (cars as well as trucks). Consequently, 1) uncertainties due to the projections of the demand in other sectors are reduced; 2) the plausibility of the scenarios of these institutions relies almost entirely on the plausibility of their projections regarding the deployment of EVs.

[11] Interestingly, total oil demand projections to 2050 from the STEPS scenario of IEA's WEO decrease by 5% between their 2023 and 2024 editions.

4.5. Conclusion

Forecasting global oil demand is crucial for anticipating potential future tensions with the oil supply, which is expected to peak and decline in the next decade (Laherrère et al., 2022; Delannoy et al., 2021a; Rabas, 2024). The present article models the evolution of the oil demand in a business-as-usual (BAU) scenario. Firstly, the road transport sector, which accounted for 44% of the global oil consumption in 2022, is modeled in a disaggregated manner. Oil demand for road transport is forecast in 8 regions covering the entire world, with specific projections for 62 countries representing the vast majority of the present and future world fleet. Several assumptions are made in the process: GDP projections by country, projection of annual oil consumption of private vehicles (PVs), as well as a set of assumptions concerning the modeling of oil consumption in the various road transport sub-sectors. These various assumptions are presented in section 4.2 and dedicated appendices. Projections of the oil demand in other sectors are made more straightforwardly, consistently with a group of existing BAU scenarios. The main discrepancy among existing oil demand projection scenarios is attributable to the uncertainty surrounding the future deployment of electric vehicles (EVs). Considering this uncertainty and the wide range of existing BAU projections on EV deployment, the present study proposes multiple oil demand scenarios based on different EV deployment assumptions.

In spite of these different assumptions, uncertainties in the present studies arise from a limited set of core parameters: vehicle ownership saturation in China and India, share of commercial vehicles in oil demand by the of road transport sector, evolution of the annual oil consumption of private vehicles. However, their effects are limited, and much less important than uncertainties in the deployment of EVs. Uncertainties are analyzed in section 4.4.

The stock of all vehicles (4Ws) is anticipated to grow by 70% between 2024 and 2050, primarily led by the increase in vehicle ownership in China and India. In the absence of EV deployment, this results in a +25% increase of the oil demand in the road transport sector. This discrepancy between the growths in stock and oil demand is mostly the consequence of the anticipated decline in the annual mileage and in fuel consumption by vehicles in China and India. Demand for oil in other sectors is also increasing, driven by the anticipated increase in demand for petrochemicals, in aviation, and in the oil and gas supply chains.

The total oil demand is projected to rise between 2024 and 2050 across all scenarios with a deployment of EVs lower than 50% of the world fleet, with a demand reaching 206—247 EJ/yr by 2050, as compared to 200 EJ/yr in 2024. Only a widespread deployment of EVs would result in a decrease of oil demand, to 165 EJ/yr by 2050 for 100% EV deployment.

We anticipate that oil demand in a BAU scenario may not decline as rapidly as oil supply itself, in most EV deployment scenarios. This would invalidate the feasibility of BAU scenarios. An investigation of this specific question will be presented elsewhere.

Appendices to chapter 4

4.A. Alpha-3 codes

Countries are referenced by 3 letters corresponding to their ISO 3166-1 alpha-3 code. Table 4.A1 lists these codes for important countries. Codes for modeled countries can be found in the Supplementary Materials, and codes for other countries can easily be found elsewhere, for example in Wikipedia.

4.B. Comparison with the results of the DyMEMDS model

The DyMEMDS (Dynamic Modelling of Energy and Matter Demand and Supply) model has been developed independently by one of the authors of the present study and was initially presented in Vidal et al. (2022). This is a multi-regional biophysical model of energy and raw material flows. It uses a bottom-up approach that models the development and replacement of infrastructures in order to model the associated energy and raw materials flows. It includes, but is not limited to, the modeling of road transport infrastructures.

Code	Country
AUS	Australia
BRA	Brazil
CAN	Canada
CHN	China
DEU	Germany
ESP	Spain
FRA	France
GBR	United Kingdom
IDN	Indonesia
IND	India
IRN	Iran

Code	Country
ITA	Italy
JPN	Japan
KOR	South Korea
MEX	Mexico
MYS	Malaysia
NGA	Nigeria
POL	Poland
RUS	Russia
THA	Thailand
TUR	Turkey
USA	United States

Table 4.A1: Alpha-3 codes of important countries.

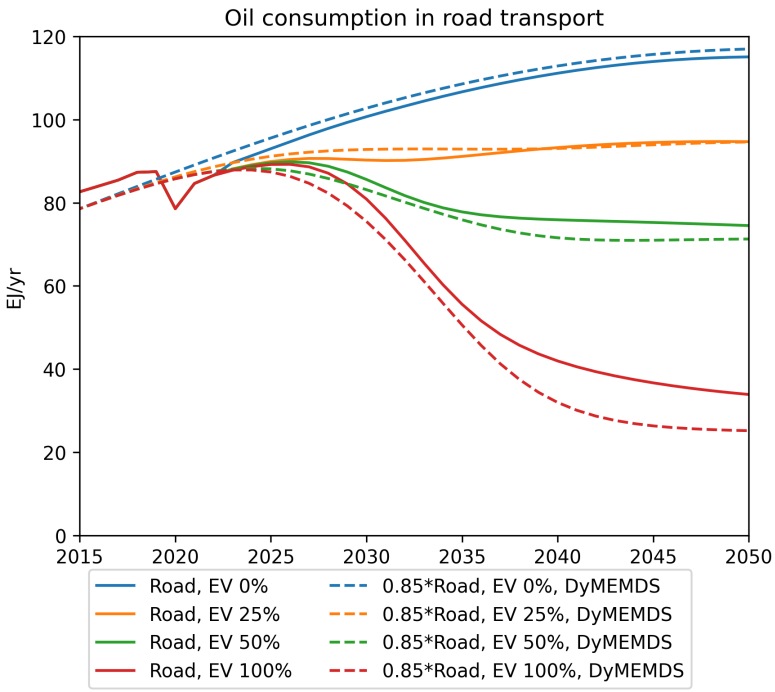


FIGURE 4.B1: Oil consumption in the road transport sector. Comparison between the results of the present study and those of DyMEMDS. The decline in vehicle annual oil consumption is adjusted to match the present study.

The results of DyMEMDS are compared with the present study, as this constitutes a useful point of reference, due to somewhat different assumptions. We focus on the results on oil consumption in the road transport sector. To this end, the final level (saturation) of the share of EVs in the vehicle stock is specifically configured in DyMEMDS to match the scenarios used in the present study.

The decrease in annual oil consumption (GJ/vehicle/yr) in DyMEMDS (-1.5%/yr) is steeper than the country average of the present study. We found that a signification fraction of the difference arises from the decline in annual oil consumption of vehicles in DyMEMDS. We then decided to set DyMEMDS' annual decline to -1.1%/yr for further comparisons, i.e., the mean of the decline range in the present study (from -1.3%/yr in 2020 to -0.9%/yr in 2050).

Fig. (4.B1) shows the results on oil consumption in road transport obtained after this matching. The results generated by DyMEMDS have been adjusted by a constant coefficient (0.85). Indeed, DyMEMDS aims to model energy and raw material flows using a reduced number of laws. This results in a less precise match between its results and historical data in the road transport sector. This adjustment is therefore made in order to make the comparison between the trends resulting from DyMEMDS and from our model relevant.

DyMEMDS projections lead to a higher vehicle stock than obtained in the present study. This can be traced back to the logistic projections of vehicles in DyMEMDS, with saturation levels for China and India exceeding the present study's corresponding levels.

Otherwise, the trends exhibited by DyMEMDS then closely mirror the present study's. The only remaining differences relate to the assumptions on GDP growth, vehicle ownership, trucks modeling, annual oil consumption of a vehicle (although the annual decline rate is defined to best fit the results of the present study) and the choices in the form of the projections of the stock of electric vehicles (of which the saturation level in 2050 is chosen to make the comparison possible with the scenarios of EV deployment of this present study).

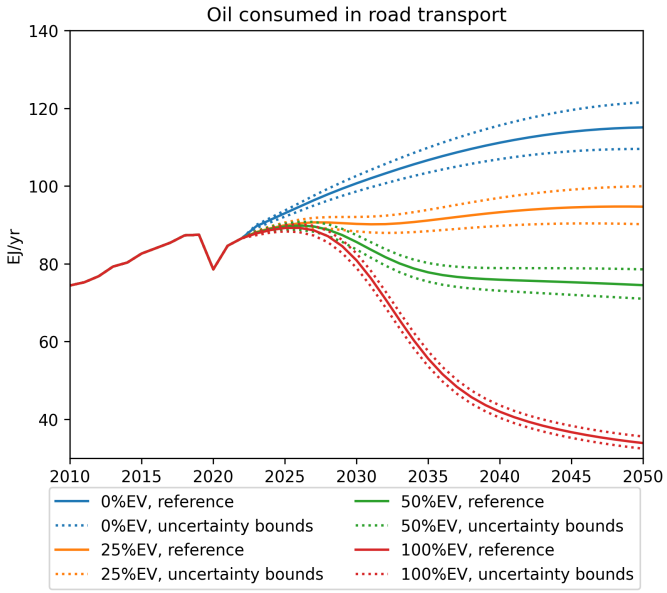


FIGURE 4.C1: Effect of the uncertainty of the saturation level of Chinese and Indian's vehicle ownership on oil consumption of the road transport.

This allows to conclude that the results on the oil consumption of road transport found in this study are not very sensitive to uncertainties in the modeling of GDP, trucks, and of vehicle ownership.

4.C. UNCERTAINTY ANALYSIS: ADDITIONAL FIGURES

Figs. 4.C1, 4.C2 and 4.C3 show the uncertainty range associated with the bounds of the five most critical parameters.

4.D. INTERPRETATION OF THE GOMPERTZ FUNCTION PARAMETERS

The simplest parameter is γ: taking the limit of large y in Eq. (4.6) (and with some simplification of the notation), one finds that

$$\lim_{y\to\infty} V(y) = \gamma. \tag{4.D1}$$

Thus γ represents the saturation limit of the number of vehicles per capita.

The other two are more difficult to interpret, but can be related to two useful characteristics of the Gompertz function: the location (in GDP per capita) of its maximum slope y_s, and the change of its rate of growth at the origin. The first is obtained from the analysis of its derivative V' and the second from the analysis of its second derivative at the origin, $V''(0)$: the larger this

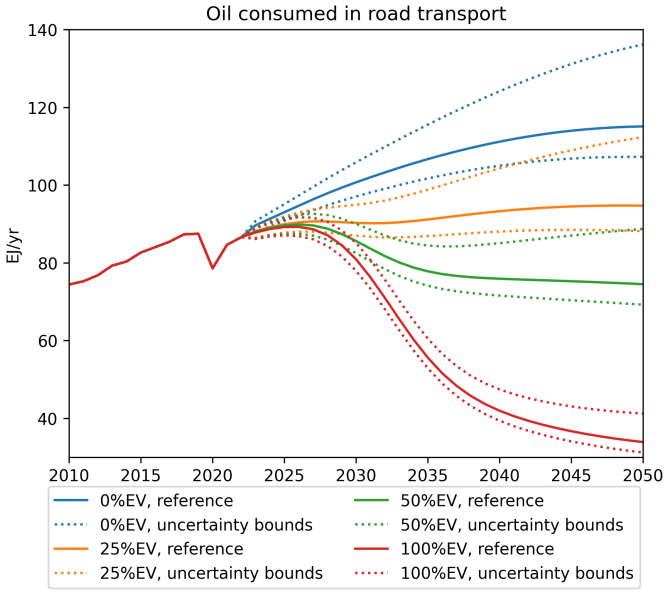


FIGURE 4.C2: Effect of the uncertainty of the annual oil consumption of an internal combustion PV in China and India on oil consumption of the road transport sector.

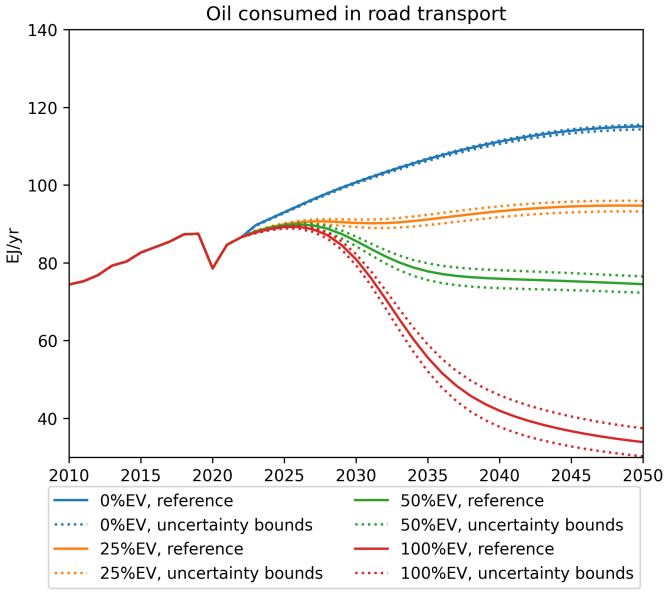


FIGURE 4.C3: Effect of the uncertainty of the share of CV in the energy consumption of 4W on the oil consumption of the road transport sector.

second derivative at origin, the faster the Gompertz starts growing in a noticeable way. One has:

$$V'(y) = \alpha\beta\gamma \exp(-\beta y) \exp[-\alpha \exp(-\beta y)], \tag{4.D2}$$

$$V''(y) = -\alpha\beta^2\gamma \exp(-\beta y) \exp[-\alpha \exp(-\beta y)] \times [1 - \alpha \exp(-\beta y)], \tag{4.D3}$$

The maximum of the derivative obtains when $V''(y) = 0$, i.e., when

$$y_s = \ln(\alpha)/\beta. \tag{4.D4}$$

As α varies little from country to country compared to β (see Table 4.G1), and as the dependence of y_s on α is only logarithmic, the location of the maximum slope depends mostly on β. Note that the associated slope is

$$V'(y_s) = \frac{\beta\gamma}{e}. \tag{4.D5}$$

Finally,

$$V''(0) = \alpha\beta^2(\alpha - 1)\gamma \exp(-\alpha). \tag{4.D6}$$

It is in principle possible to formally express α and β in terms of y_s and $V''(0)$ but this is not very informative. Instead, it is of more interest to quantify these two quantities for major countries. This is done in Table 4.G1.

This table indicates that both y_s and $V''(0)$ depend more sensitively on β than α at least for the range of values characteristic of the various countries. In particular, one observes that the smaller y_s (location of the maximum slope), the larger $V''(0)$ and the larger the maximum slope, which is consistent with the dominance of the variation of β among countries. This feature is also visible on Fig. 4.5 and 4.4. This is not a necessity. Increasing substantially α would produce a rather flat initial curve, due to the exponential dependence of $V''(0)$ on α, while maintaining the location of the maximum slope and its amplitude in the same vicinity due to the logarithmic dependence of y_s on α.

4.E. Number of in-use passenger vehicles vs number of vehicles

Disaggregating vehicles into categories (2W, PV, CV) serves several purposes. The evolution of the 4-Wheelers fleet is modeled by a Gompertz function on 4-Wheelers ownership, but this does not account for the presence of motorcycles and mopeds whose oil consumption is modeled separately for certain countries (see Appendix 4.L). Secondly, in the case of 4-Wheelers, one needs to model changes in the oil consumption of private vehicles (PV) and commercial vehicles (CV) in different ways. This is due to the fact that the use of commercial vehicles is entirely distinct from passenger cars'. Furthermore, the oil consumption of road freight vehicles (included in "commercial vehicles") represents over a third of the oil consumption of the road

transport sector (see Appendix 4.M), despite representing approximately 3% of CVs' number (ACEA, 2023).

Concerning data, for each country and each year for which it provides data, OICA (2022) gives information on the stock (in-use vehicles) of "passenger cars" and "commercial vehicles". It should be noted that their "commercial vehicles" category does not correspond to our definition. Indeed, private light trucks or pickups are counted in the commercial vehicles category by OICA, whereas it is more appropriate in terms of purchase and use patterns to gather these in the "private vehicles" category. This distinction is of particular significance for countries in which these vehicles account for a very large proportion of the number of 4-wheelers[12].

According to OICA (2022), passenger cars represent approximately 85% of the number of 4-Wheelers in a majority of countries. ACEA (2023) provides data on the number of vehicles in several European countries between 2017 and 2021, categorized into "passenger cars", "light commercial vehicles", "medium and heavy commercial vehicles" and "buses". The data demonstrate that in 2021, passenger vehicles constituted 80% of 4-Wheelers that were not passenger cars, medium and heavy trucks constituted 17%, and buses 2%. The proportion remained consistent over 4 years, with a variation of less than 1%. Among light commercial vehicles, the data provided by SDES (2022) indicates that the share of private vehicles was 50% in France. We deduce from this that approximately 40% of non-passenger cars 4-Wheeled vehicles are private vehicles. In the absence of more information, this figure is extrapolated to all countries.

Based on this information, we adopt the following model:

$$v^c_{F,PV} = K^c_v v^c_{F,4W} \text{ , with:} \tag{4.E1}$$

$$K^c_v = K^c_1 + K_2\left(1 - K^c_1\right) \text{ if } K^c_1 \text{ data are available,} \tag{4.E2}$$

$$K^c_v = K_3 \text{ else.} \tag{4.E3}$$

Eq. (4.E1) is a rewriting of Eq. (4.19). OICA (OICA, 2022) provides the ratio of "passenger cars" over 4-Wheelers in some countries. In these cases, K^c_v is defined by Eq. (4.E2), with K^c_1 deduced from these data (approximately 85% in a majority of countries as aforementionned) and $K_2 = 0.40$ deduced from the previous information. In other cases, the aforementionned common values found in OICA data lead us to use Eq. (4.E3) with $K_3 = 0.90$[13].

In practice, the lack of data for modeling changes in oil consumption of commercial vehicles leads us to correlate it to changes in oil consumption by passenger vehicles (see Appendix 4.M). In this way, given that the modeling of vehicle ownership is carried out on 4-wheelers and that we are seeking to obtain an aggregated trend in oil consumption in the road transport sector on a global scale, disaggregating 4-wheelers into PV and CV is of less interest. Nevertheless, there are several advantages to this distinction. Firstly, it is useful to separate their oil consumption from a conceptual point of view. Secondly, it makes it possible to compare the annual energy consumption of PVs calculated in section 4.2.2.2 to data found in several sources. Last but not least, the penetration of electric vehicles must be modeled differently between PVs and CVs at it is expected to be different (see section 4.2.2.3).

[12] This is in particular the case for the United States where trucks represent 60% of the vehicles stock (Davis and Boundy, 2022), but this is also the case for Ecuador, Colombia, Irak, Mexico, Peru, Thailand and Turkey among countries for which data is available.

[13] $0.85 + 0.4\,(1 - 0.85) = 0.91$, rounded at 0.90

4.F. Data used for historical vehicle stocks

Data on the number of vehicles in use at any given time are rather difficult to obtain. If registration or sales data are quite well collected today, cars' end-of-life are much less documented, making vehicle in use estimations difficult. Vehicle in use data are uncertain and can vary following sources. As an example, we observe a 13% difference in the OICA (*Organisation Internationale des Constructeurs d'Automobiles* or International Organization of Motor Vehicle Manufacturers) 2015 vehicle in use data between their 2005-2015 and their 2015-2020 data series (OICA, 2022). This kind of difference is not systematic, but exemplifies the type and level of uncertainty that can be found in vehicle data.

For vehicle in use time series, we use a dataset elaborated by Michel Freyssenet[14] (Freyssenet, 2016). This is based on data series from the OICA (2022), International Road Federation (2024), ACEA (2023) (*Association des Constructeurs Européens d'Automobile*, European Automobile Manufacturer's Association), CCFA (*Comité des Constructeurs Français d'Automobiles*, French Automobile Manufacturer's Committee), UNECE[15] (United Nations Economic Commission for Europe), WardsAuto, the former AAMA (American Automobile Manufacturers Association), and some country-specific institutions.

To this we add data from the Bureau of Transportation Statistics[16] (Bureau of Transportation Statistics, 2024) from 1990 onwards, for the use of vehicle stock data between 2016 and 2022. In particular, this information enables us to refine the saturation value of the vehicle ownership rate for the USA, which accounts for 18% of the world's vehicles in 2020.

2015-2023 chinese data have also been added from the National Bureau of Statistics of China[17]. The source is official and the data are consistent with those of Michel Freyssenet between 2004 and 2015. This source is important because the vehicle fleet of China is the largest of the world, and because having more data points of its exponential growth constrains our projection.

Similarly, supplementary data for India and Indonesia are obtained. The Indian data from 2003 to 2022 are retrieved from the Ministry of Road Transport and Highways (2024) and are consistent with the preceding Freyssenet's data. In the case of Indonesia, the data (BPS Statistics Indonesia, 2024) cover the 2015 – 2023 period. However, an examination of these data reveals inconsistencies with previously published data series (1976-1998 data series, as documented in Freyssenet's data). These data are therefore retained instead of those from Freyssenet, given that they originate from a reliable official source and that, given the country's rapid transformation and growth in GDP per capita, the more recent the data, the more accurate the projections are likely to be.

[14] This database was long accessible on Freyssenet's website at GERPISA, *Groupe d'Etudes et de Recherches Permanent sur l'Industrie et les Salariés de l'Automobile*, but can no longer be found since his demise. GERPISA has confirmed to us that it will soon be again available on their website. In any case, we provide it as part of our Supplementary Information.

[15] See `https://w3.unece.org/PXWeb2015/pxweb/en/STAT/STAT__40-TRTRANS__03-TRRoadFleet/01_en_TRRoadTypVehR_r.px/`

[16] BTS, part of the United States Department of Transportation. The data come from the National Transportation Statistics, and are available at the following URL: https://www.bts.gov/content/number-us-aircraft-vehicles-vessels-and-other-conveyances

[17] `https://data.stats.gov.cn/english/easyquery.htm?cn=C01`, data used is the "Possession of Civil Vehicles" set.

Country	α	β	γ	r^2 score	y_s	$V''(0)$
Brazil	5.8	15.5 e-5	0.8	0.958	11.3e3	1.6e-9
China	5.3	15.3 e-5	0.55	0.999	10.9e3	1.5e-9
France	3.9	8.0 e-5	0.73	0.995	16.9e3	1.1e-9
Germany	4.5	6.9 e-5	0.77	0.996	22.1e3	0.6e-9
Indonesia	5.3	27 e-5	0.5	0.989	6.1e3	4.3e-9
India	5.1	42 e-5	0.4	0.986	3.9e3	8.9e-9
Japan	5.8	9.8 e-5	0.73	0.992	17.9e3	0.6e-9
Mexico	26	32 e-5	0.75	0.865	10.2e3	2.7e-16
Russia	6.2	20 e-5	0.8	0.828	9.0e3	2.2e-9
United States	5.3	9.9 e-5	0.85	0.985	16.8e3	0.9e-9

Table 4.G1: Fitted Gompertz parameters, shown together with mathematical characteristics of the fits. y_s is the Gompertz location of the maximum slope, and $V''(0)$ is the rate of slope variation at the origin

4.G. Parameters of the Gompertz fits

Some data points are excluded from our fits. The 2019 data point in France, the 1992-2006 period for Germany German and the 1976-1998 one for Indonesia are excluded because of differences in accounting methods. This is rooted in changes in the data source institute in the case of France, while the incriminated German and Indonesian data points are clearly inconsistent with the rest of the data. 1986-1988 data points were excluded for Brazil because of their inconstancy with other points in the time series. We further exclude the 1990-1999 period for Russia and the 1995, 1996, 2009, 2010, 2011 data points for Mexico because of economic instabilities and economic recession. Indeed, modeling vehicle ownership in unstable or recessives period requires a more complex modeling than a Gompertz function fit (Dargay, 2001).

Some countries have experienced temporary GDP per capita decline in the past. A Gompertz model predicts a related temporary decline in vehicle ownership. However, it is observed in all cases that vehicle ownership has continued to increase over time. This is the case for Argentina, Brazil, Finland, Greece, Italy, Mexico, South Africa, Syria and Ukraine.

Consequently, it is assumed that vehicle ownership cannot fall back during temporary recessions. Within our modeling framework, we imposed that projected values cannot fall below historical data. This ensures consistency between historical data and projections.

Finally, table 4.G1 summarizes the parameters of the Gompertz functions obtained for some major countries.

4.H. Gompertz saturation levels

The saturation level ($gamma$ parameter) of the Gompertz fits we use to model vehicle fleets is the most sensitive of the three fit parameters, in particular for India and China, the two countries that dominate the uncertainty in our analysis on oil demand in the transport sector, due to the potential size of their respective fleets. We therefore devote particular attention to the determination of this parameter in our Gompertz models.

For France, Germany, Japan and United States, we perform an unconstrained Gompertz fit

on the fleet data. For these countries the last few years points seem to show the beginning of a saturation trend, which significantly reduces the uncertainty of the performed projections. Moreover, the United States current vehicle stock today represents 18% of the world fleet and the country seems to already have reached its vehicle ownership saturation level. Japan, France and Germany represent at most 5% of global vehicle stock each. For some countries (e.g., Germany or Indonesia), the data present suspicious discontinuities. These are either artefacts of the data collection methods or results from economic downturns and recessions. This is discussed in more detail at the end of this Appendix.

The data of China, India, Brazil, Mexico and Russia do not show any signs of inflection points, consistently with the fact their vehicle ownership rates are still quite low. In other words, they are in the accelerating (or early) stage of their vehicle fleet constitution. Extrapolating vehicle ownership with an unconstrained Gompertz fit could then result in late uncertainties on the decelerating and stabilized (or late) stage of evolution of the fleet. Setting independently the saturation level before performing the fit is then a relevant way to constrain the late stage of the Gompertz, but one needs guidelines to do so in a non arbitrary way.

Dargay et al. (2007) computed saturation levels based on population density and urbanization rate at the country level, compared to the United States. Some articles studying vehicle deployment in China seem to propose a saturation level of 0.3 — 0.6 4-Wheeled vehicles per capita (4W/cap), based on population density and urbanization comparison with advanced economies(Lu et al., 2018; Huo and Wang, 2012; Huo et al., 2007; Zheng et al., 2015; Wu et al., 2014). However, these studies (and references therein) do not discuss extensively the assumptions made. Li et al. (2019) proposes a 0.33 4W/cap saturation level assuming that every household would have a car and that the mean household size would be 3 person per household. Similarly Arora et al. (2011), cited by Singh et al. (2020), propose a 0.15 — 0.25 4W/cap vehicle ownership saturation level for India, based on the same "1 car per household" assumption, with a 3 members mean household size. They also qualitatively consider the addition of other vehicle types to the total vehicle ownership, and the rural population rate is assumed to be 60% in 2040. Nevertheless, current advanced economies contradicts the "1 car per household" hypothesis. For all of these reasons, we do not consider these literature values as reliable.

Generically speaking, though, and to first order, the spatial distribution of the population is a determining factor of vehicle ownership saturation. For example, population density is indicative of the average distance between individuals, services and work places. Furthermore, transport needs vary between urban and rural areas, with the urban population's share of territory being a key factor. Secondly, while cars have become the predominant means of transport in Western economies, local political decisions can influence the importance of cars in mobility, through the development of public transport or not, and by influencing urban planning. Finally, vehicle sharing within a household or a community also influences the number of vehicles per inhabitant.

As previously discussed by (Dargay et al., 2007), population density (people/km^2) is identified as the most significant factor determining saturation. However, a limitation of using population density as an explanatory indicator of vehicle ownership saturation is the presence of uninhabitable areas (e.g. deserts, dense forests) which tend to increase the density of the territory without necessarily increasing the demand for transport. To address this limitation, we employ the "Quality Adjusted Population Density" (QAPD) metric proposed by Henderson et al. (2020). This metric aims to adjust for geographical peculiarities by focusing exclusively on economic factors, thereby enhancing the relevance of population density for explaining vehicle ownership saturation. However, QAPD is not directly calibrated for our specific needs, which introduces some limitation in its use.

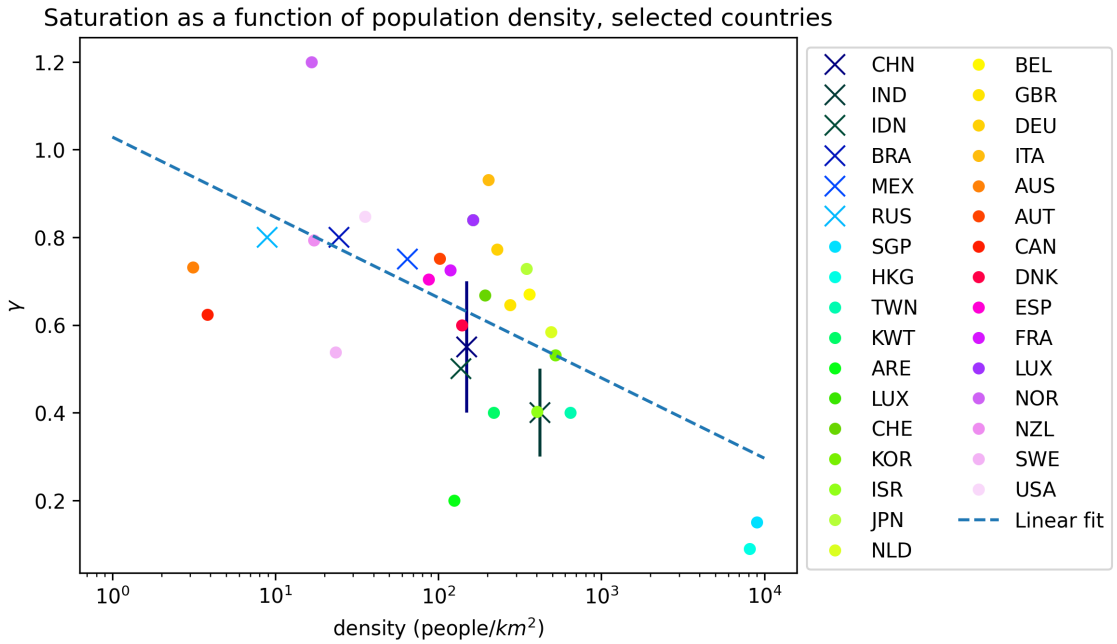


FIGURE 4.H1: Log-linear regression between countries' saturation level γ and population density. Major countries for which the saturation level cannot be constrained from a Gompertz fit are shown as crosses; the saturation shown for these countries comes instead the analysis of the present Appendix. Uncertainty ranges are shown with vertical bars for China and India. All countries are designated by their alpha-3 code. γ is in 4W/cap unit.

Gompertz fits performed on countries with high GDP per capita yield sufficiently robust saturation values (gamma parameter), shown in Figs. 4.H1 and 4.H2 as a function of the country's density or QAPD. The saturation levels of other major countries (Brazil, China, India, Indonesia, Mexico and Russia), deduced from the analysis of this Appendix, explained below, are represented by crosses.

Population density and QAPD values, taken from Henderson et al. (2020), are likely to increase somewhat with population growth. However, these increases are relatively contained. For example, according to data from World Bank (2024a), the population density of India, a country with a very high population growth rate, is set to increase by 20% between 2020 and 2050.

A log-linear fit is also shown in the figures. Denoting population density by d and QAPD by q, this fit is expressed as $\gamma = -0.065e - 2\log(d) + 0.94$ 4W/cap with $R^2_d = 0.30$, and $\gamma = -0.099\log(q) + 0.99$ 4W/cap with $R^2_{qapd} = 0.50$.

Some deviations can be noted for high density countries. Singapore and Hong Kong resemble more large metropolises than countries, which necessarily implies differences in transport needs and habits. The United Arab Emirates is particular, especially as 90% of its population are expatriate workers, which could explain differences in car ownership habits.

India has a density $d = 420$ km^{-2} and QAPD $q = 299$ km^{-2}, which is projected to rise by 20% by 2050. We have chosen to set India's saturation level at 0.4, a figure comparable to Taiwan and close to the log-linear fit of QAPD. Based on the density comparision, we estimate that the saturation value could reasonably fall between 0.3 and 0.5 4W/cap. In the uncertainty analysis of section 4.4.2, this is increased to 0.6, i.e., closer to the value quoted in Dargay et al. (2007), and the lower value decreased to 0.25 as reported in Arora et al. (2011).

China, with $d = 148$ km^{-2} and $q = 144$ km^{-2}, exhibits a saturation level of 0.55 4W/cap, a figure determined by the reasonable range of 0.4-0.7 4W/cap, as deduced from the analysis of

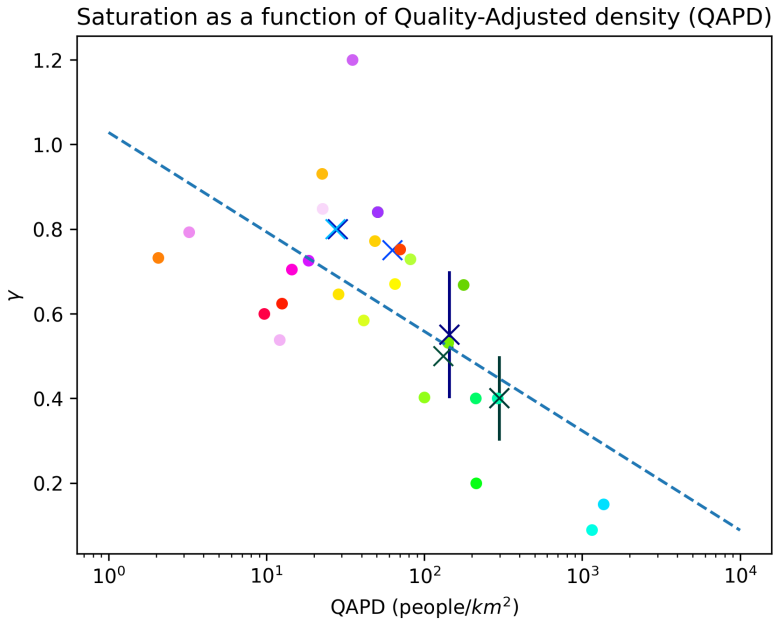


FIGURE 4.H2: Same as in Fig. 4.H1 except that the log-linear regression is performed between saturation level γ and QAPD. Uncertainty ranges are shown with vertical bars for China and India

saturation levels in countries with analogous densities and with log-linear fits. In the uncertainty analysis of section 4.4.2, the upper bound of the uncertainty is increased to 0.8 in order to include values found in Dargay et al. (2007) and in DyMEMDS (Vidal et al., 2022). The values obtained by our an analysis fall outside the shown correlations to take into account in a semi-qualitative way historical trends and the effects of both correlations.

We proceed similarly with Indonesia, Brazil, Mexico and Russia. The current QAPD and unadjusted density of Indonesia are in close proximity to those of China, 0.5 4W/cap has thus been chosen. 0.75 4W/cap saturation level is chosen for Mexico as its QAPD falls between those of Germany and Japan, but has a smaller unadjusted population density. 0.8/cap is chosen for Brazil and Russia as their QAPD as similar to the United States'. For these three countries we note that saturation level estimations are less critical than for China and India. Indeed, our GDP and population projections allow us to forecast future time vehicle ownership levels based on Gompertz fits and this indicates that the vehicle ownership for these 3 countries will stay in the mid-range of the Gompertz function. This makes projections less sensitive to the chosen saturation levels (see Figs. in Supplementary Materials).

Table 4.G1 summarizes the Gompertz parameters used for vehicle ownership projections. Table 4.H2 presents the Gompertz saturation levels used in this study and compare them with values from the specialized literature. The values from Dargay et al. (2007) result from a computation based on countries' population densities and urbanization levels relative to those of the United States. We consider that this method is generally valid, as they have convincingly argued that population density does indeed appear to be the primary determinant of saturation levels. The values provided by Felis Rota et al. (2016) are derived from straightforward unconstrained Gompertz fits to their data. Therefore, we expect that the saturation values for China, India, Indonesia, Brazil, Mexico and Russia (with vehicle ownership still far from saturation) might not be highly relevant. The saturation levels calculated by Silva et al. (2022) involve a formula with five parameters, calibrated with available data. Using 5 parameters could be misleading, particularly since many countries are still far from saturation. We therefore consider

Country	Current study[a]	Dargay et al[b]	Felis Rota et al[c]	DyMEMDS [g]	Silva et al[d]	Lu et al[e]	Singh et al[f]
Brazil	0.80	0.831	0.289	—	—	—	—
China	0.55	0.807	0.089	0.74	—	0.3 - 0.6	—
France	0.73	0.823	0.852	0.75	0.595	—	—
Germany	0.77	0.728	0.921	0.70	0.615	—	—
Indonesia	0.50	0.808	0.144	—	—	—	—
India	0.40	0.683	0.141	0.63	—	—	0.15 - 0.25
Japan	0.73	0.732	0.672	—	0.515	—	—
Mexico	0.75	0.840	0.306	—	—	—	—
Russia	0.80	—	0.409	—	—	—	—
United States	0.85	0.852	0.865	0.90	0.672	—	—

[a] Partially constrained method described in the text and in Appendix 4.H.
[b] Dargay et al. (2007); using US saturation and countries' relative population density and urbanism.
[c] Felis Rota et al. (2016); output from direct, unconstrained Gompertz fits to the data.
[g] Andrieu (2023); computed using a linear function of the logarithm of population density.
[d] Silva et al. (2022); using 5 parameters, calibrated through regression.
[e] Lu et al. (2018); from semi-quantitative literature.
[f] Singh et al. (2020); from semi-quantitative literature.

Table 4.H2: Vehicle ownership saturation level comparison. The unit is 4W/cap.

their results to be uncertain. Finally, the estimates from Lu et al. (2018) and Singh et al. (2020) are based on semi-quantitative arguments discussed in this Appendix.

4.I. Oil demand projections of other sectors

Figs. 4.I1 and 4.I2 illustrate respectively the projections of oil demand in the different sectors of transport excluding the road transport sector, and in the different sectors excluding all forms of transport. It is reminded that the figure 4.9 shows the cumulative consumption of all sectors excluding road transport and the oil and gas supply chains. The historical data come from the IEA's World Energy Balances (IEA, 2024d).

Fig. 4.I3 shows a comparison of this work's projections with DyMEMDS' (Vidal et al., 2022). The projections of oil consumption in the different sectors are more elaborate in DyMEMDS, although the data shown before 2020 is the result of model fitting rather than historical data. The trends exhibited by the projections are quite similar between the present modeling and the DyMEMDS results, giving confindence in our results.

4.J. Oil demand quantities

The documentation of the IEA's World Energy Balances database or WEB (IEA, 2024b) provides relatively little information about the formal relations between quantities. This appendix presents the equations used in our model.

In the WEB database, at the world level, the total energy supply $E_{o,\mathrm{TES}}$ of an energy source — here, oil — is defined as the sum of the production $E_{o,\mathrm{INDPROD}}$ and of the year-to-year change

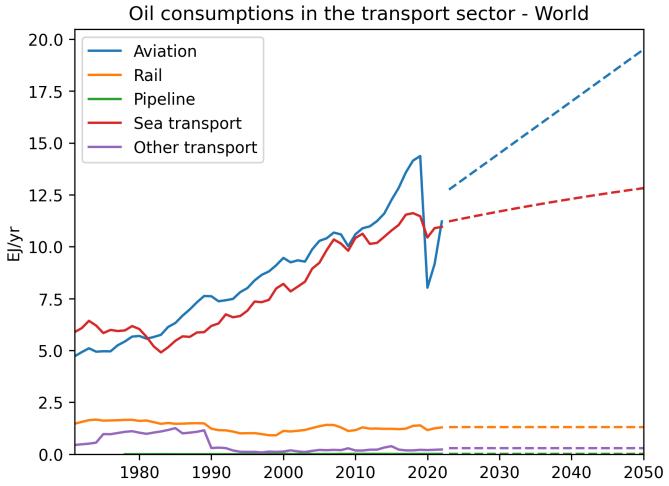


FIGURE 4.I1: Breakdown of oil consumptions within the transport sector. The dashed lines represent projections. All transport sectors are represented except the road transport sector.

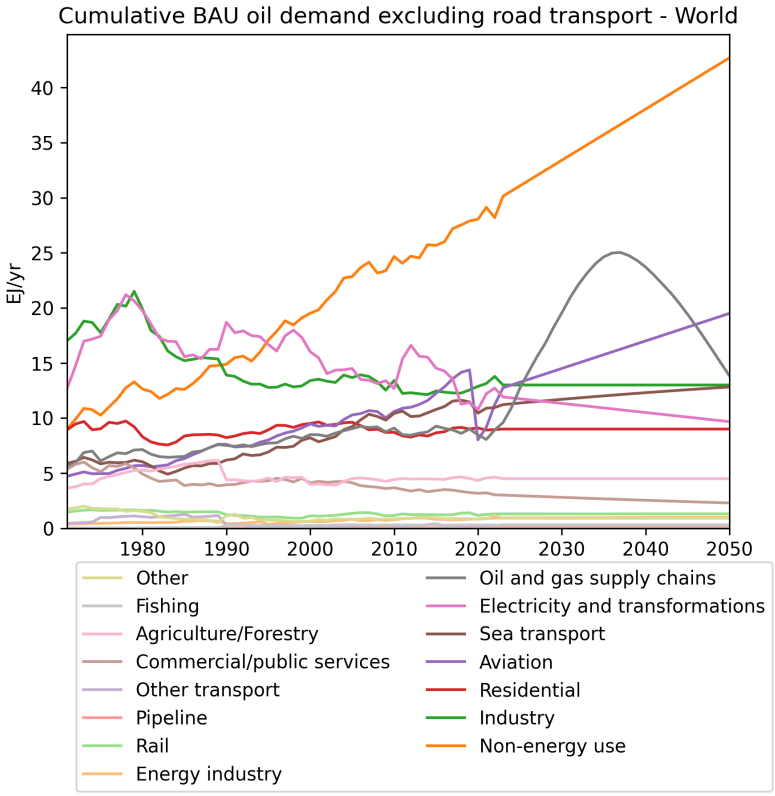


FIGURE 4.I2: Breakdown of oil consumptions by sector. The dashed lines represent projections. All sectors are represented except the transport sector.

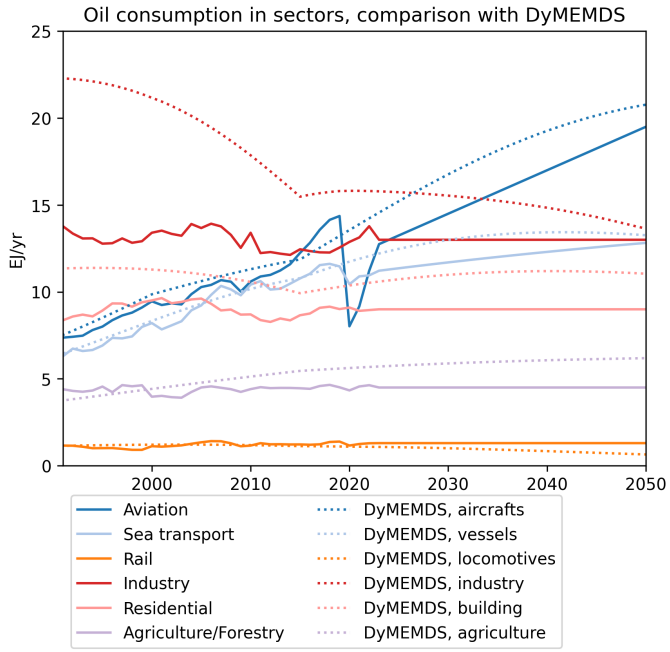


FIGURE 4.I3: Comparison of the projections of oil consumption in some sectors, between results of the present study and those of DyMEMDS.

in stocks $E_{o,\text{STOCKCHA}}$ (t)he last subscript of each quantity of this appendix is the variable name provided by the WEB database):

$$E_{o,\text{TES}} = E_{o,\text{INDPROD}} + E_{o,\text{STOCKCHA}}. \tag{4.J1}$$

In the model, the historical supply data from GlobalShift, Rystad and Laherrere are corrected to fit to the total energy supply (TES) rather than to the energy production (INDPROD) reported by the IEA. This approach is justified because stock changes fluctuate around 0 EJ/yr, with absolute values below 1.5 EJ/yr.

By definition of the other quantities, the total energy supply $E_{o,\text{TES}}$ is also equal to the sum of total final consumption $E_{o,\text{TFC}}$, energy transformations $E_{o,\text{TOTTRANF}}$, energy industry own uses $E_{o,\text{OWNUSE}}$, losses $E_{o,\text{DISTLOSS}}$, inter-products transfers $E_{o,\text{TRANSFER}}$, and statistical differences $E_{o,\text{STATDIFF}}$. Making all flows positive, this can be expressed as:

$$\begin{aligned} E_{o,\text{TES}} = {} & E_{o,\text{TFC}} - E_{o,\text{OWNUSE}} - E_{o,\text{TOTTRANF}} \\ & + E_{o,\text{DISTLOSS}} + E_{o,\text{TRANSFER}} + E_{o,\text{STATDIFF}}, \end{aligned} \tag{4.J2}$$

where $E_{o,\text{TOTTRANF}}$ is computed as the sum of all transformation flows at the level of aggregated oil products.

The right-hand side quantities constitute the total oil demand of this article, as shown in Fig. 4.17. The energy industry own uses $E_{o,\text{OWNUSE}}$ constitute the direct (d) energy investment of the oil and gas supply chains, of which all energy investments are modeled in section 4.2.3, based on an earlier work. The remaining oil demand from these own uses represent less than 0.5 EJ/yr and constitute the "energy industry" flow of Fig.4.I2. Losses $E_{o,\text{DISTLOSS}}$ then add to the energy transformations $E_{o,\text{TOTTRANF}}$ to constitute the "Electricity and transformations" quantity of the same figure. Total final consumption $E_{o,\text{TFC}}$ aggregates all other oil demand sectors of Fig.4.I2, excluding the "oil and gas supply chains", "Electricity and Transformations"

and "energy industry" ones.

Statistical differences $E_{o,\text{STATDIFF}}$ are assumed to be zero in the future since this flow fluctuates around 0 with absolute values that are usually below 1EJ/yr. Transfers between products $E_{o,\text{TRANSFER}}$ however represent a growing inflow of 1.7EJ/yr in 2022. This inflow (oil supply) is very likely composed of recycled oil products, i.e. feedstocks re-processed into oil after an initial use. Consequently, we model this inflow as a reduction in the demand for non-energy use products. This ensures that the projected total energy supply remains consistent with IEA's. The transfer quantity is projected linearly, reaching 2.45 EJ/yr in 2050, consistently with the trend observed since 2000.

4.K. Gross oil supply and oil products

The IEA's WEB classification (IEA, 2024b) distinguishes between gross products (primarily crude oil, but also small amount of other products such as NGLs or refinery feedstocks) and final oil products such as diesel, gasoline or naphtha. In IEA's WEB, quantities of gross products are consumed in the refining process to produce final oil product[18]. Only final oil products are used in all other sectors, whereas gross products are consumed in almost no other sectors than in the refining process. Consequently, almost all of the oil demand quantified in this study corresponds to the demand for final oil products.

This work aims to model gross oil demand. The energy investments in the oil supply chain (to the point of use, which includes refining) as well as the evolution of the losses in the refining process are modeled in section 4.2.3 and 4.2.4. This enables the gross oil demand to be computed by adding these quantities to the demand for final oil products. However, the energy investments of the oil supply chains as well as the losses in the refining are modeled independently of the evolution of the final oil product mix. Still, changes in the proportion of each final product would affect the refining process. Nevertheless, the evolution of these proportion has historically been limited, apart from the continuous decline in fuel oil use. Moreover, the oil demand projections and the assumptions in the energy investments in the oil supply chain follow a business-as-usual scenario. Consequently, this should marginally change the results.

4.L. Motorcycles modeling

International Road Federation (2024) indicates that there were 640 million motorcycles in 2020, compared with 1450 million 4-Wheeled vehicles. For the sake of simplicity, the category referred to as "motorcycles" (also labeled "2W") encompasses all motorized 2-wheelers and 3-wheelers, including mopeds. Assuming that the annual consumption of a motorcycle is at least 40% lower than that of other vehicles (Álvarez Antelo et al., 2024), it can be deduced that motorcycles consume no more than 15% of the global oil used by the road transport sector in 2020.

India, Indonesia and China account for more than two-thirds of the world's motorcycle stocks (see table 4.S1). While this stock exceeds the 4Ws' one in India and Indonesia, and is important in China, motorcycles represent a very small share of the number of vehicles in ad-

[18] In the IEA accounting, gross products refining flows are negative, while final oil products flows are positive. The sum of these two flows results in a loss of 4EJ in the process in 2022.

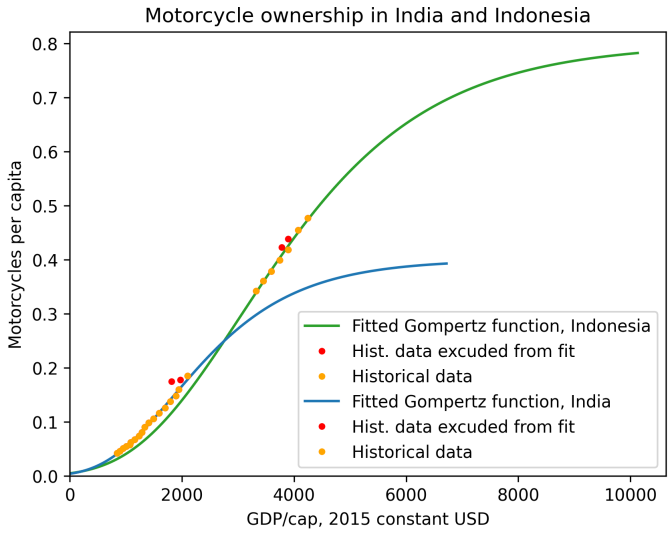


FIGURE 4.L1: Motorcycle ownership Gompertz projection for India. Then end of the fitted curve represents the value in 2050.

vanced economies. Some articles in the literature (Bastos et al., 2020; Chu et al., 2024; Chiu and Guerra, 2023; Law et al., 2015), conclude that income, population density and road density are the primary factors increasing motorcycle ownership. Some articles have noted and theorized that motorcycle ownership stagnates and decreases above a certain level of GDP per capita (Chu et al., 2022, 2024; Tuan, 2011; Law et al., 2015, 2023; Pongthanaisawan and Sorapipatana, 2010) in favor of increasing car ownership. This leads Nishitateno and Burke (2014) to assume that motorcycle ownership as a function of GDP per capita follows a Kuznets curve whose levels depend on population density. This assumption is subsequently often repeated in the literature (Bastos et al., 2020; Chu et al., 2022, 2024).

We start with India, where motorcycles use more oil than cars. This consumption is growing, already reaching around 2EJ in 2020 (International Road Federation, 2024). The forecasts of this study give a GDP per capita in 2050 of 8600 $ 2015/yr, which corresponds to the stagnation zone of the Kuznets curve (Nishitateno and Burke, 2014; Chu et al., 2022). Our projections stop in 2050, and we note that the first half of the Kuznets curve can be assimilated to be of a Gompertz curve. Therefore, we model motorcycle ownership by a Gompertz function as a function of GDP per capita, following Arora et al. (2011); Saurabh and Majumdar (2023), and based on the rationale presented in Dargay et al. (2007) for cars. The aforementioned articles propose a saturation level ranging from 0.2 and 0.5 for various scenarios. In the present study, a saturation of 0.4 is adopted, based on out fit of the data[19], see Fig. 4.L1. The data on the number of motorcycles comes from the Ministry of Road Transport and Highways of India (Ministry of Road Transport and Highways, 2024).

Arora et al. (2011) predicts that the annual energy consumption of motorcycles will decrease over time, both through a decrease in mileage and an increase in fuel efficiency. Nevertheless, few data on these parameters are available (Álvarez Antelo et al., 2024; Chong et al., 2018; Deendarlianto et al., 2020), and the diversity of the data as well as the date on which they were obtained questions their robustness. Furthermore, no longitudinal data series are available. Thus, and for lack of better guideline, we assume that the annual energy consumption of a motorcycle

[19]The best fit results in a saturation of 0.47. However, this is not robust as the data do not show any inflection point. This value is reduced to better match literature values, while still providing a good fit.

is proportional to cars, which is also set to decrease in India (see section 4.2.2.2):

$$\frac{E^c_{o,2W}}{v^c_{o,2W}} = K_{2W}\frac{E^c_{o,PV}}{v^c_{o,PV}}, \tag{4.L1}$$

where $E^c_{o,2W}$ and $E^c_{o,PV}$ (in EJ/yr unit) represent the annual oil energy consumption of all motorcycles and passenger vehicles respectively. $v^c_{o,2W}$ and $v^c_{o,PV}$ represent the total number of motorcycles and then passenger cars. K_{2W} (dimensionless) is a constant, determined from the 2015 data found in the WILIAM model (Álvarez Antelo et al., 2024), from which the $E^{\text{IND}}_{o,x}(2015)/v^{\text{IND}}_{o,x}(2015)$ ratios are deduced by multiplying the energy consumption per km (MJ/km) by the annual mileage (km/year). This leads to $K_{2W} = 0.4$. This value is not applicable to advanced countries[20].

The same reasoning is employed for Indonesia.

Firstly, a Gompertz curve is fitted to the historical evolution of motorcycles ownership using data from the Indonesian BPS (BPS Statistics Indonesia, 2024), with a saturation at 0.8 from this fit. As for India, a Gompertz fit is performed instead of a Kuznets one, for the same reason (valid for GDP per capita maximum values lower than $\sim$ 10000$/cap, which apples to both India and Indonesia. In the absence of data on motorcycle consumption in Indonesia and on the average mileage, the change in annual energy consumption of a motorcycle is indexed on cars according to Eq. (4.14). The coefficient used is $K_{2W} = 0.4$ again, the same as for for India. This approach is reasonable given that Indonesia and India are two countries with similar GDP per capita.

In the case of China, however, the stock of motorcycles has stagnated since 2007[21], and in 2020 represent around 30% of the stock of cars, or less than 5% of the oil consumption of cars if we assume that the annual energy consumption of a motorcycle is 6 times lower than that of a car (Álvarez Antelo et al., 2024). Because of this, we do not model motorcycles in China. This is equivalent to assuming implicitly that the oil demand from motorcycles is proportional to 4-Wheelers', an assumption made for all other countries.

Figs. 4.L2 and 4.L3 show the data on and projections of oil demand of motorcycles, along with of PVs' and CVs'.

4.M. MODELLING COMMERCIAL VEHICLES

The road transport category of energy consumption encompasses motorcycles (2W) passenger vehicles (PV) and commercial vehicles (CV). The modelling of motorcycle consumption is described in section 4.L. Although the number of vehicles dedicated to commercial use generally represents less than 15% of the number of 4-wheelers in a country (see section 4.E), their oil consumption represents around 35-45% of the oil consumption of road transport as mentioned in that section. It is therefore necessary to model the share of energy consumption dedicated to commercial vehicles to model future oil demand.

The CV category encompasses different types of vehicles: medium and heavy trucks dedicated to transport of goods over medium and long distances, buses used for passenger transport

[20] While energy consumption (MJ/km) is slightly lower (by 30%) than in more advanced economies, annual distances are higher by a factor of 2.

[21] From International Road Federation (2024) data combined with `https://www.ceicdata.com/en/china/no-of-motorcycle/cn-no-of-motorcycle`, `https://www.statista.com/statistics/278741/china-number-of-motorcycles-per-100-urban-households//`

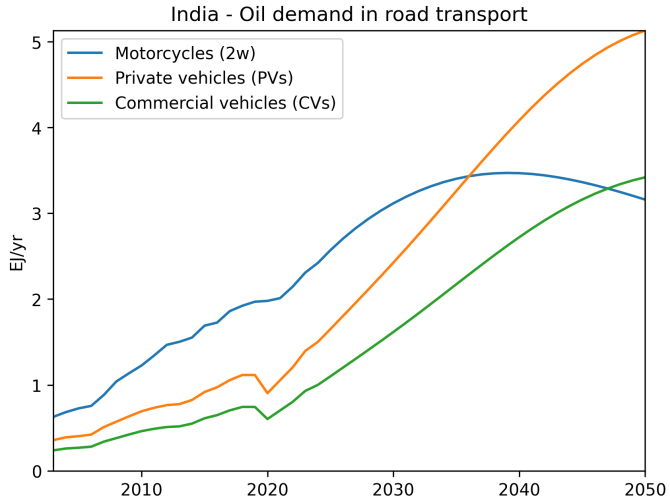


FIGURE 4.L2: Data and projections of the oil demand of 2W, PVs and CVs in India.

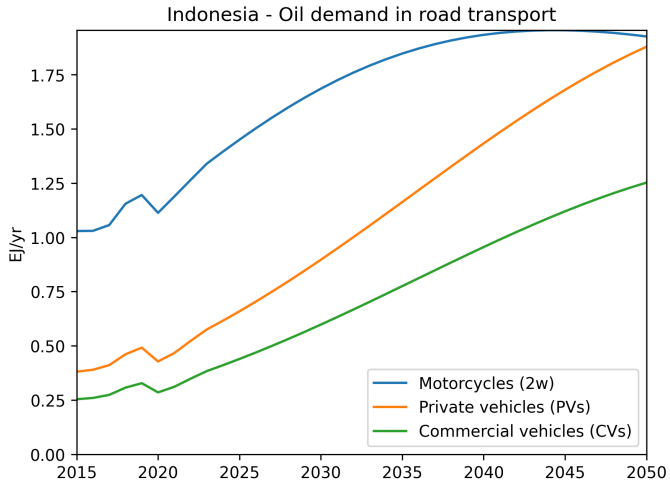


FIGURE 4.L3: Data and projections of the oil demand of 2W, PVs and CVs in Indonesia.

within cities or on long range, and light commercial vehicles, both for the transport of goods or people on short distances, and special vehicles dedicated to specific uses in the industrial sector. Heavy-duty trucks represent the vast majority of the energy consumed in CVs, while they represent approximately 20% of the stock of CVs in Europe (ACEA, 2023).

The literature on the energy consumption of commercial vehicles is scant, making elaborate modeling impossible. Instead, based on some data and elements of the literature, we have chosen to model the oil consumption of commercial vehicles as proportional to the sum of oil and electricity consumption of the 4-Wheeled vehicles (4W). This leads to

$$\frac{E_{o,PV} + \kappa E_{e,PV}}{(E_{o,CV} + \kappa E_{e,CV}) + (E_{o,PV} + \kappa E_{e,PV})} = K_E, \text{ and} \tag{4.M1}$$

$$\frac{E_{o,CV} + \kappa E_{e,CV}}{(E_{o,CV} + \kappa E_{e,CV}) + (E_{o,PV} + \kappa E_{e,PV})} = (1 - K_E), \tag{4.M2}$$

consistently with Eq. (4.18) and with the notations of section 4.2.2.4. K_E is assumed constant by lack of relevant data, an idealization of reality. This energy proportion is used as a proxy to formulate the relationship between the services provided by PVs and CVs. The useful energy consumed by PVs and CVs would therefore be proportional. However, the present study only accounts for oil primary energy. The κ coefficient is defined to reflect the difference between the energy consumption of EVs and ICVs. Therefore, it is assumed that $E_{o,y}$ and $\kappa E_{e,y}$ would result in the same useful energy quantity. This explains the appearance of κ in Eqs. (4.M1) and (4.M2) (see also Appendix 4.Q).

Based on IEA (2024d), US EIA (2023), SDES (2023), IEA (2017a), IEA (2017b) and DyMEMDS (Vidal et al., 2022), we set $K_E = 0.6$. Its range of uncertainty used in Appendix 4.4.2 is ± 0.05.

The energy efficiency of commercial vehicles is assumed to be constant over time. According to IEA (2017a); Ruzzenenti and Basosi (2009), most efficiency gains were achieved between 1970 and 1990, but few were observed between 1990 and 2007. While Ruzzenenti and Basosi (2009) notes that energy efficiency has remained virtually constant over time after 1990, he also observes that it varies from region to region. In parallel, IEA (2017a), Mulholland et al. (2018) and Lu et al. (2018) observe a linear log-log correlation between road freight activity (measured in vehicle-km or ton-km) per capita and GDP per capita, at different levels per country. This may be misleading, however, since the trajectory of vehicle ownership as a function of GDP per capita in our historical data also presents a correlation in log-log coordinates, although lots of studies have shown that it follows a Gompertz function on the longer terme (see section 4.2.2.1).

Assuming, as we do (see Eq. 4.M1), that the ratio of CV oil consumption to the sum of oil and electricity consumption remains constant over time is tantamount to considering that the activity of CV is proportional to the activity of PV. Our only justification for this assumption is that the development of these two phenomena (transport by PV and CV) has common root causes: economic development, development of road infrastructures, and population density but this justification is weak and indicates only that they grow together.

The indexation of the energy consumption of CVs on PVs' combined with the constant ratio between the stock of PVs and CVs assumption made in made above implies that the annual oil consumption of CVs must decline over time. This may not be realistic as it could be argued instead that the annual mileage of a commercial vehicle (CV) is constant over time, given that transport companies have an economic interest in maximizing the use of their vehicle capital. In any case, this implies that the model of the present study would tend to minimize the energy consumption of CVs and thus minimize oil demand, consistently with the philosophy of this work.

In all cases, the values of consumption per PV per year (GJ/PV/yr) obtained in this way are consistent with the values of consumption per kilometer (MJ/km or L/100km) and annual distances (km/year) found in the literature (see section 4.2.2.2). As the consumption per PV (GJ/PV/yr) is computed using these assumptions on CV, this consistency supports the validity of the assumptions on CVs. Still, as mentioned in Appendix 4.P, this assumed relation between PVs and CVs energy use may not be observed in India and China in the last decade as a consequence of the decrease in the annual mileage of PVs observed in these countries. This however may be a transient effect, given the early stage of development of their fleets and the rapid growth observed in vehicle ownership.

We nevertheless deem our results reasonable, as the growth of oil consumption by CVs in our no EV CV deployment scenario (+30% between 2023 and 2050) is lower than heavy duty trucks consumption in the World Energy Outlook STEPS scenario (IEA, 2024d) (+43% between 2023 and 2050), and is larger than the reference case's of the US EIA (2023) (+17% between 2022 and 2050).

4.N. Electric commercial vehicles

In 2024, electric commercial vehicles constitute a negligible fraction of the global fleet (IEA, 2024d). Their market share remains modest (less than 5%) across all regions, including in China, and this share in China exhibited variability (instead of a steady increase) due to shifts in subsidies. The steady exponential deployment of electric cars is not observed in the case of commercial vehicles (CV), indicating that the technology (in particular for heavy trucks) or type of sales is still in its experimental phase.

Indeed, the Global Electric Vehicle Outlook from IEA (IEA, 2024d) forecasts a negligible total of electric trucks and electric LCVs ("light comercial vehicles", following IEA's classification) in 2035 in the STEPS scenarios. In the STEPS scenario, the sales of electric trucks are forecast at 20% of truck sales. The share of electric buses is predicted to be higher (30%), but these vehicles are less significant in the CV category of the present study as they represent a small percentage of the total number of vehicles and energy consumption.

In fact, electrification is more difficult for CVs than PVs due to several technical and economic arguments centered on the cost of batteries (which represent approximately 40% of the price of an electric car König et al. 2021; IEA 2022), and the autonomy and charging times of these batteries (Shirizadeh et al., 2024; Mao et al., 2024; Jin and Mao, 2024; Möller, 2024; Ghosh, 2025; Burnham et al., 2021; IEA, 2024d). PVs are primarily used for short to moderate distances (5-50 km) with breaks between uses, enabling charging during periods of non-use. However, for long trips (exceeding 150km, which is often the minimum autonomy of an electric car), it is possible to use a supercharger. These are often found in highway stations and provide a full charge in less than an hour (30-45min), allowing for long journeys provided the driver and passengers can manage this pause every couple of hours.

The uses of CVs are different. Medium and heavy duty trucks are typically operated for extended periods with infrequent stops, primarily to maximize economic efficiency. In addition to that, their high energy consumption requires larger batteries, which are more expensive and bulkier and need longer charging times. The development of "battery as a service" (BaaS) — in particular "battery swapping" — is starting, particularly in China. However, this model is not yet widespread and it is unlikely to be in the near future due to the high cost associated with the

surplus of batteries required for this application and the number of swapping sites[22]

Moreover, in the case of cars, the adoption of electric vehicles is driven not only by economic and operational arguments, but also by social status perceptions and ecological considerations. In contrast, these factors hold less sway over the commercial vehicle sector, where fleets are primarily driven by operational efficiency and cost-effectiveness. Technological advancements are anticipated to mitigate the technical and economic impediments associated with electric vehicle adoption. However, the extent of this impact is expected to be limited due to the substantial technological progress already achieved in battery technologies for automotive applications, which suggests that further cost reductions are unlikely to occur in a short time frame (IEA, 2024d).

In this work, the deployment of CVs, is modeled as a logistic function of time, with saturation varying across different scenarios. Based on the information summarized above, the saturation is set at 40% of PVs' as shown in figure 4.N1. This choice is our best guess to represent the information presented above. One has:

$$v_{e,CV} = \frac{l_{e,CV} v_{F,CV}}{1 + \exp[-k_{e,CV}(t - t_{0,CV})]}, \tag{4.N1}$$

with the notations of section 4.2.2.4, $l_{e,CV} v_{F,CV}$ being the actual saturation level ($l_{e,CV} = 0.4 l_{e,PV}$ the fraction of the total $v_{F,PV}$), $k_{e,PV}$ the slope and $t_{0,CV}$ the year of inflection in CV EV deployment.

Heavy trucks represent a low proportion of the CV stocks, but a high proportion of the CV energy consumption. Consequently, considering that the electrification of small trucks is easier than this of heavy trucks, it can be anticipated that the real proportion of EVs in the CV stocks will be higher than the actual energy shift from oil to electricity. However, the model of the present study assumes a unique conversion coefficient between stocks and energy consumption (in equation 4.12). In this study, the results on the proportion of EV CV in the total stock is not of interest, but the oil displacement induced is. Consequently, it should be understood that the projections of the EV CV stock has be chosen not to best depict assumption on future EV CV stock itself, but in order to best depict assumptions on the displacement of oil by electricity in CVs instead.

Eq. (4.Q9) expresses how one can calculate the oil reduction due to EV deployment.

In any case, and in line with the philosophy of this analysis, the assumption regarding this logistic deployment of CV leads to underestimate oil demand. Indeed, the growth of oil use by heavy duty trucks in EIA's reference case (US EIA, 2023) corresponds to our 25% EV deployment scenario (which assumes a 10% penetration of electric CVs at saturation). Furthermore, the oil consumption growth of heavy duty trucks is identical in their high and low zero-carbon technology cost scenarios, which suggests that the EIA does not take their deployment into account.

Conversely, the growth of oil demand by heavy-duty trucks in IEA (2024d) World Energy Outlook is higher in their BAU scenario (STEPS) than CVs' increase of oil demand in the "0% EV" deployment scenario of this work. Furthermore, oil demand growth by heavy-duty trucks in IEA's APS (Announced Pledges) scenario aligns with the "40% EV" scenario of this work, and their NZE scenario (Net Zero Emission, a normative one respecting the 2°C global warming limit), is in line with our "100% EV" scenario (which assumes a 40% penetration limit of electric CV alongside a 100% of electrification of PVs). This implies that our scenarios assuming more than a 10% of electrification of CVs are not BAU scenarios (they are more optimistic from the

[22] This conclusion is drawn from an analysis of multiple gray literature articles on this subject.

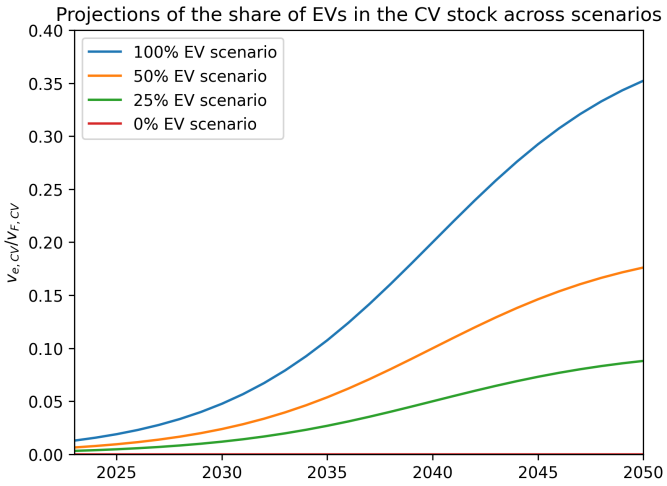


FIGURE 4.N1: Projections of the proportion of electric vehicles in the stock of commercial vehicles, across the EV deployment scenarios of this present study.

point of view of the energy transition).

4.O. NON-OIL ENERGIES USED IN ROAD TRANSPORT

Oil constituted 99% of the energy consumed by the road transport sector until 2005, but this figure had fallen to 93% by 2022 (IEA, 2024b). This decline was the result of the gradual deployment of biofuels (bioethanol and biodiesel) and natural gas (LNG, for liquefied natural gas, or CNG, for compressed natural gas). In 2022, biofuels accounted for 5% of the energy consumption of road transport, natural gas 3% and electric vehicles 0.4%. This figure on the share of the energy consumption by electric vehicles (while EVs represent 3% of vehicles) is explained by the facts that there is a negligible number of electric CV (see Appendix 4.N), that oil, biofuels and natural gas are primary energy sources while electricity accounted is not and that the efficiency of internal combustion engines (30%) is lower than electric engines (more than 95%).

Natural gas as a fuel is consumed only by natural gas vehicles. The development of natural gas fuels and vehicles has been driven in part by environmental considerations (Osorio-Tejada et al., 2017). However, the compressed nature of the fuel introduces additional constraints on vehicles and service stations. Furthermore, the sector is partially reliant on price discrepancies between gas and oil (which are not anticipated to undergo significant alterations in a BAU scenario) and on subsidies, which are increasingly allocated towards the electric sector (Le Fevre, 2019; IEA, 2017a). Accordingly, IEA and BP (IEA, 2023c; BP, 2024) have forecast only slight transitional increases before a decline in consumption in their various scenarios.

Biofuels are consumed with oil as a constituent of gasoline[23]. The development of biofuels was driven by two objectives: the reduction of the carbon footprint of fuel and the transition away from fossil fuels. Nevertheless, the carbon footprint of biofuels remains a subject of considerable debate, and they give rise to significant land-use conflicts, particularly with food production (Moriarty and Honnery, 2022; IPCC, 2023). For these and economic reasons (prof-

[23]The fuels are commonly designated "BX" for biodiesel and "EX" for bioethanol, with X representing the blend percentage of these biofuels.

itability, subsidies redirected towards electric vehicles), IEA and BP are forecasting a slight transitional increase in consumption, followed by a decrease in climate-ambitious scenarios.

We recall that biofuels are included on the supply side in "all oil liquids", which is the scope of the oil category in the present study. The consumption of natural gas is neglected as it only accounts for 3% of the energy consumption of road transport and is expected to remain low. Consequently, it can be posited that only oil (which encompasses all liquids in the present study, among which biofuels) and electricity are used in road transport.

4.P. Construction of the projections on the annual oil consumption per private vehicle

This Appendix discusses the arguments leading to the assumptions made on the projections of the annual oil consumption of PVs. This is based on projections of annual mileage of a vehicle, and fuel use per year, per vehicle and per kilometer. The product of the two giving the fuel used per year per vehicle. Total oil demand follows from this result, from vehicle fleet numbers. Figures are available in Supplementary Materials.

4.P.1. United States

The National Transportation Statistics (NTS) of the Bureau of Transportation Statistics (BTS) (Bureau of Transportation Statistics, 2024) provides data on the evolution of vehicle-kilometers in the United States. From this and data on fleet size (Bureau of Transportation Statistics, 2024), it is possible to deduce changes in annual mileage of a vehicle in the United States. There was a notable surge between 1970 and the end of the 1990s. This reached a plateau in the early 2000s, and started to decline as a consequence of the 2008 economic crisis. Travel distances stabilized once more until the decline linked to the consequences of the pandemic caused by the Covid-19 pandemic. In a business-as-usual scenario, we assume that the annual mileage in the United States will remain stable at their pre-Covid level in the future, i.e. 18900 km/year/vehicle (see Supplementary Materials).

On the other hand, Lutsey and Sperling (2005); Frey (2018); Schipper (2005) found that vehicle fuel consumption (which can be measured in L/100km or in MJ/km) remained constant between 1985 and 2005. This is linked to the changes in certain vehicle characteristics (size, engine, speed and comfort) (Moawad et al., 2016; Zhou et al., 2023; Global Fuel Economy Initiative, 2017) compensated by technological progress in engine consumption. By combining the previously deduced annual mileage data with the calculated annual consumption per vehicle (GJ/PV/year), we can derive the fuel consumption in megajoule per kilometer . This illustrates the reduction in fuel consumption during the 2008 economic downturn, which has persisted. It is assumed that this decline in consumption will continue along the trend observed between 2009 and 2019, with efficiency gains of approximately 3% per year, resulting in consumption levels (in MJ/km) that are similar to European values in 2050 in the US[24]. The resulting trend is illustrated in Supplementary Materials.

[24]Fuel consumption in MJ/km is derived from three sources: data available in the WILIAM model, data obtained from different specific country sources, and cross-referencing annual distance data (km/year) obtained from different sources with annual oil consumption data per vehicle (GJ/vehicle)

4.P.2. Europe

It can be reasonably assumed that European countries (France, Germany,...) follow the same trends in fuel consumption and annual mileage, given the observed similarity in the data sets (In the observed GJ/PV/yr data as well as in Schipper 2005; Hu and Chen 2016; ODYSSEE-MURE 2023). In their study, Craglia and Cullen (2019) examine the evolution of the fuel consumption of vehicles in the UK. They compare data from the vehicle certification process, also known as 'type-approval', with data from real-world driving conditions. The former is typically used to assess the fuel efficiency of new vehicles, while the latter provides a more accurate representation of actual fuel consumption. Despite a reduction in "type-approval" fuel consumption of approximately 30% between 2001 and 2019, the real-world data only declined by $\sim$ 10% between 2001 and 2012 and then remained constant until 2019. As mentioned above, this is due to the fact that the gains in energy efficiency achieved through technological progress are offset by changes in vehicle attributes. An ADEME study for France (ADEME, 2024) demonstrates that the values and changes in average consumption announced (equivalent to 'type-approval') correspond to the type-approval values provided by Craglia and Cullen (2019) for the UK.

Based on this information, we assume that fuel consumption in the UK, and therefore in European countries by extension, will remain constant in the future. In accordance with the assumption of constant fuel consumption from approximately 2010 onwards, the data on decreases in annual mileage provided by the European (ODYSSEE-MURE, 2023) project (ODYSSEE-MURE, 2023) between 2010 and 2019 correspond to the decreases in the quantity of fuel per vehicle observed in our data for France, Germany and Italy. In practice, we use the observed decrease in oil consumption per passenger vehicle per year from 2010 to 2019 to project an annual decrease rate for the future (varying between 0.2 and 0.7% per year, depending on the country). These trends are shown in figures available in Supplementary Materials.

4.P.3. China and India

In the case of China, Ma et al. (2022) observe a historical decrease in annual mileage of 15,000–10,000 km/year between 2010 and 2019, a 33% reduction (or 4% per year). Similarly, our data on annual oil consumption per passenger vehicle has decreased by 50%, which suggests a reduction in the kilometer consumption of passenger vehicles (MJ/km) of approximately 25%. This is for the past. For the future, as the data from the WILIAM model indicate that Chinese consumption per kilometer has reached European levels, we assume that the decline will be limited in the future, given that European levels are stagnating. Indeed, it can be reasonably assumed that the decline in annual mileage (km/PV/year) will be the primary driver of the decline in annual consumption per passenger vehicle (GJ/PV/year). Lu et al. (2018) model the evolution of the annual mileage of light duty vehicles (LDVs) as the ratio of transport demand (km/yr/cap) to vehicle ownership. They thus posit that the decline in vehicle mileage is attributable to an acceleration in the rate of vehicle ownership growth relative to the expansion in demand for LDVs. The model then predicts that annual mileage will reach a threshold in 2020 before increasing very slightly until 2050. However, increasing urbanization may be a significant factor in the change in annual mileage, given that urban areas are denser and public transport infrastructure more accessible than in rural areas. The World Bank anticipates that this trend in urbanization will continue over the coming decades.

Finally, for both China and India, DyMEMDS (Vidal et al., 2022) project a 1.5%/yr decrease in the annual oil consumption per kilometer (GJ/km/PV) and a constancy of the annual mileage, which thus results in a 1.5% decrease in the annual oil consumption of PVs.

On the basis of the historical decline in annual consumption and the historical rate of decline in mileage, it is reasonable to assume an annual decline in consumption (GJ/PV) of 2% per year for China. This implies a reduction in consumption (GJ/PV) by 45% between 2019 and 2050 (shown in Supplementary Materials). Based on the aforementioned assumptions, this is equivalent to an average annual distance of approximately 5,000 km per year in China. This value is lower than that observed in European countries, but remains plausible given the higher urban density in China compared to Europe.

Similarly, annual mileage in India are also declining to a comparable degree. According to Arora et al. (2011), this figure was 15,000 km/year around 2000—2010, whereas WILIAM (Álvarez Antelo et al., 2024) estimated it to be approximately 11,500 km in 2015. In line with the findings of Arora et al. (2011), we posit that annual mileage in India will decline due to the country's higher population density than China. Without further information, we assume a 2% annual decrease in the annual consumption of passenger vehicles (GJ/PV/year). This covers both a slight decrease in fuel consumption (MJ/km), which we can expect to reach European values, and a decrease in annual mileage.

In the uncertainty analysis of section 4.4.2, we set a lower bound for the decrease of annual oil consumption of PV of 3% per year. For an upper bound, as PV annual oil consumption in India and China is already lower than in advanced economies, it is possible that these would in fact plateau due to the deployment of larger cars like SUVs which is seen in advanced economies. The upper bound for the annual oil consumption of PV is then defined to be a constant projection of the 2019 level.

4.P.4. Other countries

For all remaining countries, the available literature is very scant to non existent. Consequently, we will assume that fuel consumption (MJ/km) varies to a lesser extent between countries (Álvarez Antelo et al., 2024) and changes to a lesser extent over time (Craglia and Cullen, 2019; Lutsey and Sperling, 2005; Frey, 2018; Schipper, 2005; ADEME, 2024) than annual mileage (km/PV/year), with the exception of developing countries. In general, an annual rate of decrease of annual consumption per passenger vehicle (GJ/PV/year) is adopted for each country. This value is set empirically and depends on both recent historical trends and on the lower limits of fuel consumption (MJ/km) and annual distances (km/PV/year/) that are implicitly assumed depending on the considered region.

4.Q. Solution of the system of equations

The solutions are not performed in quite the same way for historical data and projections.

For historical data, $E_{o,PV}$, $E_{o,CV}$, $E_{e,PV}$, $E_{e,CV}$, $E_{o,2W}$, $v_{o,PV}$ and $v_{o,CV}$ are unknown quantities while $E_{o,r}$, $v_{F,4W}$, $v_{e,PV}$, $v_{e,CV}$, $v_{o,2W}$ (parameters) and K_v, K_E and K_2W (constants) are known from historical data.

Eq. (4.19) directly yields

$$v_{o,CV} = \frac{v_{o,PV} + v_{e,PV}}{K_v} - v_{o,PV} - v_{e,PV} - v_{e,CV}, \tag{4.Q1}$$

which combined with Eq. (4.11) yields

$$v_{o,PV} = K_v v_{F,4W} - v_{e,PV}, \tag{4.Q2}$$

Eq. (4.14) also directly yields:

$$E_{o,2W} = K_{2W} v_{o,2W} \frac{E_{o,PV}}{v_{o,PV}}, \tag{4.Q3}$$

with $E_{o,PV}$ still unknown.

Substituting $\kappa E_{e,PV}$ and $\kappa E_{e,CV}$ from Eqs. (4.16) and (4.17) into Eq. (4.18) yields

$$E_{o,CV} = E_{o,PV} \frac{\left(1 + \frac{v_{e,PV}}{v_{o,PV}}\right)\left(\frac{1}{K_E} - 1\right)}{1 + \frac{v_{e,CV}}{v_{o,CV}}}. \tag{4.Q4}$$

Eq. (4.10) combined with Eqs. (4.Q3) and (4.Q4) allows us to find $E_{o,PV}$ and thus $E_{o,2W}$ and $E_{o,CV}$:

$$E_{o,PV} = E_{o,r} \frac{1}{1 + K_{2W}\frac{v_{o,2W}}{v_{o,PV}} + c\frac{\left(1+\frac{v_{e,PV}}{v_{o,PV}}\right)\left(\frac{1}{K_E}-1\right)}{1+\frac{v_{e,CV}}{v_{o,CV}}}}. \tag{4.Q5}$$

κ has disappeared from the previous expressions. Actually, it only appears in the following final expressions of $E_{e,PV}$ and $E_{e,CV}$:

$$E_{e,PV} = \frac{v_{e,PV} E_{o,PV}}{\kappa v_{o,PV}}, \tag{4.Q6}$$

$$E_{e,CV} = \frac{v_{e,CV} E_{o,CV}}{\kappa v_{o,CV}}. \tag{4.Q7}$$

However, $E_{e,PV}$ and $E_{e,CV}$ are of no interest in the present study.

For projections, $E_{o,r}$ is not a known quantity. Instead, we add $C_{o,PV}$ add to the known parameters, projected as explained in section 4.2.2.2. Eq. (4.12) yields:

$$E_{o,PV} = C_{o,PV} v_{o,PV}. \tag{4.Q8}$$

This replaces Eq. (4.Q5) in the equation system. In the end, Eqs. (4.Q1), (4.Q2), (4.Q3), (4.Q4) and (4.Q8) yield $v_{o,CV}$ and $v_{o,PV}$, $E_{o,2W}$, $E_{o,CV}$ and $E_{o,PV}$. $E_{o,r}$ is then deduced from Eq. (4.10). $E_{e,PV}$ and $E_{e,CV}$ (unused) follow from Eqs. (4.Q6) and (4.Q7).

Note that, alternatively, the reduction of oil demand due to EV deployment, denoted $E_{av,CV}$ may be obtained in the following way:

$$E_{av,4W} = C_{o,PV} v_{e,PV} + C_{o,CV} v_{e,CV}. \tag{4.Q9}$$

This expression takes into account our assumption that EVs are used in the same way as ICVs. This could be used as an alternative way to deduce oil demand in EV deployment scenarios, from

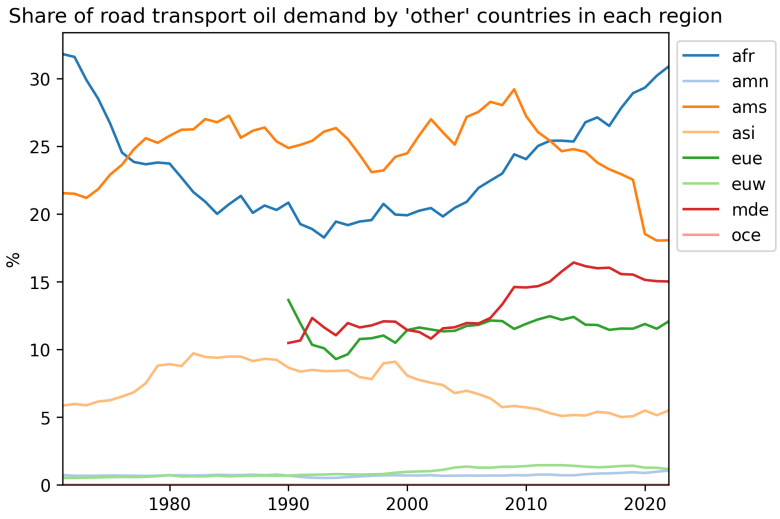


FIGURE 4.R1: Historical data on the share of the oil consumption in other countries relative to their region. Note that the dissolution of the Soviet Union led to redefine countries in 1990, which explains why the data of Eastern Europe and Middle East begin in 1990.

the scenario 0% EV.

4.R. MODELING OTHER COUNTRIES

The equation system of section 4.2.2.4 has only been solved for 62 countries (labeled modeled countries) as explained in 4.2.2.5 due to the lack of data on vehicle stocks, and its lack of robustness. The ignored countries are nevertheless accounted for in the following way. They are first aggregated in each region and collectively labeled other countries. We then assume that the aggregation of the modeled countries in each region is representative of the economy of whole region, including these other countries. The evolution of the oil consumption in road transport of other countries is thus proportional to the evolution of the sum of the modeled countries. Even though the regional major countries probably have a more dynamic economy and fleet evolution than other countries, the rationale is that they most likely share more characteristics with the other regional countries than other countries elsewhere.

In practice, we proceed as follows. Historical data on the oil consumption in the road transport sector for nearly all countries are available in the IEA World Energy Balances (IEA, 2024b). The aggregation of all countries in this database represents 99.6% of the global oil consumption in road transport in 2022. Fig. 4.R1 represent the share of other countries in the total road transport oil consumption of the region extracted from these historical data. In this figure, the proportion of oil use in the road transport sector of other countries varies over time in most regions. The trends are often unclear, making projections difficult. Moreover, the lack of robust data on the vehicle stocks prevents modeling more countries. Therefore, the projections are assumed to be constant. The projection coefficient is 0.30 for Africa, 0.008 for Northern America, 0.21 for Southern America, 0.05 for Asia, 0.12 for Eastern Europe, 0.014 for Western Europe, 0.16 for Middle East and 0 for Oceania.

In the case of Asia — which is the central region of our model — other countries only represent around 6% of regional oil consumption in road transport, stable since 2010. This limits

uncertainties in Asia. Projecting by a constant may underestimate the overall oil consumption in Africa as this does not depict the present growing trend, which may continue in the future. However, the vehicle stocks of Africa is expected to represent 4% of the global stock in 2050 in the present model, and its road transport oil consumption is projected to account for 7% of the total at the global level. Consequently, uncertainties in the projected share do not induce significant uncertainties at the global level. Similarly, trends in South America and Middle East are unclear, but other countries in these regions collectively account for approximately 3% of road transport oil consumption. The trend in Eastern Europe seems quite stable. In the case of North America, Western Europe and Oceania, the proportion of other countries is quite negligible, making uncertainties in projections negligible.

Projections of the share of the vehicle stock of each other countries' subgroup are extrapolated from this coefficient. The absence of data on vehicle stocks has led to the aforementioned assumption. This is reasonable given the similarity in annual oil consumption of PVs within a region. However be there is some variability in this annual oil consumption of PVs between regions.

4.S. Identifying major/important countries

It is useful to identify the countries that have the greatest weight on the evolution of the vehicle stock over time. These countries allow us to find a good balance between precision and model size: countries or regions considered to have more influence on the result will be modeled more precisely.

Our analysis is based on the number of vehicles in 2020 for each country according to OICA data (OICA, 2022), the value of their GDP per capita and its growth, and their population. Table 4.S1 summarizes this data for the countries identified as most important in this way.

In 2020, OICA estimates the global vehicle fleet at 1.590 billion vehicles. First of all, China, India and the United States are essential. In 2020, China is the country with the most vehicles, with 320 million. Moreover, China and India (with 46 million vehicles in 2020) have the largest populations in the world (around 1.4 billion inhabitants each in 2024) and are experiencing strong growth and industrialization. These two countries are expected to have the largest vehicle fleets in the world in 2050. In 2020, the United States had the 2nd largest fleet of vehicles in the world, with 276 million, well ahead of the 3rd largest (Japan, with 77 million vehicles).

On this basis, Brazil, France, Germany, Japan, Mexico, Russia and the United Kingdom are selected; they all have fleets of more than 40 million vehicles in 2020. Brazil, Mexico and Russia are also developing countries whose vehicle fleets are expected to grow. We finally add Indonesia because of its population and growth. These 11 countries account for 65% of the vehicle fleet in 2020 and are called "major" countries.

Finally, we consider another group of countries for which we estimate that the evolution of their fleet would have a second order influence on the global fleet, but nonetheless not negligible, which we designate as important countries. Several criteria can be used to determine whether the country in question has or will have an important vehicle fleet. The first criterion is simply the number of vehicles in 2020. We then estimate whether or not the vehicle fleet is likely to grow considerably by 1) the population, which gives an order of magnitude of the maximum fleet; 2) the trend in GDP/cap growth between 2015 and 2020; 3) the value of GDP/cap in 2020, which makes it possible to deduce whether or not GDP/cap in 2050 will reach typical

values at which vehicle ownership increases.

Wih these criteria, Australia, Canada, Iran, Italy, Nigeria, Malaysia, Poland, South Korea, Spain, Thailand and Turkey are selected and account for 15% of the world's vehicle fleet in 2020. These countries, gathered with major countries, are called "important" countries.

However, this papers aims to project the oil consumption of road transport globally, and these 22 countries are not sufficiently representative of their respective regions in terms of road transport oil consumption trends. Consequently, an additional 40 countries were incorporated to allow us to infer the evolution of the oil consumption of other countries in each region, as outlined in section 4.2.2.5. The selection of these additional countries is determined by the availability of sufficient data on the vehicle stock, although they should be less robust than for the 22 first countries. A total of 62 countries is modeled in the end. This set of countries is referred to as "modeled countries".

Country	**Stock**	**Population**	**GDP/cap**	**GDP/cap Growth**	**Motorcycles stock**
	10^6 vehicles	10^6 people	10^3 2015$/cap/yr	Annual % (2015-2020)	10^6 vehicles
Major countries					
China	**320**	**1400**	**10**	**6.1**	71
United States	**276**	330	59	1.8	8
Japan	**77**	130	35	0.8	10
Russia	**57**	**140**	**9.9**	1.7	2
Germany	**52**	83	42	1.3	5
Brazil	**46**	**210**	**8.3**	-0.6	5
India	**46**	**1400**	**1.8**	**5.2**	244
France	**45**	68	36	1.5	3
Mexico	**45**	**130**	**9.3**	0.3	5
United Kingdom	**42**	67	42	1.2	1
Indonesia	21	**270**	**3.8**	**4.0**	115
Important countries					
Italy	**45**	59	29	1.5	10
Spain	**30**	47	25	2.2	4
Poland	**29**	38	15	**4.6**	3
Canada	**27**	38	42	0.9	1
South Korea	**24**	52	31	**2.4**	2
Thailand	20	**72**	**6.0**	**3.1**	22
Australia	**19**	26	58	1.0	1
Turkey	19	**84**	**12**	**2.4**	4
Malaysia	18	**33**	10	**3.5**	1
Iran	16	**87**	5.1	0.1	12
Nigeria	12	**210**	2.4	-1.7	8

Table 4.S1: Selected major and important countries with data indicating the trend of their vehicle fleet in 2020. The values in bold represent the main arguments for choosing a country. The value of the stock of vehicles in 2020 is often the main argument. We then estimate the growth potential of the vehicle fleet using 3 elements: the total population (and its growth), the growth trend in GDP/capita and the value of GDP/capita (the growth potential of the fleet will be low if GDP/capita is very low). Vehicles stocks are taken from (OICA, 2022), population and GDPs from the World Bank (World Bank, 2024a,b) and motorcycles stocks from International Road Federation (2024).

CHAPTER 5 | PEAK OIL VS ENERGY TRANSITION: WHICH WILL WIN THE RACE?

Based on the gross oil supply assessed in Chapter 2 and the BAU oil demand modeled in Chapter 4 (using Chapter 3), the present chapter confronts oil demand to oil supply in BAU scenarios with varying electric vehicle deployment.

The present material is intended for submission to Nature Energy or Energy and Environmental Science.

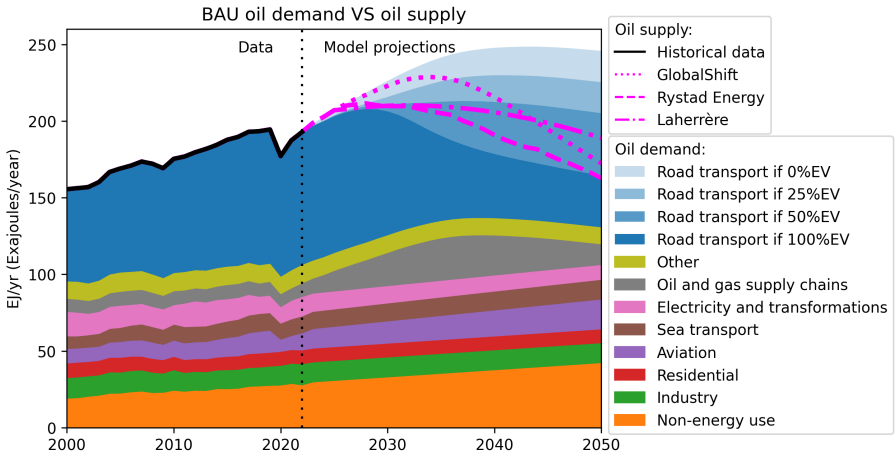
ABSTRACT

A peak in oil supply is expected around 2035, as a consequence of the cliff effect in the end of life of many oil fields. Concurrently, oil demand is predicted to rise, primarily due to:
1/the expansion of the road transport sector in China and India;
2/the growth of petrochemicals production;
3/the increase of demand in the oil and gas supply chains due to EROI decline;
4/the modest growth in other sectors.

The deployment of electric vehicles (EVs) could mitigate this increase in oil demand. In order to assess the effects of this upcoming issue, oil supply and demand are projected within a business-as-usual (BAU) scenario. We find that oil supply may not meet demand as soon as 2030 in the most probable scenario, although our results are sensitive to EV deployment and to a lesser extent to oil supply projections uncertainty.

This finding challenges the possibility and consistency of BAU scenarios at this time horizon. Due to the critical role of oil in transport and, consequently, for the whole economy, this anticipated tension will also produce structural adverse economic impacts. This emphasizes the need to revise the narratives and GDP growth assumptions in model reference scenarios (including Integrated Assessment Models).

Graphical abstract



5.1. Introduction

Business as usual (BAU) GDP growth is a common assumption in institutional models (IEA, 2024c; OECD, 2023; US EIA, 2023). Moreover, other model assumptions often implicitly reflect BAU rationales. More generally, few (in any) governments and institutions anticipate mid- or long-term disruptions or post-growth policies.

Nevertheless, the credibility of such BAU scenarios is often questioned in some academic fields, particularly in light of biophysical limits such as the planetary boundaries and their economic back-reaction (Meadows et al., 1972; Steffen et al., 2015a; Rockström et al., 2009, 2023; Fanning et al., 2022; Capellán-Pérez et al., 2020). In particular, the effects of climate change are expected to be quite severe especially in the second half of the 21st century (Capellán-Pérez et al., 2020; IPCC, 2023). Other risks (environmental or not) are also identified (Nieto et al., 2020; World Economic Forum, 2025).

BAU scenarios may in particular be challenged from an energetic point of view. Indeed, fossil fuels still constitute 80% of our primary energy supply, with oil representing 90% of the energy source of the transport sector (IEA, 2024b). This simple fact in itself calls for a scrutiny of our collective ability to shift out of fossil fuels to a large extent within one or two decades while maintaining a steady GDP growth at the global as well as regional scales, in a context of energy tension. It may be worth recalling at this point that a comparison with the speed of deployment of ICTs (information and communication technologies) is misleading, these being the exception and not the rule. Historically, massive new energy technological deployment took decades if not more (Smil, 2016) and the high material intensity of renewable energies (due to their spatial dilution and intermittency) requires significant heavy industry investments, from mining to construction and on-site deployment (Capellán-Pérez et al., 2019; IEA, 2025a).

Focusing on oil in particular, the forthcoming gross oil supply peak is expected around 2035 (Laherrère et al. 2022; Campbell and Laherrère 1998; Sorrell et al. 2009; Rabas 2024; Chapter 2), primarily due to the age of most wells[1] and the steady decline of new discoveries.

[1] In 2019, approximately 70% of the oil supply came from oil fields discovered prior to 1970 (Michaux, 2020).

This gross energy peak leads to net oil supply having already reached a plateau, see Chapter 3. Oil will be the first fossil fuel to reach a supply side peak, but gas is expected to follow closely (see Chapters 2 and 3).

This gross and net energy peak issue is hidden behind the need of a fast energy transition due to climate change. Indeed, it is often considered that, as oil (and) gas resources are plentiful, there is no fossil fuel abundance issue. However, the problem pointed out here is not one of stocks, but one of flows, and a sizable fraction of resources cannot be converted into reserves, see Chapter 2.

On the other hand, oil demand is expected to grow in a BAU scenario, at least at the 2035 horizon, and possibly beyond, depending on the speed of the electrification of the road transport sector, see Chapter 4. This trend is led by the growth of the vehicle fleet in China and India, by the increase in non-energy uses (mostly for petrochemistry), and by the rise of oil demand in the oil and gas supply chains due to the decline of their energy return on investment ratio (EROI). Oil is also largely non substitutable in aviation and shipping (at least on the short- and mid-term), two sectors expected to grow in BAU scenarios.

Finally, oil is a crucial resource in the global economy. Indeed, oil is critical to the functioning of all supply chains at least through transport and, by extension, critical to the global economy (Michaux, 2020). A tension or mismatch between oil demand and oil supply would have major consequences on the economy (Tverberg, 2012a; Murphy and Hall, 2011; Sorrell et al., 2009; Brandt, 2017).

The present study tests the hypothesis that — under a typical BAU scenario — gross oil demand can be met by supply, and the conditions under which this is possible, through an analysis of the temporal evolution of both demand and supply.

Section 5.2 describes the methods used for modeling oil demand from road transport, oil and gas supply chains, and other sectors, and for modeling oil supply. Section 5.3 presents our results, while section 5.4 addresses their uncertainty, robustness and relevance. The final section synthesizes the key conclusions of this work.

5.2. Materials and methods

BAU gross oil supply and demand projections have been quantified in our previous studies (see Chapters 2, 3 and 4). We summarize here the relevant results for the present analysis.

5.2.1. Oil supply

Three different oil supply data sources are used. GlobalShift's[2] and Rystad Energy's on the one hand (two well-known oil intelligence companies), and Laherrère et al. (2022) (well-known oil experts, with, in the case of Jean Laherrère, decades of experience in the oil industry). All three of these data series are retrieved and reused from Delannoy et al. (2021a) (which has a common co-author with the present paper).

These data include the forecast of the production of all oil liquids, in particular biofuels and gas liquids (NGLs) besides the various types of crude oil[3], up to 2050. In this paper, the term

[2] `https://www.globalshift.co.uk/`

[3] Oil demand projections are also quantified for all liquids, thus including NGLs and biofuels. Including biofuels and NGLs in oil liquids is the most common convention

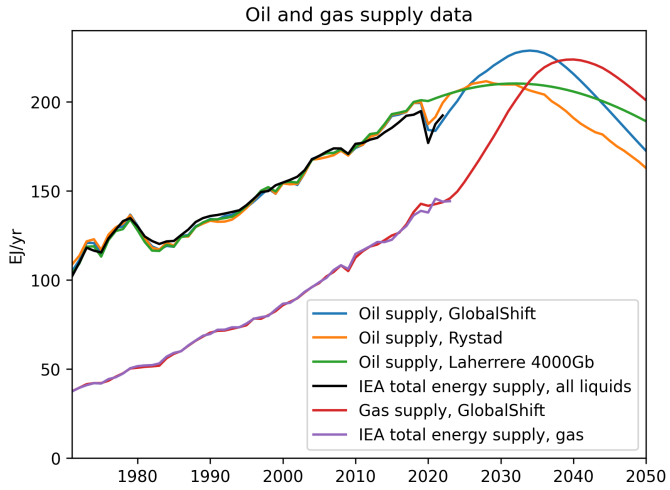


FIGURE 5.1: Gross supply data of all liquids from multiple sources as indicated in the figure legend. The projections data begin at year 2020 or 2021, which explains why the decline in oil consumption in 2020 (due to the COVID pandemics) is not reflected in Laherrere's data. IEA's historical oil supply data are also shown. "Oil" refers to all liquids.

"oil" actually refers to all liquids (a common convention in the literature is to include various oil-type liquids in oil production). Volumetric data are converted into energy data (including for non energy uses of oil) with appropriate conversion factors, and IEA's World Energy Balances database (IEA, 2024b) is used in particular to quantify oil demand in the oil and gas supply chains (See Chapters 2 and 3 for details.).

Our first paper (see Chapter 2) pays particular attention to the issue of oil reserves vs oil resources by crude oil type, as this has a direct impact on oil supply. This analysis compares quite a few references and data sources in the academic and gray literature, and also discusses the economic conditions making oil exploitation profitable. We pinned the technically and economically ultimate recoverable reserves (URRs) in a rather narrow window (3750 – 4300 Gbbl), implying that gross oil supply will peak around 2035, in agreement with the three main sources of gross oil data quoted above. We stress again that this is an issue of flows (annual gross oil production), a point that is often misunderstood in our experience.

The three main sources above cover the identified range of uncertainty (not only on URR, but on maximum annual production), and are shown on Fig. 5.1. Projections of oil intelligence companies (such as the ones shown here) are widely regarded as reliable, both in the academic and gray literature, and also by oil producers themselves (see comments in Laherrère et al. 2022 on this point).

5.2.2. OIL DEMAND

Oil demand has been modeled in detail our earlier articles.

First, BAU oil demand in the oil and gas supply chains has been quantified in Chapter 3. We disaggregated the energy invested in the oil and gas supply chains among energy sources. The ease of exploitation of oil and gas fields is expected to decrease significantly, because the cheapest (more accessible and/or concentrated) sources have been exploited first in the past. This is associated to the decline of the energy return on investment (EROI) of oil. We found that oil demand in the oil and gas supply chains is expected to increase by 50% between 2022 and 2035 (up to 53EJ/yr). This is followed by a decrease due to the decline in gross oil (and later

gas) supply. See our previous work, where uncertainties in these estimations are also discussed in detail.

Second, a detailed model of the evolution of oil demand in the road transport sector has been elaborated in Chapter 4. This is motivated by the large oil demand of this sector (44% of the total oil demand in 2022). This model primarily forecasts the stock of private and commercial vehicles in each country as well as the evolution of the average annual oil consumption by vehicle and by country. Based on this model, the oil energy demand of the road transport sector is expected to increase by 25% between 2022 and 2050, in the absence of further EV deployment. This is essentially due to the expansion of the vehicles' fleet of China and India, themselves produced by an increase of their GDP per capita, while their population nowadays represents 2.8 billion people combined. In this model, the main sources of uncertainty are due to five main parameters. Their influence on the ensuing tension between oil supply and demand is discussed in section 5.3.2.

Third, the oil demand in all other sectors is projected based on historical trends, consistently with BAU projection scenarios from IEA (2024d), BP (2024), US EIA (2023), and OPEC (2025). In particular, the demands from the petrochemical industry and in the aviation sector are anticipated to grow steadily, while oil substitutability in these sectors is limited on the short- or mid-term. Uncertainties due to these assumptions are relatively small compared to uncertainties in the road transport sector.

The largest source of uncertainty on oil demand, by far, comes from the future deployment of electric vehicles (EVs), and our results and discussion focuses on this aspect of the problem. We have handled the wide range of possible deployment pathways[4] through different scenarios of saturation of EV penetration in the private vehicle stock[5]. Each scenario projects a logistic (S-shaped curve) evolution of the share of electric vehicles in the private vehicle stock, with a saturation value set as a percentage of this stock[6] (0%, 25%, 50%, 100%). The other parameters of the logistic function are found through fits on historical data. These scenarios are identified by their respective associated saturation values (e.g., 25%EV). The oil not used because of the deployment of EVs is subtracted from oil demand in each scenario.

It is important to note that the oil demand growth modeled here as a consequence of a BAU GDP growth scenario is not an option, but a necessity, due in particular to the limited possibilities of substitution of oil in a number of economic sectors at the time horizon of interest in this work.

5.3. Results

5.3.1. Gross Oil supply vs BAU oil demand: central result

Fig. 5.2 shows the projections of oil demand in our adopted BAU scenario, as well as the projections of oil supply. Fig. 5.3 zooms on demand and supply where they start to diverge. These two figures summarize the most central results of the present work.

Only scenarios with a level of EV deployment $\gtrsim 50\%$ are able to match the gross oil supply

[4] Existing BAU projections of the penetration of EVs are found to vary tremendously between the reports quoted above — anything between 10% and 80% of the world fleet — while these reports are otherwise consistent in other respects, in particular GDP growth; see IEA (2024d); BP (2024); US EIA (2023); OPEC (2025).

[5] Commercial vehicles are modeled consistently with the private vehicle saturation level.

[6] 0% means near stagnation at the present level.

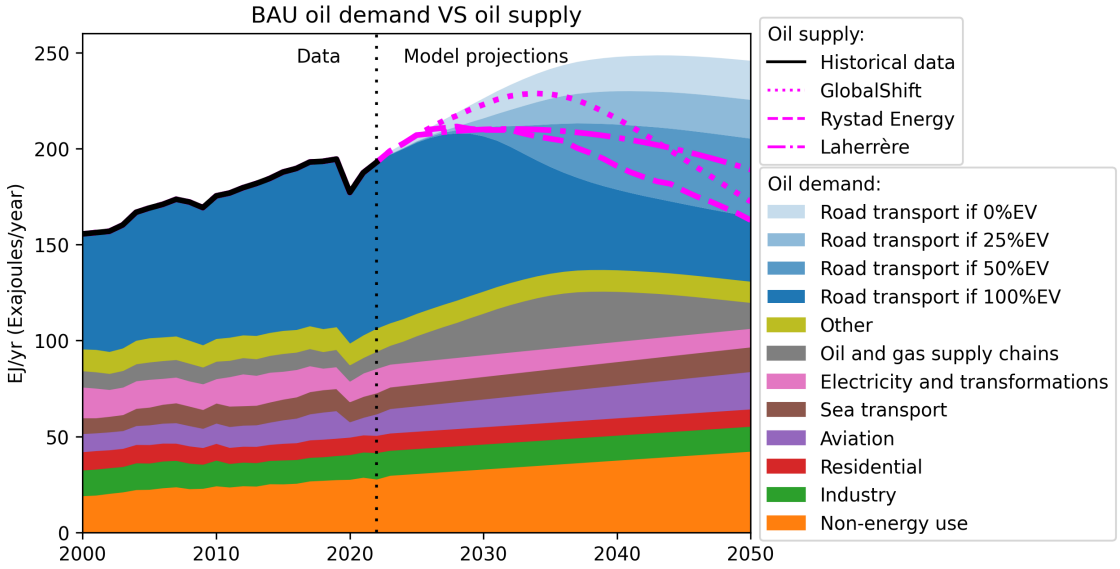


FIGURE 5.2: Cumulative oil demand in a Business as Usual (BAU) scenario, confronted to different projections on future oil supply representing the amplitude of ultimate recoverable resources (URRs). Oil demand in the road transport sector is shown according to different scenarios of electric vehicle (EV) deployment. The legend ("0%EV", "25% EV", "50%EV", "100%EV") indicates the saturation of the share of EVs in the total stock of private vehicles in 2050. The total oil demand in each of these scenarios corresponds to the upper limit of the associated colored zone.

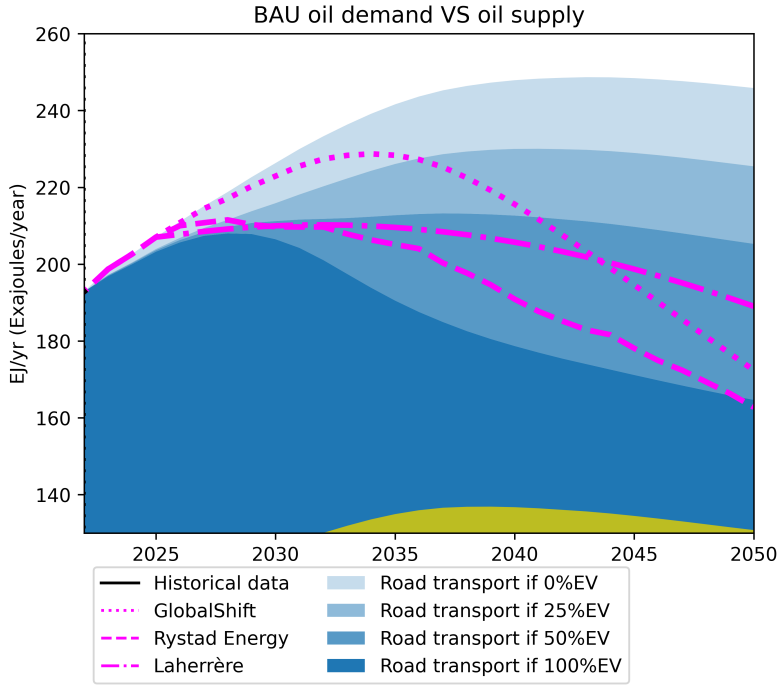


FIGURE 5.3: Zoom on zone of tension between oil supply and BAU oil demand. Signification of colored blue zones identical to Fig. 5.2.

projections of Rystad Energy and Laherrère before 2030. They require even larger EV deployment levels after 2030 to compensate for the decline in gross oil production. The gross oil supply projection of GlobalShift needs very little EV deployment until 2030; however, beyond this date the decline in oil supply is sharp, and demand can only be covered by supply for fractions of EVs in the world fleet exceeding 50% in 2040 and almost 100% in 2050.

Eventually, even with a 100% EV world vehicle fleet, oil supply cannot meet demand, although this occurs only past 2050. Part of this is due to the remaining demand in the transport sector (non or little substitutable energy uses) and part to the cumulative demand in all other sectors, in particular non energy uses (petrochemistry foremost). For the transport sector, e.g., aviation or long distance heavy trucks have little prospects to rely on anything but oil in the next decade or two in the future (see Chapter 4).

5.3.2. Gross Oil supply vs BAU oil demand: effects of demand modeling uncertainties

The largest source of uncertainty, by a large margin, is due to the level of EV deployment in 2050. Uncertainties in gross oil supply come second. The remaining uncertainties arise from the demand model, in particular in the transport sector, discussed now.

These uncertainties are not shown on the previous figures, and arise from five main parameters, grouped into three categories: i/ most importantly, the saturation levels of the vehicle ownership in China and India; ii/ the evolution of the annual oil consumption of a vehicle (GJ/PV/yr) in China and India; iii/ the proportion in transport oil demand due to trucks. The combined effects are shown on Fig. 5.4.

Table 5.5 provides a summary of the year when oil demand starts exceeding supply. This table supports the hierarchy of uncertainty mentioned at the beginning of the subsection.

This analysis points out that in order to avoid a tension or, worse, an unwanted gap between oil demand and supply in the typical BAU scenario underscoring our demand modeling, a considerable deployment of electric vehicles would be necessary, although this may not be possible due to limitations in their deployment, e.g., high upfront costs. Conversely, a stagnation of the deployment of electric vehicles at or near the current level (approximately 3% of the PV stock following IEA 2025b) would result in an immediate (2025-2026) tension on oil.

5.4. Discussion

A deployment of EVs between our 25% and 50% scenarios is most likely (as a matter of fact, US EIA 2023 forecasts a fraction of 25% of EVs of the PV stock in 2050.). Consequently, a tension on oil at the 2030 horizon is highly probable and in any case inevitable at some (possibly later) point. This implies that BAU growth scenarios may become unfeasible at the beginning of the next decade, at least at the global scale.

In this respect, let us recall a generic feature underlying all our work on gross oil supply and demand, namely, that our modeling tends to minimize demand and maximize supply when in doubt, in a reasoned way. This implies that the results presented above do minimize the expected tension between supply and demand in a moderate BAU GDP growth scenario.

Before delving into the discussion *per se*, let us dispel a potential issue. At least one of our supply projections (GlobalShift's) tends to exceed demand in all scenarios except for no further EV deployment. As this is a maximum supply projection, one may contend that unused oil

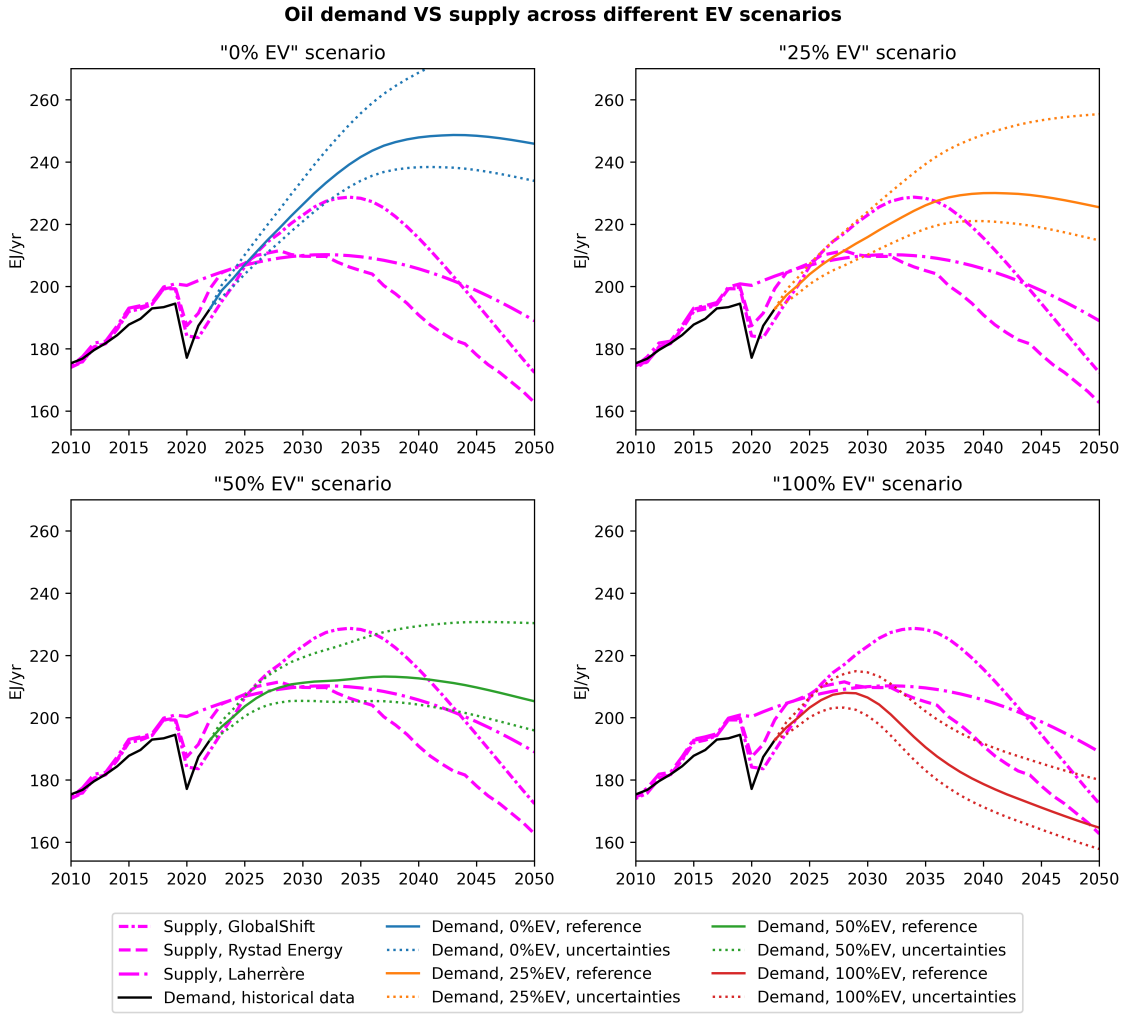


FIGURE 5.4: Oil demand scenarios and their uncertainty ranges compared to oil supply scenarios in the BAU GPD growth scenario of this study.
The oil demand scenarios in the subplots are identical to the EV deployment scenarios of Fig. 5.3. In each figure, the colored solid demand line represent the reference case and dotted lines represent the bounds of the uncertainty range.

	Rystad Energy	Laherrère	Globalshift
0% EV, Reference	2026	2026	2026
0% EV, High tension	2025	2025	2025
0% EV, Low tension	2027	2027	2033
25% EV, Reference	2029	2027	2036
25% EV, High tension	2025	2025	2025
25% EV, Low tension	2030	2030	2039
50% EV, Reference	2029	2028	2041
50% EV, High tension	2026	2026	2037
50% EV, Low tension	2035	2043	2043
100% EV, Reference	2050	2050+	2050+
100% EV, High tension	2027	2026	2048
100% EV, Low tension	2050+	2050+	2050+

FIGURE 5.5: Summary the year when oil demand overtakes supply, for each of the four EV deployment scenario discussed in this paper. "Reference" refers to the scenario baseline, as shown on Fig. 5.2; "high tension" (respectively "low tension") to the highest (resp. lowest) demand, taking into account modeling uncertainties. The colors indicate the proximity in time of the mismatch year: red from 2025 to 2029; orange from 2030 to 2034; yellow/-green from 2035 to 2039; and finally darker and darker shades of green beyond 2040. Early tension (high tension 100% EV scenario, Rystad Energy and Laherrère supply) are eased after in 2032—2033.

should delay some of the dates reported in table 5.5, e.g., through the constitution of oil stocks or through delaying EROI decay if production is adjusted to demand. However, the oil quantity involved is so small compared to URRs that the effect is very small (at most a couple of years of production).

5.4.1. DEPLOYMENT OF ELECTRIC VEHICLES

Assumptions about the future deployment of private electric vehicles (PV EVs) are highly controversial. EIA (US EIA, 2023) and OPEC (OPEC, 2025) project the global private electric vehicles' stock to a level closely resembling a 20—25% EV scenario from the model of the present study, whereas IEA (IEA, 2024d) and BP (BP, 2024) projections are closer to a 50—75% scenarios. However, the higher upfront cost of EVs compared to ICVs is expected to be an important barrier to their deployment (Virmani et al., 2023; Muratori et al., 2021; Rajper and Albrecht, 2020; Zhuge and Shao, 2019; Fevang et al., 2021; Purwanto and Irawan, 2024; Naseri et al., 2024; Soszynska et al., 2024; Pulido-Sánchez et al., 2022; IEA, 2022, 2023b, 2024d), driven by the high costs of batteries. Moreover, technological progress in batteries has reached a stage at which their future potential for costs reductions is limited, and since prices are now primarily sensitive to variations in the prices of raw materials and to technology choices[7](IEA, 2025b, 2024d). This reduces the potential for EV price decrease. Furthermore, battery technologies currently mainly rely on lithium, with 85% of its supply chain dedicated to batteries. It is therefore questionable whether the lithium supply chain could cope with the required increase in demand.

Studying the aforementioned barriers is critical for assessing the feasibility of a fast and large-

[7]For example, the LFP (lithium iron phosphate) batteries are cheaper than NMC (lithium nickel manganese cobalt oxides) ones, and their market share is expected to grow further. This would reduce the weighted-average battery price.

scale deployment of EVs — which accounted for 4% of the global vehicles stock and 23% of the sales in 2024 (IEA, 2025b, 2024d).

5.4.2. Demand underestimation due to the neglect of oil investments in renewable energies

In one of our previous articles (see Chapter 2), we estimated oil and gas energy investments in the deployment of solar and wind energy at a level designed to meet energy demand up to 2050 under the mild BAU growth scenario adopted in this work. This has not been included in oil demand, as these estimates are quite limited, representing 1.5 – 3 EJ in 2035.

5.4.3. Implications

This work focuses on oil because this is the first fossil fuel that will undergo a supply peak, soon in the future, and because a tension on oil supply has always had major macroeconomic impacts in the past, e.g., during the oil shocks of the 1970s/1980s, or, more recently, as a trigger of the 2008 economic crisis (Hamilton, 2009). Even though oil is no longer our major source of primary energy worldwide, there is little doubt that an economic crisis will be triggered from an oil crush in the time frame of interest in this work. This follows because oil is used directly in a number of productive sectors (such as, e.g., agriculture) or indirectly through transport. Indeed, 57% of the oil is used by transport in 2022, with 30% specifically in commercial transport (commercial vehicles, aviation and sea transport) while conversely transport relies on oil at 90%. As a tension on oil results in an increase in oil price, this dependency translates into a general rise of all prices, depending on the importance of oil in the different supply chains (Murphy and Hall, 2011; Sorrell et al., 2009; Michaux, 2020; Tverberg, 2012b). This has been recently largely witnessed at least in Europe as a side effect of the Russia-Ukraine war.

One may argue that a rise in oil price would result in the exploitation of more expensive oil liquids. However, this has already been taken into account in our analysis of oil URR and supply projections, resulting in the gross oil projection uncertainty adopted in this work. In particular, an oil price above $\sim$ 150$/bbl would be untenable (see Chapter 2): such a high price would make a number of companies and even some economic activities to go bankrupt, by lack of demand for more expensive products reflecting energy price increases in their own prices in a context where households would cut down on non essential spending (Tverberg, 2012b). This argument focuses primarily on high income countries, but similar effects are likely to happen elsewhere, although oil exporting countries may witness large trade surpluses.

Possibilities of oil substitution by gas and coal are rather limited. Gas supply is expected to peak by 2040 (see Delannoy et al. 2021b and reference in Chapter 2). Coal is not expected to peak before 2060-2070, but with limited margins of progression of annual production ($\sim$ 10%, see reference in Chapter 2). More importantly, gas and coal demand presently increases for electricity production, even in a context of fast growing renewable sources of energy as these still constitute a small fraction of electricity production worldwide (coal represents 35% of the world electricity production and gas 22% in 2022). Furthermore, the supply chains of oil and gas also require an increasing amount of gas, coal and renewable energies due to the present and future decrease in the EROIs of oil and gas. This is amplified by the present decline of oil and future (beyond 2045) decline of gas in the energy mix in a BAU growth scenario (see Chapter 3).

The same arguments follow for oil substitution by electricity. In fact we already concluded

in Chapter 2 that meeting the global world energy demand in a moderate growth scenario requires a rather steep rate of deployment of solar and wind energies, which themselves need fossil fuels in their development phase. It is useful to have some orders of magnitude in mind. We estimate that approximately 10 PWh/yr of electricity would be required to fuel a 100% EV scenario in 2050. In comparison, the production of electricity in 2023 was 30 PWh, and this figure is expected to grow linearly to 58 PWh by 2050 in IEA's STEPS scenario (IEA, 2024d). This is a short time scale for such an expansion in electricity production.

On a different topic, the deployment of electric vehicles is not free of environmental impacts. In particular, levels of deployment exceeding 50% of the world fleet need a really fast growth of various infrastructures. The flows of energy and raw materials towards the deployment of EVs must increase significantly in such scenarios, in spite of expected forms of energy demand reduction from (partially or totally) phasing out internal combustion engine vehicles (ICVs). See reference in Chapter 4, and Pulido-Sánchez et al. (2022) and IEA (2024d).

The main differences between ICVs and an EVs in terms of raw materials is the battery of EVs. Especially, the growth in the production of EV batteries is largely the main driver of lithium demand worldwide. The widespread deployment of EVs (which represent only 3% of the vehicle stock in 2023) would thus necessitate a significant expansion of the lithium supply chain, with major environmental impacts. The demand for some structural materials such as copper and nickel would also increase significantly, and one may question the very possibility of this growth at affordable prices, especially for copper (Vidal et al., 2022).

5.5. Conclusion

The present study aims to assess the feasibility of business-as-usual (BAU) scenarios by quantifying the possible tension between oil supply and demand. This perspective challenges the common implicit assumption that oil resources are abundant and that there are no reserve or annual supply issues. This implicit assumption leads to a focus on the question of phasing out fossil fuels for climate change considerations, while leaving aside considerations on other structural issues related to the reliance of the economy on fossil fuels. However, this assumption is incorrect, due to the limitation in conversion of oil resources into technically and economically exploitable reserves and annual supply (see Chapter 2).

It appears from the present study that a BAU GDP growth scenario implies a level of growth in oil demand that eventually cannot be met by oil annual supply, possibly as soon as around 2030 and most probably no later than ~ 2040, depending on scenarios of deployment of electric vehicles (EVs), as summarized in Fig. 5.2 and table 5.5. This tension between oil supply and demand in a BAU growth scenario primarily results from an expected decline in oil supply in conjunction to an increase in oil demand on several fronts: growth of the vehicle stock of China and India, oil demand rise in the oil and gas supply chains, and the continuous growth of some other sectors like aviation, sea transport, petrochemicals and other oil products, with realistic levels of oil substitution taken into account (most importantly in the transport sector).

More precisely, in the most likely event of an EV deployment between 25% and 50% of the world vehicle fleet and in a moderate BAU growth scenario, a growing gap between supply and demand inevitably occurs, most probably starting between 2030 and 2035. Even for a 100% level of deployment of EV, demand will eventually not be met by supply due to the limited substitutability of oil in some sectors (including some transport sub-sectors). Moreover, the

gross oil supply projections of Rystad Energy are most likely more robust than Laherrère et al. (2022) and Globalshift's because of the much larger level of resources invested in the collection and analysis of oil production data. Combined with our reasoned bias to maximize oil supply and minimize oil demand when uncertain in our modeling, it is probable that BAU expectations of unimpaired growth may fail as soon as 2030 no matter what.

The largest source of uncertainty is the level of EV penetration in the world fleet, which is not modeled but tackled through scenarios in this work. The largest uncertainties on this front arise primarily from the purchasing overcosts barriers and other issues mentioned in section 5.4.1.

This study calls to phase-out of oil and more generally of fossil fuels, not only to address climate change issues, but also to avoid severe structural macroeconomic recessional effects at the global level. Additionally, this study highlights that BAU scenarios may not be feasible for energy-related reasons as soon as within the next decade, thereby questioning the relevance of models based on BAU assumptions.

CHAPTER 6 | Modeling Private Vehicle Ownership as a Function of Income instead of GDP per Capita

The main uncertainty in the results of Chapter 5 arises from the future deployment of EVs.

The higher purchase price of EVs is beyond the reach of poorer households, but not to richer ones. Indeed, most of EVs sold are priced above 30 000 constant 2024 dollars, particularly in Western countries (IEA, 2025b). The present chapter and Chapter 7 seek to model the influence of EV prices on their future deployment.

The present section is thus dedicated to create mathematical tools allowing to distribute the stock of private cars (PVs) as a function of households income, across countries and over time.

The present material is intended for publication in Transportation Research Part D: Transport and Environment.

Abstract

Vehicle ownership is often modeled in the literature through the use of Gompertz functions to characterize the mean number of vehicles per capita as a function of GDP per capita.

However, this model takes into account the major determinant of private vehicle (PV) ownership — income — only in an indirect way. A more direct model of the dependence on income would be very useful to produce new and reliable models of vehicle stock projections, in particular in the perspective of modeling the energy transition in the transport sector. Unfortunately, data on the relation between actual income and vehicle ownership are not widely available, and existing models trying to overcome this limitation are neither widespread nor simple enough for generalized use.

We address this problem by showing that the distribution of the number of private vehicles per capita as a function of income may, to a reasonable level of approximation, be represented by a Gompertz function inasmuch as vehicle ownership can itself be represented by a (different) Gompertz function of GPD per capita, as a consequence of the mean value theorem. We

produce the resulting model parameters for a large array of countries. The potential usefulness of this characterization of private vehicle ownership in the context of the deployment of electric vehicles is also briefly pointed out.

6.1. Introduction

The average number of vehicles per capita, for a given country and a given year, is a key quantity both for historical data analysis and future projections of vehicle stocks and their energy demand implications. In particular, several studies have modeled the year-to-year PV fleet (or more generally, all-types of road vehicles) at the country level by a Gompertz function of GDP per capita. A major step forward accomplished in Dargay et al. (2007) is to improve significantly on the saturation level of the vehicle ownership model at large GPD per capita. This parameter has long been recognized as crucial (see, e.g., Greenman 1996 and references therein), and lack of precision on this point could indeed ruin all efforts to obtain reliable projections of vehicle stock models.

It is important to note that Dargay et al. (2007) and many others assimilate income to GDP per capita, but GDP per capita y is an imprecise proxy for income. In fact, as will be seen later on in this work, a given country median income M is generically comprised between 0.15—$0.2y$ and 0.4—$0.5y$, and is not a constant fraction of y over time. Thus representing vehicle ownership as a function of GDP per capita or of income are two different things. The first is not a very precise approximation of the second as recognized in a number of publications (e.g., Greenman 1996 or Lescaroux 2010 and references therein). For example Storchmann (2005) has pointed out that the level of inequality has a noticeable influence on vehicle ownership at the country level.

Thus, although a GDP per capita model gives a synthetic view of the total vehicle fleet and its evolution, it represents only in a crude and very aggregated way the causal influence of one of the major drivers of vehicle ownership, i.e., the income distribution. It is therefore desirable to have at hand a description of the average number of vehicles per capita as a function of income for a large number of countries in order to make somewhat more detailed projections of the world vehicles fleet evolution.

Some authors (e.g., Greenman 1996 and Lescaroux 2010, already quoted above) have attempted to take into account the role of income in a more precise way. The starting point is always the same: the mean vehicle ownership per capita in a given country is the result of the integral of some function describing vehicle ownership per capita as a function of income, weighted by the distribution of income. The main bottleneck of this approach is to find a prescription for the vehicle ownership dependence on actual income; a direct approach through available statistical data is limited to a very small number of countries where the data is collected, usually a subset of developed countries, at the notable exception of China (Huo and Wang, 2012; Lu et al., 2018; Gan et al., 2020; Berrill et al., 2024). These works furthermore suggest that ownership as a function of income can also be represented by a Gompertz function.

Lescaroux (2010) appears to be the first to point out that ownership as a function of income can be obtained from the widely better known and constrained vehicle ownership characterization as a function of GDP per capita. However, his model, although mathematically correct, is convoluted and not very transparent for routine use. Here we adopt a somewhat similar but much simpler approach and show that a Gompertz function can be an appropriate model of

vehicle ownership as a function of income from the known Gompertz functions of vehicle ownership as a function of GDP per capita, at a sufficient of precision.

Using the direct relation between the two types of Gompertz, we provide the relevant parameters of the new Gompertz functions for a large collection of countries.

Also, when using GDP per capita, there is some hesitation on whether simple deflated measures of GDP or more complex deflated purchase power parity (PPP) GPD indicators should be used. In this work we have adopted simple (non PPP) deflated GDP, because these are substantially more robust than their PPP counterparts. However, one can work with either type of GDPs, and the conversion between the two, if needed, is explained in detailed in the "GDP and income conversion methods" section of Supplementary Materials.

We have highlighted in Chapter 5 that modeling the deployment of electric PV under the barrier of their economic accessibility (among others) is a pivotal element in the modeling of the potential tension between oil supply and demand. The results of this study will then be used to model the distribution of the PV fleet as a function of income in countries over time. This will provide insight into the timescale of this key element of the energy transition, as well as offer a more precise idea of this possible tension between oil supply and demand.

The article is organized as follows: The data used are presented in section 6.2, the modeling methods developed and used in this work are presented in section 6.3, section 6.4 presents the results, section 6.5 the discussion and section 6.6 the conclusion. The more technical aspects of this work are presented in dedicated appendices and Supplementary Material.

6.2. DATA SOURCES

This work relies a lot on econometric concepts and data. For these, we mostly use World Bank data series. These include historical and projection population data, and various forms of GDP data, for a number of countries. We paid particular attention to not mixing data series from different programs and surveys (even in the same institution), otherwise the probability of introducing inconsistencies is not negligible, and these may in turn lead to spurious or incorrect results, even at the qualitative level.

The second type of data used bears on vehicle fleet over time, at the country level, from which average number of vehicles per capita can be obtained.

6.2.1. ECONOMETRIC DATA

Income distributions are provided by the World Bank "Poverty and Inequality Platform", or PIP[1]. The data series provide centile income distributions for a number of country in constant PPP dollars per day per capita[2]. PPP stands for purchasing power parity.

The last two benchmark years of PIP data are 2011 and 2017; in this work, the 2017 data series are used. However, we found it preferable to work in constant, non-PPP (2015) US dollars than in PPP dollars, because PPP conversions are more fragile from a methodological point of view than the more common constant GDP conversion of current GDP, and because we do

[1] `https://pip.worldbank.org/about`. More precisely, welfare aggregates are provided. These correspond either to direct income data provided by relevant country level surveys, or indirect income data through country level consumption surveys. The exact approach used (income or consumption surveys) depends on countries, and is one of the difficulties in making international income distribution comparisons.

[2] `https://datacatalog.worldbank.org/search/dataset/0063646/-Poverty-and-Inequality-Platform--PIP---Percentiles`

not actually need to make income comparisons between different countries. Conversions from local currencies to international constant dollars or PPP dollars are not completely straightforward operations. These can also be performed with the help of various World Bank data series, involving various sorts of deflators and of conversion factors. The procedures are explained in our "GDP and income conversions methods" Supplementary Material.

Appendix 6.B gives a detailed description of the type of data provided by the PIP database, along with the method of fit of the income distributions described by these data and used in section 6.4.1.

We also rely on Chapter 4 for projections of GDP and related GDP per capita. These GDP per capita projections were obtained from extrapolations of World Bank data. The reader is referred to this previous piece of work for details.

6.2.2. Private vehicle Fleet data

The rest of the data needed for this work bears on series of numbers of vehicles per capita as a function of GDP per capita at the country level. In practice these have been derived from primary data of Chapter 4 and are used directly here. These data series have been constructed from Freyssenet's compilation of vehicle fleet data (Freyssenet, 2016). We again refer the reader to our earlier publication for details.

In the present study, we ultimately model the evolution of the vehicle ownership as a function of income within a country, based on the income distribution in the designated country. This modeling makes sense in the case of private vehicles (PV) for which the ownership directly depends on individual choices, largely driven by income of individuals (or households), but not in the case of commercial vehicles (CV) for which the stock relies on the general economy of the country.

For this purpose, this study only models the PV stock. The PV stock represent approximately 90% of the total four-wheeled (4W) vehicles stock, CV representing the last part of the stock.

6.3. Models

6.3.1. Income distribution: historical data modeling and future projections

It is useful for our purposes to have at hand a closed-form and precise enough formula to represent income distributions at the country level. It is well-known in the specialized literature that the log-normal distribution is a simple, reasonably good approximation of income distributions, except for the upper two or three centiles of the distribution, where a power-law (the so-called Pareto distribution) is more appropriate (Cowell, 2011). However, it is not necessary here to take this small upper-distribution deviation into account (the induced error on the PV fleet is essentially negligible), and log-normal fits to income data will be used.

Many other types of parametric distributions and generalized distribution families have been considered in the specialized literature (see, e.g., McDonald 1984 and references therein). These are as a rule more precise than the log-normal distribution, but are more cumbersome to manipulate and are less easily interpreted. Our purpose is not to study inequalities (for which precise income distribution models are indeed needed), but the relation between income and

vehicle ownership, for which the log-normal distribution is sufficiently accurate. Furthermore, the meaning of its parameters is simple enough to make future projections of income distributions easier to produce. However, for some countries, a rural and urban population need to be distinguished to represent the global total income distribution, and a log-normal distribution attributed to each independently. This follows because the log-normal distribution (as quite a few other, simple distribution laws) does not accommodate precisely enough populations with widely different types of income sources and dynamics[3].

The log-normal distribution used in this work is given by

$$g(I) = \frac{1}{(2\pi)^{1/2}\sigma^* I} \exp\left(-\frac{1}{2}\left(\frac{\log(I/U_I) - \mu^*}{\sigma^*}\right)^2\right), \tag{6.1}$$

with μ^* and σ^* being dimensionless parameters, and U_I the income unit ($U_I = 1$ 2015\$/yr in this work). The mathematical apparatus of our fitting procedure on historical data is explained in Appendix 6.B.

Future income distributions are modeled by projecting the two parameters μ^* (mean of the logarithm of income) and σ^* (dispersion of the logarithm of income) of our fitted log-normal distribution. This is most conveniently achieved by relating these two parameters to GDP per capita for each country.

More precisely, for μ^*, and taking advantage of Eq. (6.B28) which states that a country's median income depends only on μ^*, we characterize the various countries median income as a function of GDP per capita. Indeed it turns out that a country's median income is always a fraction of order unity of the country's GDP per capita, making median income easier to project. For historical data, the median income is obtained on the basis of the fitted series of μ^* produced in the present work and of our earlier GDP per capita series at the country level of Chapter 4.

Next, and on the basis of this data we fit a double logarithmic logistic evolution to the median income share in GDP per capita to each country. The rationale and details of these assumptions and procedures are presented in the section 6.4.2.1.

For the dispersion σ^*, most countries show a growing or decreasing trend at some point, that we model through a logistic function of GDP per capita, as the logistic function has convenient properties for this fitting exercise.

6.3.2. Country level distribution of average number of PVs per capita as a function of income

This section is devoted to establishing the following property:

Property

Assuming that the number of private vehicles per capita is a Gompertz function of income per capita at any given time is sufficient to ensure that the number of private vehicles per capita is a Gompertz function of GDP per capita.

This property constitutes the most central and useful result of this work. It is not exact, but precise enough for most countries, as will be shown explicitly for some major countries in the results section.

[3] The log-normal distribution is particularly appropriate for more or less homogeneous segments of the population. See, e.g., Cowell 2011, section 4.4.

The assumed behavior is motivated by the limited but direct evidence that the number of private vehicles (PVs) per capita dependence on income is indeed suitably represented by a Gompertz function (Huo and Wang, 2012; Berrill et al., 2024). The property above provides a strong support to the generalization of this evidence. Thus this property allows us to relate cross-sectional PV ownership characterization (income dependence at a given time and for a given country) to longitudinal data on PV ownership (GDP per capita dependence as a function of time, for a given country). In particular it allows us to establish a cross-sectional model from the much more documented longitudinal data (most frequently modeled as a Gompertz functions, see section 6.1) at the country level.

We adopt the following notation for the GDP per capita Gompertz function:

$$V(y) = \gamma \exp[-\alpha \exp(-\beta y)] \text{ for } y \geq 0,$$
$$V(y) = 0 \text{ for } y < 0, \tag{6.2}$$

where y is the country GDP per capita (in 2015$/yr/cap), V the average number of PVs per capita, and α, β and γ are country dependent parameters (the country index is dropped in this section as we momentarily consider a single country). These three parameters are positive by assumption. γ is the saturation level (number of PVs per capita at large GDP/cap); α varies little from country to country, so that the other most important parameter is β, which controls mostly the maximum slope of the Gompertz function. Although negative GDP values are meaningless, the function is extended to negative values to prove the property stated above in a simpler way. The results of fits of the GDP per capita Gompertz functions are produced in Chapter 4 and shown again in Fig. 6.D4.

The income Gompertz PV ownership function is defined as:

$$I^* = \beta'^* I, \tag{6.3}$$
$$V'^*(I^*) = \gamma'^* \exp[-\alpha'^* \exp(-I^*)] \text{ for } I \geq 0,$$
$$V'^*(I^*) = 0 \text{ for } I^* < 0, \tag{6.4}$$

where I is the income in 2015$/yr/cap and I^* its dimensionless counterpart. The three parameters are positive by assumption; α'^* and γ'^* (as well as α and γ) are dimensionless while β'^* (as well as β) is measured in yr.cap/2015$. The $*$ superscript added to all quantities is a reminder that the function is defined on the scaled and dimensionless income I^*.

In principle, the country level number of PVs per capita follows by integrating V'^* over the income distribution g. It is shown in Appendix 6.D.4, that

$$V'^*\left(I^*_\infty(y)\right) \equiv \int_{-\infty}^{+\infty} V'^*(I^*, \alpha'^*, \beta'^*, \gamma'^*) g\left(I, \mu^*(y), \sigma^*(y)\right) dI \tag{6.5}$$

approximates rather well $V(y)$ for a realistic range of median income $M(y)$ with an appropriate choice of α'^*, β'^* and γ'^*, and conversely, at least when the σ^* parameter of the income distribution can be considered as constant. More precisely, the parameters of V'^* are found by minimizing $(V'^*(I^*_\infty) - V)^2$ (least square fit), so that these parameters depend on the GDP per capita y for a given $V(y)$ and $g(I, \mu^*(y), \sigma^*(y))$.

The quantity $I^*_\infty(y)$ (the notation is explained in Appendix 6.D) is an average value of I^*, whose existence is guaranteed by the mean value theorem. This is shown in a somewhat styl-

ized way in Appendix 6.D.4, and in a more precise and specific way in section 6.4.3 for some major countries, using the guidelines presented in the Appendix. The mean value theorem in integral form plays an instrumental role in this result, by providing a direct relation between the two types of Gompertz functions[4]. Consequently, Eq. (6.5) is the most central and important relation in the analysis presented in the present work.

6.4. Results

6.4.1. Country level fits of income distributions through log-normal distributions

The results of our log-normal fits to the World Bank PIP data on income distributions are illustrated here for typical major countries. More complete sets of fits are provided in our Supplementary Materials.

Country, in 2008	μ^*	σ^*	μ	σ	M	G
Brazil	7.8	0.96	3900	4800	2500	0.50
China (urban)	7.7	0.59	2600	1700	2200	0.33
China (rural)	6.1	0.65	560	400	450	0.35
Germany	9.7	0.52	18000	9900	16000	0.29
France	9.7	0.53	18000	10000	16000	0.29
India (urban, 2009)	5.9	0.62	440	305	361	0.34
India (rural, 2009)	5.4	0.45	230	110	201	0.25
Indonesia (urban)	6.3	0.61	670	450	550	0.33
Indonesia (rural)	5.8	0.49	390	200	340	0.27
Japan	9.4	0.62	14000	9700	12000	0.34
Mexico	7.5	0.85	2700	2800	1900	0.45
Russia	7.8	0.70	3000	2400	2300	0.38
United States	9.8	0.73	24000	20000	19000	0.39

Table 6.1: Results of the log-normal fit of the income distribution of 10 major countries. The various columns give, successively, the mean μ^* and dispersion σ^* of the distribution of J, the mean μ and dispersion σ of the distribution of I, the median income M and finally the Gini coefficient G. The results are given for the year 2008, except for India (2009)5. The quantities μ^*, σ^* and G are dimensionless and all other quantities are in 2015 constant $/yr/cap.

Table 6.1 gives the results of our fits for the mean and dispersion of the distribution of $J = \log(I/U_I)$

$$g^*(J) = \frac{1}{(2\pi)^{1/2}\sigma^*} \exp\left(-\frac{1}{2}\left(\frac{J-\mu^*}{\sigma^*}\right)^2\right). \tag{6.6}$$

Eq. (6.6) reproduces Eq. (6.B26). The other four quantities characterize the distribution g of

[4]This also implies that the converse is not true: even if $\int_{-\infty}^{+\infty} V'^*(I^*)g(I)dI$ were an exact Gompertz function of y, this would not necessarily imply that V'^* itself is necessarily a Gompertz function. This follows because the domain of use of $V(y)$ and $V'^*(I^*)$ is always bounded in practice, and from the theorem that any continuous, differentiable bounded function on a bounded domain can always be approximated to an arbitrary level of precision by a polynomial of high enough degree, which provides a counter-example to the idea that V'^* is necessarily a Gompertz function if its weighted integral is.

income I ($g(I) = g^*/I$, see Eq. (6.B27)): the mean and dispersion, Eqs. (6.B31) and (6.B32), the median M, Eq. (6.B28), and the Gini coefficient G, Eq. (6.B29). All quantities are given for 10 major countries representing 63% of the global 4W vehicles fleet in 2020, for the year 2008, except for India where 2009 is shown instead[5]. The rural and urban population results are given separately for China, India and Indonesia (see Appendix 6.B.2.3).

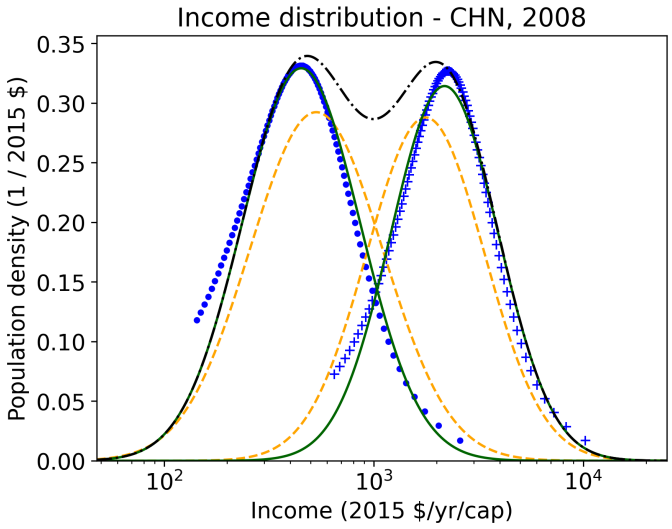


FIGURE 6.1: PIP data (blue points for the rural populations and blue crosses for the urban ones), log-normal distribution fits $g^*(J)$ (dark green plain line), and log-normal distribution deduced from the PIP database estimates of the mean and deviation of the distribution of $g^*(J)$ (orange dashed line), for China (year 2008). Both rural and urban sub-populations and their fits are shown, along with the overall distribution (weighted sum of the rural and urban distributions) for our fit only (black dashed-dotted line).

The resulting fitted distributions are represented on Figs. 6.1 and 6.2 for China and India for the parameters and year of Table 6.1 (both rural and urban subpopulations are shown). The fitted data points are also shown, along with the fit obtained from values of the distribution mean and dispersion provided by the PIP database. The next figure provides the same information for Brazil, Mexico, Germany and the United States (Figs 6.3 and 6.4). This set of figures is representative of all countries.

Several important features displayed on these figures are worth pointing out. First, the Chinese data points are very regular compared to other countries. This is because the data shown are not original data, but a Lorenz curve fit to the data (the original data is not available for China). This is discussed in detail in the "Grouped vs individual data" section of our Supplementary Materials.

The income of China exceeds the log-normal fit at low income for both the rural and urban sub-populations. The analysis in the "Grouped vs individual data" section of our Supplementary Materials indicates that this behavior is an artifact of the Lorenz curve fit just mentioned at low income. It is also shown in these Supplementary Materials that fitting a log-normal distribution on a Lorenz-curve produces very little difference with respect to a direct fit of a log-normal distribution on the original data; this analysis is performed on India, for which the original data is available, and the Lorenz curve fit of these original data can be made.

For all countries, our log-normal fits provide a better estimate of the income distribution of the various countries in the PIP database than the log-normal distribution deduced from the mean and dispersion of the distribution of J given in the database itself. This is rather

[5] There is no single year for which the PIP database provides data for all countries.

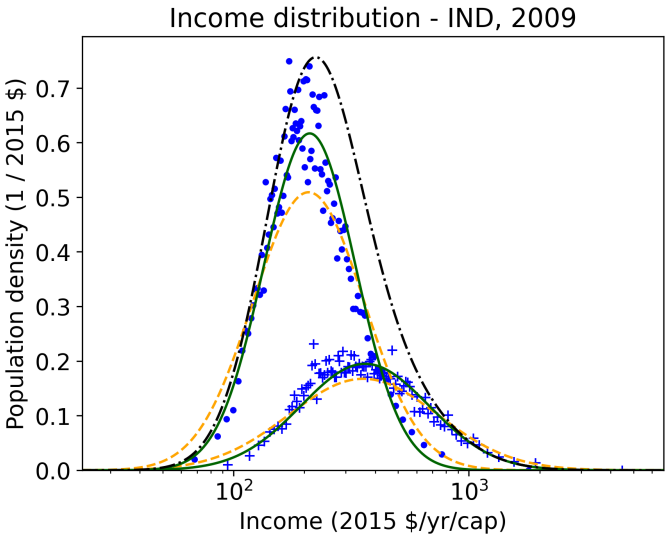


FIGURE 6.2: PIP data (blue points for the rural populations and blue crosses for the urban ones), log-normal distribution fits $g^*(J)$ (dark green plain line), and log-normal distribution deduced from the PIP database estimates of the mean and deviation of the distribution of $g^*(J)$ (orange dashed line), for India (year 2009). Both rural and urban sub-populations and their fits are shown, along with the overall distribution (weighted sum of the rural and urban distributions) for our fit only (black dashed-dotted line).

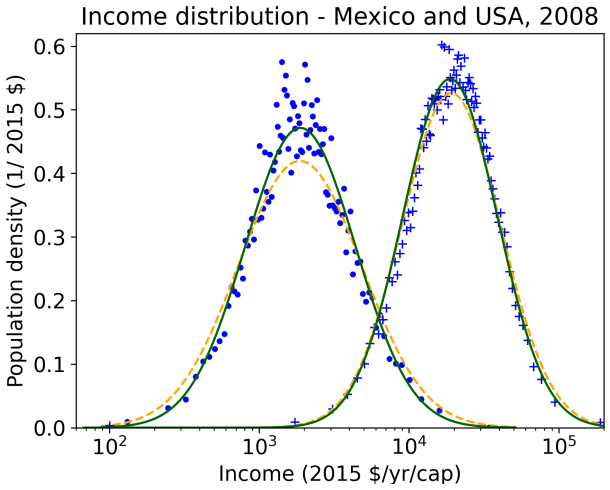


FIGURE 6.3: PIP data, log-normal distribution $g^*(J)$ fits (dark green plain line), and log-normal distribution deduced from the PIP database estimates of the mean and deviation of the distribution $g^*(J)$ (orange dashed line). Data for the year 2008, for Mexico (blue points) and the United states (blue crosses).

surprising, and possibly reflects the fact that these two quantities were not obtained through a fit in the PIP program, but directly in an approximate way from the data points themselves. In general, the value of the dispersion provided by the PIP database is systematically too large, leading to systematically too small maxima of the distribution. This effect being systematic, it may have had a systematic effect on the PV fleet model proposed in this paper. This fact is the main reason that prompted us to make our own log-normal fits of the distribution. Finally, the Chinese case displays yet another unusual feature: the PIP evaluation for the mean of J is substantially over-evaluated for the rural population and substantially under-evaluated for the urban one. No other country displays such a behavior. This was yet another reason to devise our own fits, considering the present and future weight of China in the world PV fleet.

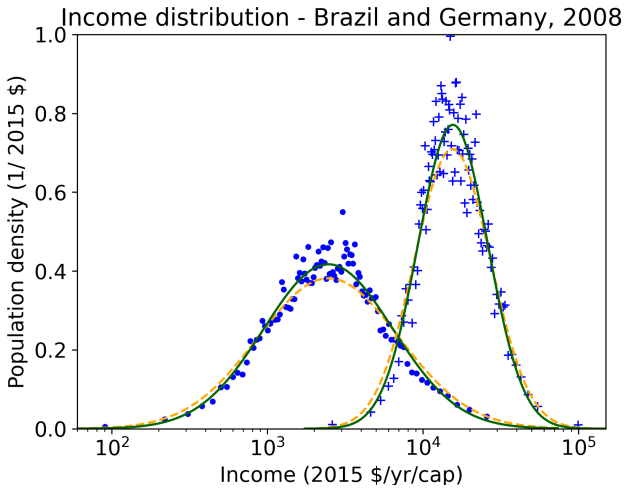


FIGURE 6.4: PIP data, log-normal distribution $g^*(J)$ fits (dark green plain line), and log-normal distribution deduced from the PIP database estimates of the mean and deviation of the distribution $g^*(J)$ (orange dashed line). Data for the year 2008, for Brazil (blue points) and Germany (blue crosses).

The fact that the few highest centiles of the income distribution should follow a power-law distribution instead of a log-normal one is usually not visible on our income distribution fits. The largest deviations occurs only for some years for India. For example, one can observe a slight difference between the fits and the data at large income, for India and China. This does not affect in any really noticeable way the final results on PV ownership as a function of income.

6.4.2. COUNTRY LEVEL INCOME DISTRIBUTION PROJECTIONS

Defining future projections of the distribution of income amounts to making projections of the two parameters of the log-normal distribution μ^* (directly related to the median income through Eq. 6.B28) and σ^* (directly related to the income dispersion through Eq. 6.B32). These projections are explained in detail in the following sections.

6.4.2.1. MEDIAN INCOME AS A FUNCTION OF GDP PER CAPITA

We base our modeling on historical observations of the evolution of the share of median income in GDP per capita as a function of GDP per capita (instead of a function of time) as this is the information needed for the PV ownership as a function of income modeling, see Appendix 6.D.4. Time projections are then be derived using our GDP and population projections.

Fig. 6.5 shows the historical data of median income shares in GDP per capita for a number of countries. The weighted average (weighted by the population) is computed and represented on the figure, as well as a fit to this weighted average, described below. In spite of the large variations exhibited between countries and with GDP per capita for a given country, this weighted average shows a trend that emerges not only collectively, but individually as well for the various countries, as shown more clearly in Appendix 6.C for China and India and in Supplementary Material for a selection of other countries. In particular, the share of median income in GDP per capita tends to converge at high GDP per capita toward the value found in rich countries, which are assumed to have reached a stable economic state.

This idealized trend is therefore assumed for future projections, namely that, generally speaking, the median income share in GDP per capita for each country follows a logistic decline to-

ward a stable middle value, and then a logistical growth toward 0.4. For example, the Chinese and Indian median income shares show a logistic (S-shaped) decline from 1980 to a minimum value in 2010 (see Appendix 6.D.4). This assumption reflects a Business As Usual (BAU) trajectory.

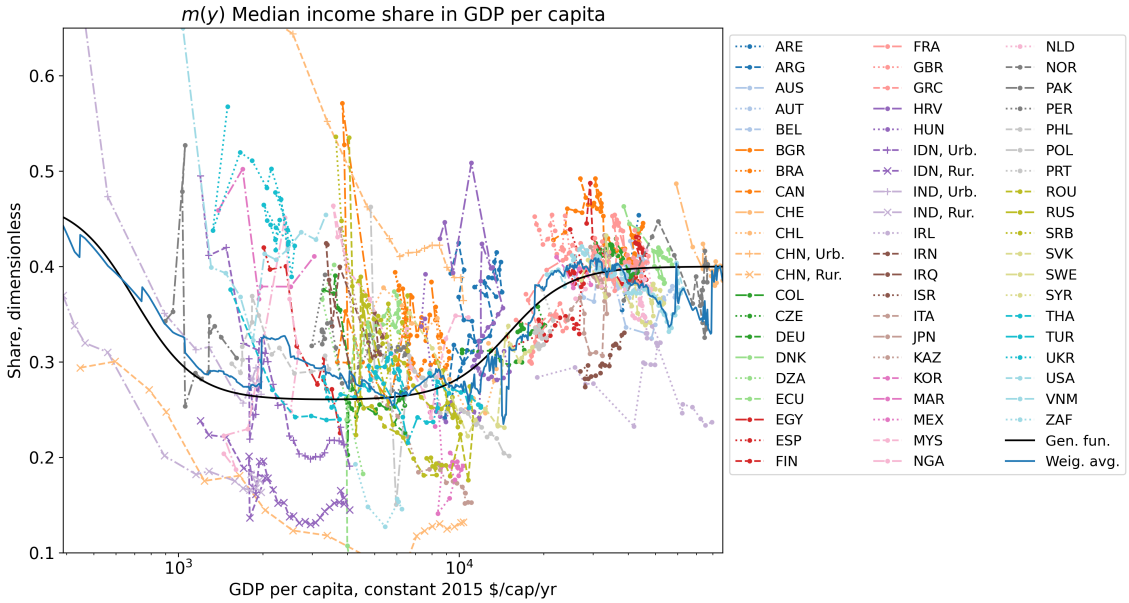


FIGURE 6.5: Median income share in GDP per capita as a function of GDP per capita. Historical data for all modeled countries, labeled by their alpha-3 country code. The weighted average of all data and its functional fit are also shown. Although the figure is rather crowded, individual countries display trends similar to the weighted average.

This leads us, for any country c, to model the median income share $m^c(y)$ in the country's GDP per capita (y) in the following way:

$$\begin{aligned} m^c(y) = L_l^c \\ - \frac{L_l^c - L_m^c}{1 + \exp\left[-k^c U_y \left(\log(y/U_y) - \log(y_{0,l}^c/U_y)\right)\right]} \\ + \frac{L_r^c - L_m^c}{1 + \exp\left[-k^c U_y \left(\log(y/U_y) - \log(y_{0,r}^c/U_y)\right)\right]} \end{aligned} \tag{6.7}$$

where y denote GDP per capita. L_l^c, L_m^c and L_r^c (dimensionless) represent the value of past (left), intermediate (middle) and future (right) saturation values. $y_{0,l}^c$ and $y_{0,r}^c$ (constant 2015$ per capita) are the past and future x-axis values of logistic inflection points. k^c (1/constant 2015$ per capita) is the slope of the logistic functions. The logarithm of the GDP per capita values is used as we describe the logistic function in a logarithmic scale on the horizontal axis (see figure 6.5). U_y is the unit of GDP per capita (1 2015$/cap/yr). Note that the exact shape of the function used for extrapolation (here, a logistic function) does not matter much, what matters most are the asymptotic levels in GDP per capita.

The weighted average over all countries of the median income share is fitted by the same formula, with parameters L_l^{gen}, L_m^{gen}, $y_{0,l}^{gen}$, $y_{0,r}^{gen}$ and k^{gen}. Appendix 6.C.1.1 presents a table with the fitted parameters for 10 major countries.

In practice, the GDP per capita y and median income m for a country c are given by

$$y = \frac{Y^c_{R,\$}(t, t_0)}{P^c_t(t)}, \tag{6.8}$$

$$m^c(y) = \frac{M^c_{R,\$}(t, t_0)}{y}. \tag{6.9}$$

where the country's GDP Y^c is given in inflation corrected dollars (subscripts R and \$) at time t, t_0 being the reference year for deflation; P^c_t stands for the country's population at time t.

The income distribution in China and India is divided between urban and rural populations. The median income share in GDP per capita of these sub-populations in the same way, by first computing the population weighted average of their respective median incomes to obtain the country's median income:

$$M^c_{R,\$}(t, t_0) = \frac{\left[M^{c,u}_{R,\$}(t, t_0)P^{c,u}_t(t) + M^{c,r}_{R,\$}(t, t_0)P^{c,r}_t(t)\right]}{P^c_t(t)}, \tag{6.10}$$

which is then divided by y to obtain the median income share.

In some rich countries, the median income share in GDP per capita is modeled by a constant as this represents quite well the historical data over the relevant range of GDP per capita.

In other countries, L^c_l, $y^c_{0,l}$, L^c_m and $y^c_{0,r}$ are obtained by iterative adjustments to find a plausible fit to historical data make plausible projections. However, the data do not provide clear insights in the past or future behavior for a number of countries. In this case, the information from the general function are adapted to the country for completing the fit.

The uncertainty in the projection of median income share to 2050 appears to be negligible for all countries except China and India as only limited growth in GDP per capita is expected for most countries. This allows to compute the evolution of median income M itself, as shown on Fig. 6.6 for major countries.

6.4.2.2. Income dispersion as a function of GDP per capita

The standard deviation σ^* of the log-normal income distribution of any country is a measure of income inequalities and is in fact directly connected to the country's Gini coefficient [see Eq. (6.B29)]. The literature does not provide a clear view on the main drivers of this coefficient evolution, nor on its likely future evolution. In addition, historical data do not show a general trend in the evolution of σ^*.

At this point, it is of interest to know whether this evolution is driven by uncertainties in the income distribution measurement collected by the World Bank PIP program or reflect a real evolution, as this parameter variation has a noticeable influence on the quality of the main results of this work. This question is directly connected the robustness of the Gini coefficient itself. The income percentiles provided by the World Bank are collected by national statistical institutions. This makes it impossible to estimate the global measurement uncertainties as this could only be done (with substantial work) for some countries. However, it is possible to make some observations. First, the variation in income data between one point and the following as shown on Figs. 6.1, 6.2, 6.3 and 6.4, although non negligible, is limited enough to ensure some level of the robustness of the data. Second, if Cowell and Flachaire (2007) conclude that inequality measures can be strongly influenced by outliers in the high income tail (although this is less the case for the Gini coefficient), we also observe fairly smooth data for higher in-

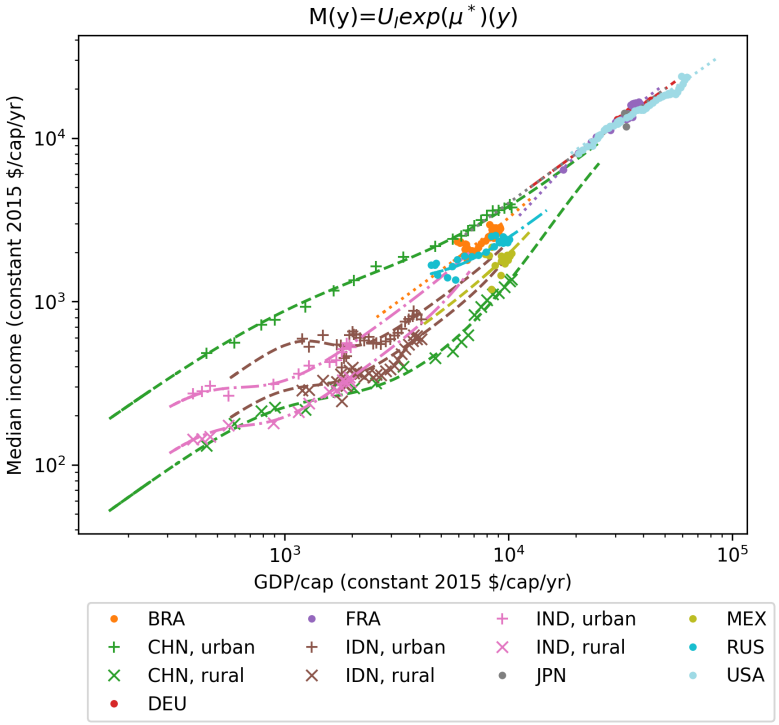


FIGURE 6.6: Median income $M(y)$ (2015$/yr/cap) as a function of GDP/cap for 10 major countries. Points represent data and lines represent our fits and projections from 1960 to 2050. Countries are labeled by their alpha-3 codes

come points allowing us to observe in some case their power-law nature. Third, if income data are measured from both income and consumption metrics, Alvaredo and Gasparini (2015) observe that on average the Gini coefficient is 15% smaller for consumption data. Smeeding and Latner (2015) also find a 10% difference between multiple measures of the Gini coefficient in the United States, although the trend of the measures are consistent over time between different series. Fourth, the $\sigma^*(y)$ variability between successive points (shown in Fig. 6.7) is generally small compared to the trend observed.

We therefore conclude that the general observed trends for $\sigma^*(y)$ most likely reflect real phenomena rather than uncertainties and errors in the income distribution.

A logistic function has again been chosen to represent σ^* as some countries' data seem to show temporary increase or decrease surrounded by stable values:

$$\sigma^*(y) = L_{\sigma^*,l} + \frac{L_{\sigma^*,r} - L_{\sigma^*,l}}{1 + exp(-k_{\sigma^*}(y - y_{0,\sigma^*}))}, \tag{6.11}$$

with $L_{\sigma^*,l}$ and $L_{\sigma^*,r}$ left and right constants, k_{σ^*} the slope and y_{0,σ^*} the GDP/cap inflection point. $\sigma^*(y)$ is modeled as a constant value for some countries where we do not observe a clear trend. When the last data do not depict a clear trend we assume that it will tend towards values between 0.4 and 0.6 as it seems to be the general trend (see Fig. 6.7).

This modeling is sufficient to capture the trends observed in all countries. The $\sigma^*(y)$ data are displayed on Fig. 6.7 as a function of GDP/cap and the projections are available in Supplementary Materials. The logistic parameter fits of 10 major countries are summarized in Table 6.C2.

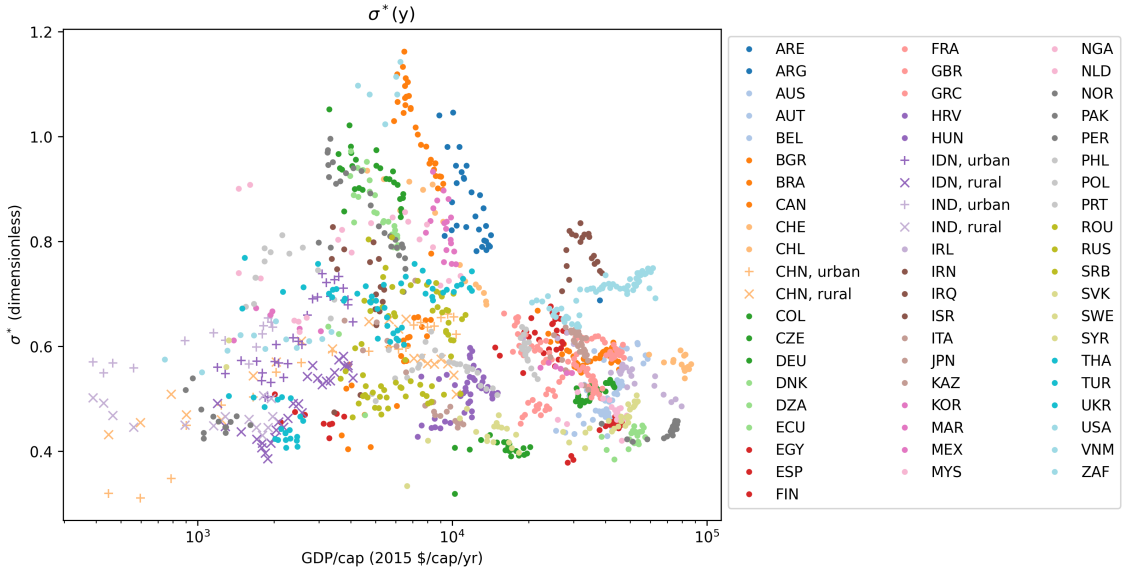


FIGURE 6.7: σ^* (dimensionless) historical data for all 58 countries as a function of GDP/cap. Countries are labeled by their alpha-3 codes.

6.4.3. COUNTRY LEVEL GOMPERTZ DISTRIBUTIONS OF AVERAGE NUMBER OF PVS PER CAPITA AS A FUNCTION OF INCOME

PV ownership as a function of income $V'^*(I^*)$ found from the fit of $V'^*(I^*_\infty(y))$ on $V(y)$ through Eq. (6.5) are shown on Fig. 6.8 for countries representing 80% of the 4W vehicle fleet in 2020.

It is useful to know the income range over which information about $V'^*(I)$ is required to perform these fits. Since $g^*(J, \mu^*, \sigma^*)$ follows a normal distribution, we know that 95% of the income distribution is contained in the $[\mu^* - 2\sigma^*, \mu^* + 2\sigma^*]$ range. Given Eq. (6.B28), the upper bound of the prediction interval of the log-normal distribution would be $M\exp(2\sigma^*)$. In all our data, we note that $\sigma^* \leq 1.1 = \sigma^*_{max}$ and $M \leq 0.4y$. We then have, for a given country:

$$I^c_{max} = 0.4y^c_{max}\exp(2\sigma^{*c}_{max}) \tag{6.12}$$

$$\lesssim 3.6y^c_{max} < 4y^c_{max}, \tag{6.13}$$

where I^c_{max} is the maximum income bound we are looking for. This value is rounded to $4y^c_{max}$ for simplicity.

The associated fits of PV ownership as a function of GDP per capita $V(y)$ are quite good for most countries, but there are some exceptions, e.g., Brazil and Mexico which are part of the 10 major countries. For these two countries, σ^* decreases sharply over a small range of GDP per capita. This produces a flattening of the fitted $V'^*(I^*_\infty(y))$ curve. More precisely, σ^* decreases in the 6000—10000 GDP/cap range for Brazil, and in the 8000—10000 GDP/cap range for Mexico (GDP/cap in 2015$/cap/yr). As σ^* falls, the standard deviation $\sigma \simeq [\exp(\sigma^{*2}) - 1]^{1/2}\exp(\mu^*)U_I$ [Eq. (6.B32)] decreases. This makes the income distribution $g(I)$ sharper, resulting in a reduction in the number of very poor and very rich people in the distribution. Since PV ownership is lower for the poor than for the rich ($V'^*(I)$ is strictly increasing), the reduction of σ^* leads to a reduction of the overall PV ownership if μ^* is kept constant since the

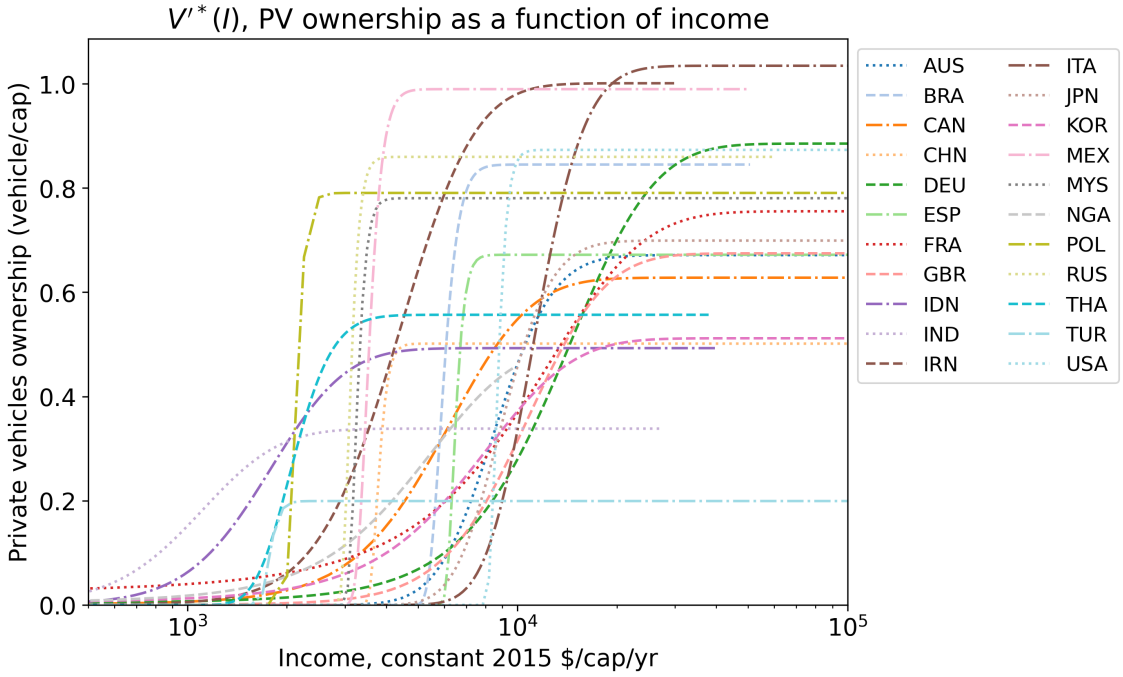


FIGURE 6.8: $V'^*(I)$ Private vehicle (PV) ownership as a function of income for some important countries that represent together 80% of the 4W vehicles stock in 2020. Countries are labeled by their alpha-3 code.

inflection point of $V'^*(I)$ is found after the maximum of $g(I)$ in these countries. This effect is particularly important for Brazil and Mexico where σ^* is higher than for other countries. Still, this phenomenon is also observed in other countries but is always less significant than in Brazil and Mexico[6].

This type of problem, leading to a less satisfactory fit of $V(y)$, happens only for some countries which represent only a small fraction of the world PV fleet (i.e., Brazil and Mexico account for about 6% of the world's PV stock, and the modeling error in the fit will amount to a fraction of this figure). Most countries are well fitted, which strengthens our argument for a simple Gompertz function choice to represent PV ownership as a function of income.

It has been necessary in 9 countries over 58 to constrain the γ'^* saturation parameters as it reaches levels that seem unrealistic (above 2 PVs per capita). In such cases, γ'^* have been set individually between 0.5 and 1.0 (high but not unrealistic).

The results of the parameter fits for 10 major countries are shown in Table 6.2. Our results are consistent with the data from Berrill et al. (2024).

There are very few countries collecting data on vehicle ownership by income quantiles, and among these, only in the case of France can a meaningful comparison between our results and available data be performed. This comparison is made in Appendix 6.A, and turns out to be satisfactory.

[6] In fact, Kazakhstan's fit is worse. This could be due to the really low values of its median income share in GDP per capita ($m(y)$).

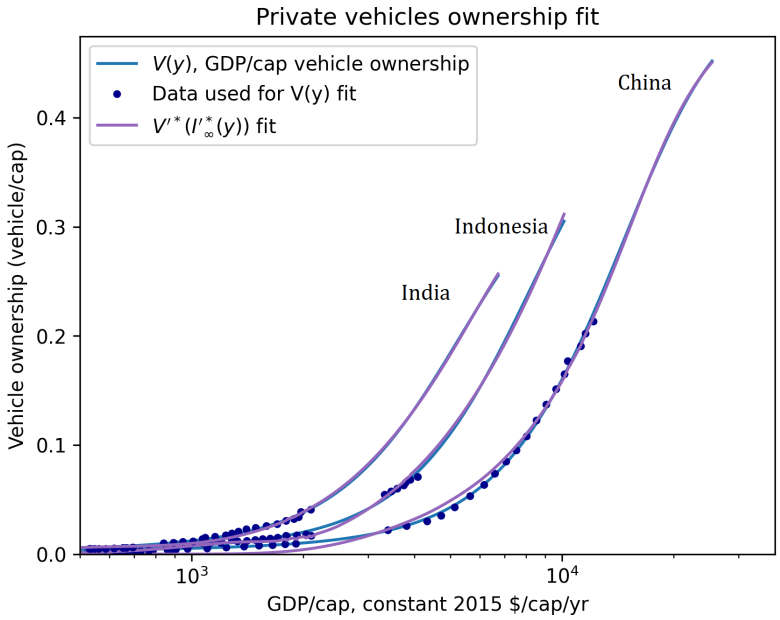


FIGURE 6.9: The $V'^*(I^*_\infty(y))$ fit (violet line) to the GDP/cap Gompertz $V(y)$ (blue line) for China, Indonesia and India, representative of Asian countries. The curves extend to the maximum projected GDP/cap in 2050. The blue points represent the data used to find $V(y)$ in Chapter 4.

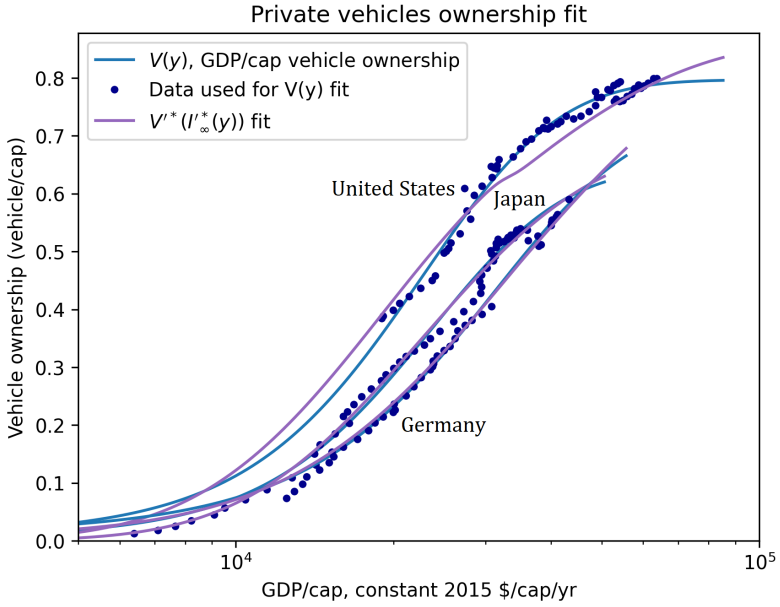


FIGURE 6.10: The $V'^*(I^*_\infty(y))$ fit (violet line) to the GDP/cap Gompertz $V(y)$ (blue line) for Germany, Japan and the United States, representative of rich countries. The curves extend to the maximum projected GDP/cap in 2050. The blue points represent the data used to find $V(y)$ Chapter 4.

Country	α'^*	β'^*	γ'^*	γ
Brazil	1e10	3.6e-3	1.0	0.80
China	1.2e5	3.0e-3	0.60	0.60
France	5.0	2.0e-4	0.84	0.73
Germany	5.8	1.6e-4	0.92	0.77
India	8.6	2.6e-3	0.24	0.25
Italy	44	3.7e-4	1.12	0.93
Japan	58	5.0e-4	0.79	0.73
Mexico	1e10	6.9e-3	1.0	0.75
Russia	1e10	7.5e-3	0.86	0.80
United Kingdom	9.1	2.5e-4	0.73	0.65
United States	1e10	2.8e-3	0.91	0.85

TABLE 6.2: Parameters for the Gompertz function modeling PV ownership as a function of income $V'^*(I) = \gamma'^* \exp(-\alpha'^* \exp(-\beta'^* I))$. The last parameter ($\gamma$) is the saturation parameter of $V(y)$, and is taken from Chapter 4.

6.5. Discussion

6.5.1. Step-function vs gradual change

Private vehicle ownership as a function of income is almost a step function for some countries. Storchmann (2005) already suggested this modeling.

We can distinguish three main cases in which this phenomenon occurs.

First, a major observation is that all countries (except Chile) in which a high and more or less steeply declining value of σ^* is observed depict a step-function form in their $V'^*(I)$: Argentina, Brazil, Colombia, Ecuador, Greece, Israel, Kazakhstan, Malaysia, Mexico, Peru, Portugal, Russia, South Africa. This is often concomitant with the fast increase of the median income in the associated periods. Moreover, $V(y)$ is generally quite steep in these countries. In fact, the decline of σ^* induces changes in the income distributions that result in a non-linear behavior of $V'^*\left(I_\infty(y)\right) = \int_{-\infty}^{+\infty} V'^*(I) g(I) dI$, often seen as a temporary reduction in the slope of $V'^*\left(I_\infty(y)\right)$, in the zone of GDP per capita where σ^* decreases. A gradual $V'^*(I)$ instead of a step-function one would then result in a bad fit of $V'^*\left(I_\infty(y)\right)$. Indeed, in some cases, we tested that choosing a non step function form of $V'^*(I)$ would even result in temporary decreases of $V'^*\left(I_\infty(y)\right) = \int_{-\infty}^{+\infty} V'^*(I) g(I) dI$ in the zone where σ^* decreases. If the majority of countries exhibiting a vertical step-function form of $V'^*(I)$ fall into this case of high and declining σ^*, China and United States do not.

Second, in the case of the United States, having a car has become almost indispensable, and it is an expensive good that is difficult to find at low prices, even second-hand (bearing in mind that a low second-hand purchase price will very likely result in higher maintenance and repair costs). For example, data from the Bureau of Transportation Statistics[7] tells us that the poorest households in the United States spend a considerably higher proportion of their budget on PVs than they do in other regions of the world (Gandelman et al. 2019a; Valenzuela-Levi 2021; Mainaud 2021).

It has also to be noted that the United States is the first country in time in which vehicle

[7] Available at `https://www.bts.gov/data-spotlight/household-cost-transportation-it-affordable`

ownership increased, reaching 0.5 4W/cap in 1970 while it was only 0.4 in Australia, 0.3 in France and 0.25 in the United Kingdom (the three next countries with a mature fleet). This is important as the price of cars, corrected by inflation, have decreased by 32% in 15 years between 1960 and 1975, and another 35% over the much longer 50 years period between 1975 and 2024[8]. Assuming that this reflects technological progresses in the automobile industry, this decrease in the prices of vehicles would then tend to make cars more affordable, changing in time the behavior of people with respect to vehicle ownership, thus on $V'^*(I)$.

Third, in the case of China, two phenomena may be at play at the same time. First, Huo and Wang (2012) documented that this $V'^*(I)$ evolved in China between 2004 and 2009, probably due to the fast progress in the Chinese automobile industry and the economic fast development of China. However, more importantly, our modeling of the income distribution of China sum the income distribution of two populations: the urban and the rural one. This translates into a distribution with two distinct peaks until 2012; which is not the case for India and Indonesia for which income distribution is also split between urban and rural areas. In addition, 1) the median income increased faster in the rural population than in the urban one (partially bridging the gap between the two), 2) the share of the rural population decreased from 80% in 1980 to 40% in 2020, and 3) the need of cars in the two populations is not the same. This can lead to strange effects in the computation of $V'^*\left(I_\infty(y)\right)$. Ideally, the PV ownership for urban and rural populations would be modeled individually, however there are no data on the disaggregation of the PV stock between the two populations. The $V'^*\left(I_\infty(y)\right)$ fit on $V(y)$ for China is still very good.

In the end, the errors induced by the modeling of these step-function form of the PV ownership as a function of income $V'^*(I)$ may be limited as the other countries concerned do not represent a big part of the global PV fleet. The same remark applies to limiting the α^* value for these countries.

6.5.2. Modeling uncertainties

The uncertainties surrounding the modeling of the income distribution $[g^c\left(I, \mu^{*c}(y), \sigma^{*c}(y)\right)$ where c stands for the country] are concentrated in the modeling of the parameters $\mu^{*c}(y)$ (mean of the distribution) and $\sigma^{*c}(y))$ (dispersion of the distribution). In terms of $m^c(y)$ (median income fraction of GDP per capita, an essential quantity to determine μ^{*c}), the uncertainty seems to be concentrated mainly in the projections of China and India[9]. Indeed, the projections for the other countries up to 2050 show a relatively weak evolution of this parameter (see Supplementary Material). Similarly, all the Western countries display a small and slow temporal and spatial variation. China and India — for which modeling the PV stock is critical because of their large population of growing affluence — have seen fairly sharp falls in their median income share in GDP per capita up to 2010 (which does not necessarily imply a fall in median income itself). Subsequently, their GDP per capita is set to rise and converge to the developed country saturation level, leading to a related increase of $m^c(y)$ for these countries of $\sim 30\%$, on a somewhat uncertain time scale. This has a strong impact on median income itself [from Eq. (6.B28)], and therefore on the product $V'^{*c}(I)g^c(I)$ for these countries [an instrumental quantity in our fits, through Eq. (6.5)] from which a strong increase in the number of PVs per capita is expected. Because of this, we may need to revise this assumption if countries

[8] This is computed from the Consumer Price Index of new vehicles found in US BLS 2024 and the GDP deflator found in World Bank 2024b.

[9] Poland as well, but this country's PV fleet represents less than 2% of the global fleet in 2020 so the consequences of this uncertainty are limited.

like China and India find themselves unable to escape the so-called "middle-income trap" in the near- to mid-term.

6.5.3. Time dependence

Our modeling strategy assumes that the number of PV per capita as a function of income, V'^{*c}, is not explicitly time-dependent, so that in Eq. (6.5), the only time dependence comes from y through $\mu^*(y)$ and $\sigma^*(y)$ (the parameters of the income distribution). This is a strong assumption that does require some discussion, although a full analysis of the conditions of validity of this assumption lies well beyond the scope of the present paper.

The fact that most countries Gompertz functions of GDP per capita, $V(y)$ are rather precisely accounted for in this way is at least consistent with this assumption. However, the fits of a number countries (like Brazil and Mexico, see Supplementary Materials) suggest that this may not be universally true, as pointed out in section 6.5.1.

It is worth noting at this point that one can *always* find a time-independent function $V'^*(I^*)$ such that $V'^*(I^*_\infty(y)) = V(y)$ *exactly*, but this function is no longer necessarily a Gompertz function. This approach was in fact followed by Lescaroux (2010). However, by proceeding in this way, one foregoes all possibilities to identify a potential time evolution of V'^*: any such evolution has been absorbed in the shape of the (time-independent) function V'^* determined in this way. This is an unavoidable artifact of the method.

Conversely, as there is at least some evidence for some countries that V'^* is indeed a Gompertz function of income, it is then natural to assume that this functional dependence may be of a general nature and that any poor fit of $V(y)$ from V'^* arises because of the neglected time dependence of V'^*. There is no clear reason why the fast decrease of σ^* with y for some countries (like Brazil and Mexico) — for GDP per capita in the 7000 — 10000 2015$/yr range — causes a time dependence of V'^* (and conversely), but both changes may be due to a common underlying cause (probably linked to the rapid growth in GDP per capita in these periods). Indeed, these two quantities merely reflect in an aggregated way at the "macro" level underlying socioeconomic phenomena at the "micro" level (which may themselves have macroeconomic determinants, or not). A well-known such underlying phenomenon is the population density, which has some influence on the saturation level of $V(y)$ and therefore on the saturation level of V'^* itself as $\gamma'^* \propto c$.

It is difficult to pinpoint what may be at work here without investigating in some detail the micro- and macroeconomics changes of these countries in the time range corresponding to the drop in σ^*. Such a time-consuming investigation lies well outside the scope of the present work.

6.5.4. Potential uses

The reader has most probably noticed that Eq. (6.5) makes the description of PV ownership in terms of income or of GDP per capita more or less equivalent, once the distribution of income is known. The natural question arising from this remark is what is gained in the somewhat involved procedure developed in this work to obtain PV ownership as a function of income.

In our view, the most prominent usefulness of this type of characterization of PV ownership is to study the maximum possible level of substitution of electric vehicles to thermal engine ones, under the constraint of owners' income. Indeed, electric private vehicles, at the present time, are 10 to 80% more onerous than their thermal engine equivalent (IEA, 2024d). Electric PVs' batteries represent most of the production costs and selling prices of these vehicles; there

is a clear trend to decreasing prices, but also some uncertainty as to the final stage of this tendency. The lifetime of these batteries is also uncertain, and this has a critical incidence on the conditions of penetration of electric PVs in the (huge) second-hand PV market. The present growing tendency of vehicle manufacturers to lease their products instead of selling them does not change these basic remarks.

In order to study these issues, one needs to first distinguish new and used PVs at the level of the different country fleets and develop a model of substitution of thermal engine vehicles by electric ones. In such a model, the income distribution of owners has a direct effect on the budget they allocate to transportation and PV ownership. This makes an understanding of PV ownership as a function of income a necessary first step. We intend to present such a model in a future work.

6.6. Conclusion

It is probably useful to summarize first the key points of the method developed and the results obtained in this work.

- The most instrumentral result is that the number of PVs per capita as a function of income $V'^*(I)$ is related to the more common Gompertz function of the number of PVs per capita as a function of GDP per capita, $V(y)$, through Eq. (6.5) and through the distribution of incomes $g(I)$, with the help of the minimization of $(V'^* - V)^2$. More precisely, $V'^*(I)g(I)$ represents the distribution of the number of PVs as a function of income.

- Our first task was then to model the distribution of incomes $g(I)$. We have used a log-normal distribution for which we modeled the future evolution of its parameters $\mu^*(y)$ (mean) and $\sigma^*(y)$ (dispersion). We have shown that the uncertainties and approximations of the log-normal distribution are suitable for our modeling, whatever the form of the data provided by the World Bank through its PIP program.

- The function V'^* itself is assumed to be time independent (see our discussion section on this point). Time evolution is captured in our model through the time dependence of the GDP per capita y at the country level, and through the dependence of the parameters of the distribution of income (μ^* and σ^*) on y. We have produced future projections of y in Chapter 4, and μ^* and σ^* in the present work, up to 2050.

- The results have been produced for 58 countries representing approximately 94% of the world PV fleet in 2020. For this work, we have needed various currency unit conversions of the World Bank data; the underlying method (which is not straightforward!) are provided in one of our Supplementary Materials, along with the most involved part of the description of the reconstruction of income distribution for some countries.

We have adopted a modeling strategy of intermediate complexity with respect to causal determinants of PV fleets evolution. In particular, only income and its evolution is taken into account in detail. This follows from the necessary compromise between the level of disaggregation of a model and its expected precision. Including more and more causal determinants requires more data, and the conceptual precision gained may be lost due to data scarcity or lack

of data quality. It is of course difficult to anticipate what the best option is, without developing an array of models of varying levels of disaggregation with respect to these causal determinants.

Our modeling choice here has been guided by an economy principle: we chose to include the smallest level of disaggregation compatible with our objectives. Another potential benefit is that this leads to models that are possibly more easily grasped, and whose relevance and robustness are also possibly more easily established or at least argued. In this respect, a Gompertz model is a well-known tool of the trade. We expect that showing this can as well be applied to PV ownership as a function of income, and not only of GDP per capita, as we did in this work, will increase the usefulness of such relatively simple and easy-to-use models.

Appendices to chapter 6

6.A. Comparison of the model results with vehicle ownership in income deciles for France

SDES (2024) provides data of the total stock of "cars" in France distributed in income deciles at 01/01/2023. This data are rare in countries, their simple existence is a sufficient argument for comparing these data with the results of the present study.

Fig. 6.A1 shows the comparison between the data of the vehicle ownership as a function of the average income of each decile and our modeling.

This figure mainly indicates that our model probably underestimates slightly the vehicle ownership in the first (poorer) deciles of income and overestimates it in the last (richer) deciles. That may be due to the importance of having a car in countries like France, that encourage lower income household to own a car anyhow, leading the curve to drift from a Gompertz curve at the beginning. We can reasonably think that this is also the case in other countries, at least in western ones in which urban planning has evolved around the widespread accessibility of cars.

The shift between the value of the inflection point derived from our model and from the data are fair as the model assume a unique $V'^*(I)$ function over time. Moreover, no real data are available for modeling the income distribution in 2023 which makes the correction of the income data in order to compare them with the model imperfect.

To further this discussion, we provide some methodological information on the construction of this figure. While vehicle ownership is a direct consequence from the data on vehicle stock from SDES (2024) divided by population in 2023, split in income deciles and average income data are retrieved from the PIP percentiles data of 2019. The mean value between the fifth and sixth percentile of each decile of the PIP data are used to define the average income in the decile. The French national statistics institute (INSEE) provides data on the standard of living ("*niveau de vie*") in constant euros 2022, but not directly on income data on their site (although these must be collected as well); hence our reliance on the World Bank PIP data, as for all other countries in this work.

The difference in the reference year of the vehicle stock data and the PIP percentile data is assumed to have little influence, as the GDP per capita did not evolve between 2019 and 2023 in France (+1%) and as $m(y)$ and σ^* are not assumed to change in our modeling in 2023 compared to 2019 in France. However, our modeling overestimates μ^* by 10% compared to real data between 2012 and 2019. As the evolution in $m(y)$ is slow, we assumed that this $\sim$10% error holds in 2023. Consequently, the income associated with the vehicle ownership data have been

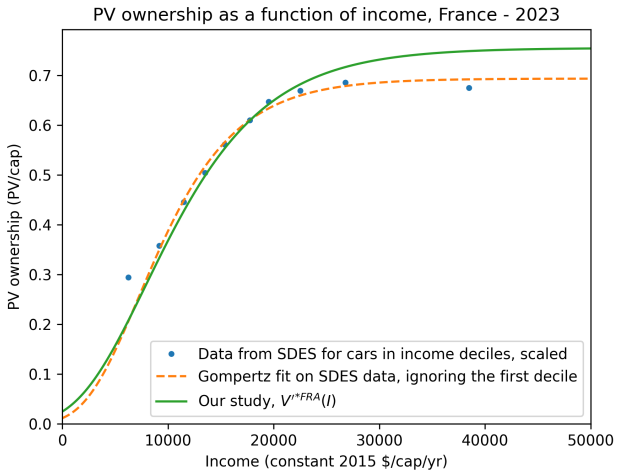


FIGURE 6.A1: Comparison between data of the car ownership as a function of income deciles in France in 2023 against our computation of the PV ownership as a function of income $V'^{*,FRA}(I)$. The SDES car ownership data have been scaled in order to match the total number of PVs.

reduced by 10% in this figure.

Finally, the vehicle stock of SDES (2024) refers to cars while we model private vehicles (PV) which encompasses cars and private light trucks. In 2023, our modeling of PVs is 6% higher than the number of cars given by the SDES. Consequently, the data of figure 6.A1 have been scaled in order to match the total sum of vehicles, allowing for an easier comparison between the curves.

Data from Fevang et al. (2021) for Norway could in principle also have been used for comparison purposes. However, the data o vehicle ownership as a function of GDP are noisy and cover a limited range of GDP per capita, so that the fit is poor, and, consequently $V'^{*NOR}(I)$ is not highly reliable.

6.B. INCOME DISTRIBUTION DATA AND FIT METHOD

6.B.1. INTRODUCTION AND NOTATIONS

6.B.1.1. DISCRETE QUANTITIES

The World Bank PIP database gives "welfare" distributions in deciles and centiles for a large number of countries and years (see section "GDP and income distribution conversion methods" of Supplementary Materials) For all practical purposes, this welfare data is in fact a direct or indirect measure of actual income (see footnote 1) and here, the term income will be used instead, keeping in mind that the error induced in the determination of actual income may not be negligible.

The problem therefore boils down to computing the best fitting log-normal probability density function (PDF) to these underlying distributions. In the remainder of this Appendix, we describe in somewhat more detail the information provided by the PIP database and the method used to provide log-normal fits to the distributions.

More precisely, the World Bank PIP database for the 2017 benchmark year (used in this

work) gives the following relevant information (not in the order of the columns in the data files):

- Country (index c), year (variable t) and type of survey (income, or consumption from which income can be reconstructed). The term welfare is used instead of income in the PIP program, as a reminder of the fact that the survey data are of different types.
- For each centile (k =1 to $k_m = 100$):
  - The average income $\bar{\zeta}_k^c(t)$ per person and per day in 2017 constant PPP dollar; c is the country, and t the year.
  - The maximum income $\zeta_k^c(t)$ per person and per day in 2017 constant PPP dollar.
  - The share of income $\iota_k^c(t)$ in the centile. The cumulative sum is equal to unity up to a negligible error: $\sum_k \iota_k^c(t) = 1$.
  - The share of the population $\varpi_k^c(t)$ in each centile. This is equal to 1% up to a small and negligible error. The cumulative sum is equal to unity up to this error: $\sum_k \varpi_k^c(t) = 1$.

It is also convenient to define here the lowest income limit[10] $\zeta_0^c(t)$. This quantity is not provided by the PIP database, but can be identified with the value of ζ symmetrical to ζ_1 with respect to $\bar{\zeta}_1$:

$$\zeta_0^c(t) = \bar{\zeta}_1 - (\zeta_1 - \bar{\zeta}_1) = 2\bar{\zeta}_1 - \zeta_1. \tag{6.B1}$$

These definitions and data do not quite correspond to the usual definition of quantiles, but this is unimportant for our purposes. Also, the data we actually use are not income in 2017 PPP dollars per capita per day, but incomes in 2015 non-PPP dollars per capita per year. The method of conversion is exposed in section "GDP and income distribution conversion methods" of Supplementary Materials. From now on, we use this converted form of the income centile distribution, expressed in constant 2015 dollars per year (instead of per day). In the notations of section "GDP and income distribution conversion methods" of Supplementary Materials , $\bar{\zeta}^c(t) = I_{R,\$}^{c,p}(t, t_1)$. Similarly, in what follows, the converted income $I_{R,\$}^c(t, t_0)$ is denoted $\bar{I}_k$. The various indices have been dropped to simplify notations, and instead we introduced the centile index. The reference and current years are also dropped from our notations, but there should be no confusion due to the two different notations introduced for pre- and post-conversion income and to the fact that this Appendix discusses a single year of data for a given but unspecified country. These indices can be restored if needed.

We define a unique conversion factor

$$\kappa = \gamma \frac{\bar{d}_{PIP}^c(t, t_1)\bar{k}_{PIP}^c(t_1)}{d^c(t, t_0)e_{LCU}(t_0)}, \tag{6.B2}$$

where $t_1 = 2017$ and $t_0 = 2015$, and using the notations of section "GDP and income distribution conversion methods". Note that κ is dimensionless.

From now on, the country index c is dropped. With the preceding definition, the average and maximum annual income per centile $\bar{I}_k$ and the income centile boundaries[11] I_k (in 2015 \$)

[10] Lower bound in income of the first centile, which is not zero.

[11] These are the maximum income of any centile, completed by the lowest income limit defined above.

are given by

$$\bar{I}_k = \kappa\bar{\zeta}_k, \tag{6.B3}$$

$$I_k = \kappa\zeta_k. \tag{6.B4}$$

The index k runs from 0 to 100 for I_k and from 1 to 100 for $\bar{I}_k$.

Similarly, the population in each centile k and the cumulative population up to centile k are given by

$$p_k = P_t \times \varpi_k \simeq \frac{P_t}{100}. \tag{6.B5}$$

$$P_k = \sum_{n=1}^{k} p_n. \tag{6.B6}$$

where P_t is the total population.

One may also estimate the total income I_t. One may expect that $I_t = \sum_{n=1}^{k_m} \bar{I}_n p_n$. If the total income is not known, this may be used as an estimate. One may also expect $\iota_k \simeq \bar{I}_k p_k / I_t$. Finally, defining the mean income $\langle I \rangle = I_t / P_t$, one also has

$$\iota_k = \frac{\bar{I}_k \varpi_k}{\langle I \rangle}. \tag{6.B7}$$

One may also introduce the cumulative population share Π and cumulative income share L_k:

$$\Pi_k = \sum_{n=1}^{k} \varpi_n, \tag{6.B8}$$

$$L_k = \sum_{n=1}^{k} \iota_n = \frac{1}{\langle I \rangle} \sum_{n=1}^{k} \varpi_n \bar{I}_n. \tag{6.B9}$$

6.B.1.2. Continuous distribution and its relation to discrete quantities

It is convenient to introduce the continuous income probability distribution function (PDF) $g(I)$ and associated cumulative distribution function (CDF) $\Pi(I)$. This allows us to define the theoretical cumulative distribution series $\Pi(I_k)$:

$$\Pi(I_k) \equiv \int_0^{I_k} g(I) dI \simeq \Pi_k. \tag{6.B10}$$

One also obtains the theoretical mean income μ

$$\mu \equiv \int_0^{\infty} I g(I) dI \simeq \langle I \rangle, \tag{6.B11}$$

and the theoretical cumulative income share series $L(I_k)$

$$L(I_k) = \frac{1}{\mu} \int_0^{I_k} I g(I) dI \simeq L_k. \tag{6.B12}$$

Note that these last three equations allow us to define $L(\Pi)$ implicitly. Note also that once $L(\Pi)$ is known, $g(I)$ can be retrieved, as explained in section 2.1 of our Supplementary Materials.

With these definitions, the observed (data-based) discrete CDF formed by all couples (I_k, Π_k) for all $k \in [1, k_m]$ has a theoretical CDF counterpart, $(I_k, \Pi(I_k))$ once an assumption is made on the expected form of g. Similarly the data-based cumulative series (Π_k, L_k) has a theoretical counterpart $(\Pi(I_k), L(I_k))$; this last type of cumulative series is used later on in relation to Lorenzian distributions (needed for grouped data analysis, see section "Grouped vs individual data" of Supplementary Materials).

The associated discrete theoretical PDF is given by the collection $(\bar{I}_k, g_k)$. Note that

$$g_k \simeq \frac{\varpi_k}{(I_k - I_{k-1})} \simeq \frac{1}{k_m(I_k - I_{k-1})}, \tag{6.B13}$$

where $I_0 = \bar{I}_1 - (I_1 - \bar{I}_1)$ has been defined by extrapolation.

Because g is assumed to be a log-normal distribution, it is also convenient to work in logarithmic coordinates. Let us introduce $J = \log(I/U_I)$ and $J_k = \log(I_k/U_I)$ where the income unit U_I has been used; in practice $U_I = 1\$/\text{yr}$. One also defines the CDF in logarithmic scale (J_k, Π_k) and an associated theoretical CDF, $(J_k, \Pi(I_k))$. Note that Π_k must not change in the change of variable $I \to J$, and correlatively the PDF in logarithmic scale, $g^*(J)$, does change[12]. Indeed $g^*(J) = Ig(I)$ for $J = \log(I/U_I)$.

Finally, this allows us to define a discrete PDF of g^*, given by the collection $(\bar{J}_k, g^*_k)$ where

$$\bar{J}_k = \log(\bar{I}_k/U_I), \tag{6.B14}$$

$$g^*_k = \bar{I}_k g_k. \tag{6.B15}$$

Note that although $\int g dI = \int g^* dJ = 1$, $\sum_k g_k \neq 1$ and $\sum_k g^*_k \neq 1$. This follows because only the sums weighted by the local density of discrete values ($d_k = I_k - I_{k-1}$ for g and $d^*_k = (I_k - I_{k-1})/\bar{I}_k$) do give back unity: $\sum g_k d_k = \sum g^*_k d^*_k = \sum \varpi_k = 1$.

The associated population distributions (density and cumulative) $p(I)$, $P(I)$, $p^*(J)$, and $P(J)$ are obtained from g, g^* and G by multiplication by P_t:

$$p(I) = P_t g(I), \tag{6.B16}$$

$$P(I) = P_t \Pi(I), \tag{6.B17}$$

$$p^*(J) = P_t g^*(J). \tag{6.B18}$$

The previous remark applies to the discrete forms p_k, p^*_k and P_k: $\sum p_k \neq P_t$ and $\sum p^*_k \neq P_t$ but instead $\sum p_k d_k = \sum p^*_k d^*_k = P_t$.

6.B.2. LOG-NORMAL FIT TO THE INCOME PDF

The simplest way to find a log-normal fit to the observed PDF just defined in a discrete way is to work on logarithmic coordinates J. To this effect, we use $J_k = \log(I_k/U_I)$ for $k \in [1, k_m]$.

[12] It might be useful to recall the origin of this well-known fact in probability theory. This follows precisely because the cumulative value of the distribution in any interval (i.e., the probability in a given interval $\mathcal{I}$ of I and associated interval $\mathcal{J}$ of J) must not change in the change of variable: $\int_{\mathcal{J}} g^*(J)dJ = \int_{\mathcal{J}} g^*(J)dI/I = \int_{\mathcal{I}} g(I)dI$. As this is true for any interval, the integrands must be identical: $g(I) = g^*(J(I))/I$.

6.B.2.1. First step

As $g(I)$ is log-normal by assumption, $g^*(J)$ is Gaussian (i.e., normally distributed), with mean μ^* and standard deviation σ^*. It is usual to denote $\Phi(x) = \int_{-\infty}^{J} \phi(u)du$ the CDF of the standard normal distribution ϕ. One has $g^*(J) = \phi((J-\mu^*)/\sigma^*)$ and defining $G^*(J)$ the CDF of g^*, $G^*(J) = \Phi((J-\mu^*)/\sigma^*) = [1+\mathrm{erf}((J-\mu^*)/\sqrt{2}\sigma^*)]/2$. For a normal distribution, the mean μ satisfies $G^*(\mu^*) = 1/2$. Let us define k_0 such that $\Pi_{k_0} < 1/2$ and $\Pi_{k_0+1} \geq 1/2$ (this is the observed CDF defined in the previous subsection). From our earlier assumption on the discrete PDFs, $g^*(J)$ is constant in each centile and $G^*(J)$ must be linearly increasing in $[J_{k_0}, J_{k_0+1}]$ so that μ^* satisfies the equation of interpolation

$$G^*(\mu^*) = \frac{1}{2} = \Pi_{k_0} + (\Pi_{k_0+1} - \Pi_{k_0}) \frac{\mu^* - J_{k_0}}{J_{k_0+1} - J_{k_0}}, \tag{6.B19}$$

or equivalently

$$\mu^* = J_{k_0} + \left(\frac{1}{2} - \Pi_{k_0}\right) \frac{J_{k_0+1} - J_{k_0}}{\Pi_{k_0+1} - \Pi_{k_0}}. \tag{6.B20}$$

The standard deviation σ^* is found in a similar way by interpolation. More than one estimate can be obtained as $G^*(\mu^* \pm \sigma^*) = 0.5 \pm 0.341$, $G^*(\mu^* \pm 2\sigma^*) = 0.5 \pm 0.477$. As the distribution is given in centiles, this is the highest number of deviations reachable. Furthermore, as the $2\sigma^*$ deviation is in the bottom/top 3% of the distribution, these may not be as precise as the $1\sigma^*$ deviation. Defining again k_0 such that $\Pi_{k_0} < G^*(\mu \pm \sigma)$ and $\Pi_{k_0+1} \geq G^*(\mu^* \pm \sigma^*)$, one finds

$$\mu^* \pm \sigma^* = J_{k_0} + (G^*(\mu^* \pm \sigma^*) - \Pi_{k_0}) \frac{J_{k_0+1} - J_{k_0}}{\Pi_{k_0+1} - \Pi_{k_0}}, \tag{6.B21}$$

from which two different estimates of σ^* follow by combining this result with Eq. (6.B20). We choose the average of the two as our first step estimate of σ^*.

6.B.2.2. Second step

We fit the CDF $G^*(J_k)$ to Π_k in the least square sense, with unknown parameters μ^* and σ^*, with the estimates of the first step as guess. The objective function for this optimization is

$$F(\mu^*, \sigma^*) = \sum_k \left(G^*(\bar{J}_k) - \Pi_k\right)^2, \tag{6.B22}$$

$$G^*(J) = \frac{1}{2}\left[1 + \mathrm{erf}\left(\frac{J-\mu^*}{\sqrt{2}\sigma^*}\right)\right]. \tag{6.B23}$$

6.B.2.3. Rural vs urban population income distribution

For three countries (China, India, Indonesia), a single log-normal distribution does not represent the data precisely enough, as there are important differences between the rural and urban populations (Chen et al., 2019). For these three countries, the total income distribution fit is therefore performed independently for the rural and urban population, providing a rural log-normal distribution $g_r(I; \mu_r^*, \sigma_r^*)$ and an urban log-normal distribution $g_u(I; \mu_u^*, \sigma_u^*)$. The total distribution $g(I)$ is thus the weighted sum of the two for these three countries, the

weights being the fraction of rural (P_r) and urban (P_u) population, respectively ($\alpha_r = P_r/P_t$ and $\alpha_u = 1 - \alpha_r = P_u/P_t$):

$$g(I) = \alpha_r g_r(I) + \alpha_u g_u(I). \tag{6.B24}$$

The population data themselves (including rural and urban sub-population data when relevant) are provided in a specific data series[13].

6.B.2.4. Relation to the World Bank PIP database median and Gini coefficient

The PIP data files also provide a median value for the distribution and a Gini index. A Gini index is a commonly used measure of income inequalities. For log-normal distributions, it is directly related to the distribution dispersion, as indicated in the next subsection; similarly the median value is directly related to the mean of the normal distribution in J. It is therefore of some interest to be able to compare the median and Gini index values provided by the PIP program with the values obtained for these quantities from our fits. Generally speaking, our fits provide better continuous approximations to the data than the log-normal distributions that are obtained from the median value and Gini coefficient provided by the PIP data. Most probably, this is due to the fact that the PIP values are directly obtained from the discrete centile cumulative distribution (ζ_k, ϖ_k) itself.

Defining $\zeta = I/(\kappa U_I)$ and $\lambda = \log(\zeta) = J - \log(\kappa)$, Eqs. (6.B26) and (6.B27) (next subsection) imply that

$$g^*(J; \mu^*, \sigma^*) = g^*(\lambda; \mu^* - \log(\kappa), \sigma^*). \tag{6.B25}$$

This implies that $\mu_{PIP} = \mu^* - \log(\kappa)$ and $\sigma_{PIP} = \sigma^*$. These relations should enable us to compare the median and Gini coefficient values of the PIP database with the ones derived with the method defined above and of the relations given in the next subsection. Note that $g(\lambda) = g^*(\lambda)/\lambda$.

6.B.3. Useful formulae

6.B.3.1. Lognormal distributions: a short compendium

$$g^*(J) = \frac{1}{(2\pi)^{1/2}\sigma^*} \exp\left(-\frac{1}{2}\left(\frac{J-\mu^*}{\sigma^*}\right)^2\right), \tag{6.B26}$$

$$g(I) = \frac{1}{(2\pi)^{1/2}\sigma^* I} \exp\left(-\frac{1}{2}\left(\frac{\log(I/U_I)-\mu^*}{\sigma^*}\right)^2\right). \tag{6.B27}$$

Denoting M the median of $g(I)$ and G the Gini index associated to $g(I)$, one has

$$M = \exp(\mu^*) U_I, \tag{6.B28}$$

$$G = \mathrm{erf}(\sigma^*/2) = 2\Phi\left(\sigma^*/\sqrt{2}\right) - 1, \tag{6.B29}$$

where Φ is the cumulative distribution function of the standard normal distribution introduced

[13] `https://databank.worldbank.org/source/population-estimates-and-projections`. Long time series are not available for all countries.

earlier. In the relation for M, the unit U_I has been added in order to obtain a quantity in dollar per year that can be converted to any other monetary unit. This follows because μ^* characterizes the distribution of $\log(I/U_I)$ and is therefore dimensionless.

Eq. (6.B28) allows us to recast Eq. (6.B27) as

$$g(I) = \frac{1}{(2\pi)^{1/2}\sigma^* I} \exp\left(-\frac{1}{2}\left(\frac{\log(I/M)}{\sigma^*}\right)^2\right). \tag{6.B30}$$

Note that μ^* and σ^* represent the mean and dispersion of the distribution of J. It is of some interest to look also at the mean μ and dispersion σ of the distribution of I:

$$\begin{aligned}\mu &= \int I g(I) dI = \exp\left(\mu^* + \sigma^{*2}/2\right) U_I \\ &\simeq \exp(\mu^*) U_I = M, \end{aligned} \tag{6.B31}$$

$$\begin{aligned}\sigma &= \left[\int (I-\mu)^2 g(I) dI\right]^{1/2} \\ &= \left[\exp\left(\sigma^{*2}\right) - 1\right]^{1/2} \exp\left(\mu^* + \sigma^{*2}/2\right) U_I \\ &\simeq \left[\exp\left(\sigma^{*2}\right) - 1\right]^{1/2} \exp(\mu^*) U_I. \end{aligned} \tag{6.B32}$$

In general, $\sigma^* \sim \mathcal{O}(1)$ while $\mu^* \sim \mathcal{O}(10)$ (see Table 6.1), so that $\mu \simeq M$ to a good approximation, while $\sigma \sim M$ is widely different from $\exp(\sigma^*)U_I$. This also justifies the approximations given in the equations right above.

6.B.3.2. A SYMMETRY PROPERTY

The function g^* is symmetrical in logarithmic coordinate with respect to μ^*. This property is directly visible on Eq. (6.B26). It is much less obvious that the function g is also symmetrical in logarithmic coordinate with respect to its maximum (which differs from both M and μ). This is most directly shown by defining $x = I/M$, $2\sigma^{*2} = 1$ and dropping the normalization factor, but the following argument is easily recast in the general case.

With the simplifications just mentioned g reduces to $g_0 = \exp(-\log(x)^2)/x$. The maximum of g_0 obtains for $\log(x) = \log(x_M) = -1/2$, as can be checked from the derivative of g_0 with respect to x. Symmetry in logarithmic scale follows by defining $u = x/x_M$ so that $\log(x) = -1/2 + \log(u)$. In terms of this variable u, $g_0 = (1/x_M u)\exp[(-1/2 + \log(u))^2]$. By using the identity $u = \exp[\log(u)]$ (for $u > 0$, the only range of interest here), one finds that $g_0 = (1/x_M)\exp[-1/4 + \log(u)^2]$.

This last relation establishes the symmetry property for g_0 and therefore for g: indeed, symmetry with respect to x_M in logarithmic scale means that g_0 has the same value for symmetrical logarithmic coordinates around $\log(x_M)$, i.e., the same value for $\pm\log(u)$ for any $u > 0$. The last expression given for g_0 obviously satisfies this criterion.

Country	L_l^c	L_m^c	L_r^c	$y_{0,l}^c$	$y_{0,r}^c$	k^c
General function	0.47	0.26	0.40	7e2	1.5e4	4
Brazil	0.47	0.31	0.40	7e2	1.5e4	4
France	0.47	0.31	0.43	7e2	1.5e4	4
Germany	—	—	0.40	—	—	—
Japan	—	—	0.40	—	—	—
Mexico	0.47	0.17	0.40	7e2	2e4	3
Russia	0.47	0.26	0.40	7e2	2e4	4
United States	0.47	0.43	0.36	7e2	3.5e4	4
China, national	0.46	0.26	0.40	1.3e3	1.1e4	2.5
China, urban	1.2	0.3	0.40	1.5e3	2.4e4	1.4
China, rural	0.32	0.08	0.40	1.2e3	2.1e4	2.3
Indonesia, nat.	0.42	0.17	0.40	1.3e3	1.5e4	3
Indonesia, urb.	0.6	0.21	0.40	1.4e3	1.5e4	5
Indonesia, rur.	0.35	0.15	0.40	1.2e3	1.5e4	4
India, national	0.48	0.205	0.40	6e2	6.7e3	4
India, urban	0.8	0.27	0.40	5.5e2	7.3e3	3.5
India, rural	0.4	0.17	0.40	6e2	6.7e3	4

TABLE 6.C1: m(y) fit and projections parameters. L_l^c, L_m^c and L_r^c represent the value of past (left), intermediate (middle) and future (right) saturation values. $y_{0,l}^c$ and $y_{0,r}^c$ (constant 2015 USD unit) are the values of the past and future logistic inflection points on the x-axis. k^c (1/constant 2015 USD unit) is the slope of the logistic functions. See Eq. (6.7)

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6.C. INCOME DISTRIBUTION FUTURE PROJECTIONS

As mentioned in the text, future income distributions are obtained by projecting the parameters of the distribution Eq. (6.B27), μ^* and σ^*.

6.C.1. PROJECTION OF MEDIAN INCOME μ^*

6.C.1.1. MEDIAN INCOME AS A FUNCTION OF GDP PER CAPITA: HISTORICAL DATA

Table 6.C1 summarizes the parameters found for the modeling of the median income share in GDP as a function of GDP per capita. Figure 6.C1 and 6.C2 show the fit for China and India. Projections of time and GDP per capita series for the median income share in GDP per capita $m(y)$ are available in the Supplementary Materials.

The U-shaped form of $m^c(y)$ as a function of GDP per capita on a logarithmic scale has also been observed by Li et al. (2009).

This feature is worth commenting upon, to some extent, in the light of the existing literature. Nolan et al. (2019) explored the divergence between median income growth and GDP per capita growth in OECD countries and found that the divergence cannot be fully explained by differences in agency definitions, data collection and processing procedures. The OECD (Causa et al., 2014) also examined trends in GDP per capita and household disposable income evolution but did not attempt to explain these trends. While direct studies of the income share in GDP appear to be scarce, there is an extensive literature on labor share. Since the labor share

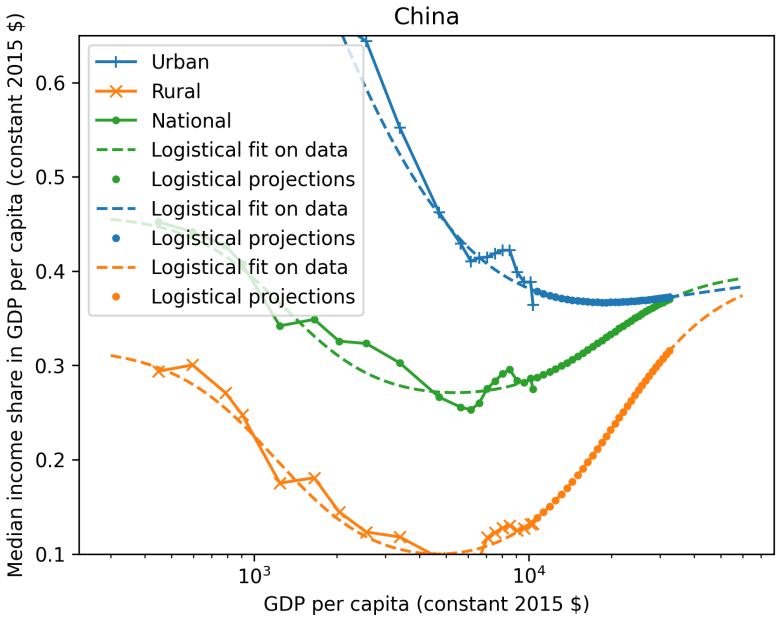


FIGURE 6.C1: Chinese median income share in GDP per capita time series and projections

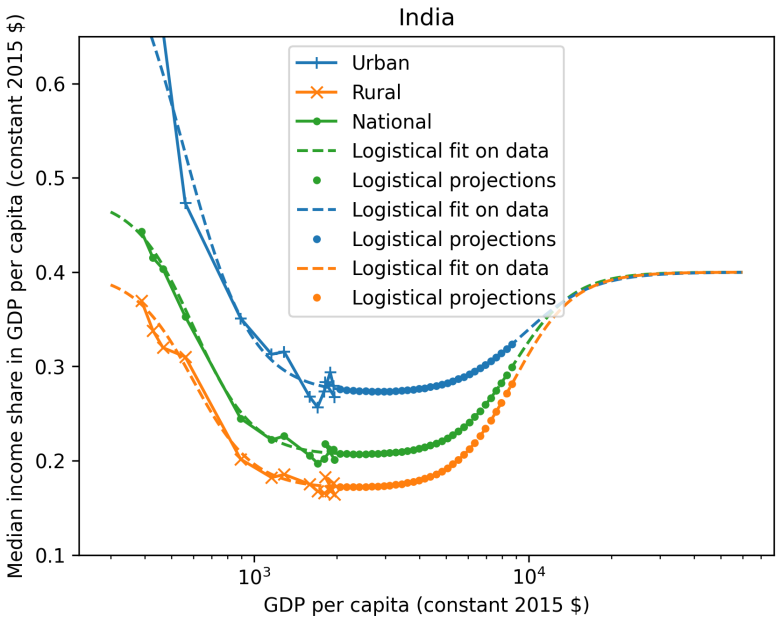


FIGURE 6.C2: Indian median income share in GDP per capita time series and projections

represents the share of wages in GDP, and since wages and income are closely related, analyzing labor share trends seems relevant at first glance.

Historical data indicate a general decline in the labor share in industrialized countries over the last 30-50 years (Karabarbounis and Neiman, 2014; Schwellnus et al., 2018; Autor et al., 2020). The exact causes of this general decline are debated within the scientific community, as it is the result of many different phenomena. However, some causes have emerged as key drivers. In a joint report, the OECD and the ILO (International Labor Organisation) OECD and ILO (2015) point out that the decline is mostly due to a reduction in the labor share within sectors rather than to changes in the sectoral composition of the economy (e.g., a shift towards less labor-intensive sectors). The report suggests that technological progress is likely to be the most important cause of this sectoral decline in labor. Bergholt et al. (2022) also supports this view. Globalization also plays a role because of its impact on wages through increased competition from other countries, or even just the threat of such competition. Another OECD report (Schwellnus et al., 2018) states that two thirds of the decline in the labor share can be attributed to technological change and globalization. This report also mentions the "winner-takes-most" phenomenon — part of the globalization effect — as a cause of sectoral labor share declines. In "winner-takes-most" scenarios, firms with lower labor shares can reduce their prices or increase their profits, making them more competitive and enabling them to gain market share, thereby reducing the overall sectoral labor share. Similarly, Autor et al. (2020) formulate and test seven hypotheses about the role of "superstar firms" in the decline of labor shares. In any case, the weakening of the workers' bargaining power (also mentioned by the OECD) may be a significant factor in this decline.

However, we do not observe a significant decline in the median income share in GDP per capita as is the case for the labor share. We therefore will not use the elements of analysis summarized above to project the evolution of the median income share in GDP per capita.

6.C.2. Income dispersion: parameters

The parameters of the logistic curve describing the evolution of $\sigma^*(y)$ found in equation 6.11 are summarized in the table 6.C2 for 10 major countries. Projections of time and GDP per capita series (also shown for all countries in Fig.6.7) for the income dispersion σ^* are available in the Supplementary Materials.

6.D. Relation between Gompertz functions of income and GDP per capita

Establishing the relation between the two forms of Gompertz functions requires several steps. It is useful to keep in mind the relations of Appendix 6.B.3 in this discussion.

The discussion of section 6.5.1 has shown or at least argued that, when the parameter σ^* decreases suddenly, in all likelihood, the function describing vehicle ownership as a function of income must be time-dependent. In order to give some robustness to and generality the relation between the two forms of Gompertz functions (which do not depend explicitly on time by assumption), we keep σ^* constant in this Appendix. Indeed our objective here is not to provide a complete and tight proof the equivalence between the two descriptions of vehicle

Country	$L_{\sigma^*,l}$	$L_{\sigma^*,r}$	k_{σ^*}	y_{0,σ^*}
Brazil	1.08	0.75	1e-3	9e3
China, urban	0	0.65	1e-3	500
China, rural	0.1	0.62	1e-3	0
France	0.56	0.50	1e-3	36e3
Germany	0.49	0.53	6e-4	35e3
Indonesia, urban	0.5	0.7	3e-3	2.3e-3
Indonesia, rural	0.4	0.57	3e-3	2.5e3
India, urban	0.56	0.64	5e-3	1.2e3
India, rural	0.47	—	—	—
Japan	0.56	—	—	—
Mexico	0.95	0.68	2e3	9.5e3
Russia	0.72	0.58	3e-3	9.5e3
United States	0.66	0.73	1e-3	33e3

TABLE 6.C2: Parameters of the $\sigma^*(y)$ logistic modeling for 10 major countries, see equation 6.11. The parameter $L_{\sigma^*,l}$ is given alone when $\sigma^*(y)$ is modeled as a constant.

ownership but solid enough arguments as to why this can be expected.

6.D.1. GOMPERTZ FUNCTIONS OF INCOME AND THE MEAN VALUE THEOREM IN INTEGRAL FORM

This section is devoted to demonstrating the following lemma:

LEMMA

There exists a value $I = I_\infty$ such that

$$\int_{-\infty}^{+\infty} V'^*(I^*)g(I)dI \equiv V'^*(I^*_\infty). \tag{6.D1}$$

We start the argument with the mean value theorem in integral form. This theorem states that for any continuous function $f(x)$ with $x \in [a, b]$ and any positive integrable function $g(x) \geq 0$ on $[a, b]$, there exists a number $\xi \in [a, b]$ such that[14]

$$\int_a^b f(x)g(x)dx = f(\xi)\int_a^b g(x)dx. \tag{6.D2}$$

In the present case, $x = I$ is income, $g(I) \geq 0$ is the log-normal distribution discussed in section 6.3.1 and Appendix 6.C, and $f = V'^*$. Note that because V'^* is strictly monotonous, there is a single ξ value[15] for a any given a and b.

Because both integrals are converging when $a \to -\infty$ and $b \to +\infty$, the mean value theorem applies in this limit as well[16]. Let us see this in a slightly more formal way, as this is rarely pointed out. To this effect, let us define $a_n = \mu - n\sigma$ and $b = \mu + n\sigma$ where μ and σ are the mean and dispersion of income and n is an arbitrary positive integer, and let us also define

[14] For a proof of this theorem, see, e.g., Taylor and Mann (1983), or any other book on advanced calculus.

[15] Assume there are two, ξ and ξ' with $\xi < \xi'$ for definiteness. The fact the V'^* is monotonically growing implies that $V'^*(\xi) < V'^*(\xi')$, by definition. But Eq. (6.D2) implies on the contrary that $V'^*(\xi) = V'^*(\xi')$.

[16] A sufficient condition of convergence of the left-hand side integral is that f is bounded, which is the case of V'^*. Probability distributions have bounded, normalized integrals, by definition.

I_n^* as the unique ξ associated to each n. One has:

$$V'^*(I_n^*) = \frac{\int_{a_n}^{b_n} V'^*(I^*)g(I)dI}{\int_{a_n}^{b_n} g(I)dI} \xrightarrow[n\to\infty]{} \int_{-\infty}^{+\infty} V'^*(I^*)g(I)dI \equiv V'^*(I_\infty^*), \tag{6.D3}$$

The fact that I_n^* exists for each n ensures that I_∞^* exists as well[17], as V'^* is continuous and bounded, and as the fractional change of the integral ratio tends to 0 as $n \to \infty$.

6.D.2. Scaling I_∞^*

To make further progress, one must relate I_∞^* to GDP per capita y. In this section, an intermediate step is first tackled, i.e., relating $I_\infty = I_\infty^*/\beta'^*$ to median income M; this will be completed by the relation of M to y in section 6.D.4.

More specifically, the following lemma is demonstrated:

Lemma

One can choose to scale $I_\infty = I_\infty^*/\beta'^*$ with M, i.e., $I_\infty = F \cdot M$, where F is a dimensionless scaling factor depending only on σ^*, α'^* and $M^* = \beta'^* M$.

Because I_∞ has the dimension of 2015$/yr/cap, it must be proportional to either μ or σ, or any related quantity with the same dimension such as the median income M. It is pointed out in Appendix 6.B.3 that $\mu \simeq M \sim \sigma$ for major countries (but this is in fact true for most countries); it is also shown that they differ by a function of σ^*. Thus, any of the 3 can be chosen to scale I_∞. We chose M because this simplifies somewhat the task at hand. Thus, we posit

$$I_\infty = FM, \tag{6.D4}$$

where F is a dimensionless quantity. F being dimensionless must therefore only depend on the dimensionless quantities that can be formed with the parameters of V'^* and g, i.e. M, σ^*, α'^* and β'^*. In practice, we choose σ^*, α'^* and $M^* \equiv \beta'^* M$.

The dependence on the parameters of g is natural, but the dependence on the parameters of V'^* is less intuitive because the right-hand side of Eq. (6.D3) already depends on them through V'^* itself. However, this can be understood through an example. Compare, e.g., the two values of I_∞ obtained for a given g and two different V'^*, one increasing very steeply and the other very shallowly, such that the first one is already saturated or nearly so at $I = \mu \simeq M$, and the other saturates at substantially higher income. Quite clearly the first one will have $I_\infty \sim M$ and the other, $I_\infty > M$.

γ'^* is excluded from the list of parameters on which M^* depends because it is just a scaling factor. To see this more formally, define $v^* = V'^*/\gamma'^*$. Applying the mean value theorem to v^* yields some I_∞^* for v^*, which by construction does not depend on γ'^*. Multiply now Eq. (6.D3) by γ'^*. Obviously, I_∞^* will also be the solution of this equation for V'^*. As I_∞^* is unique, as pointed out earlier, it must be the correct one, and does not depend on γ'^*.

Thus:

$$F = F(\sigma^*, \alpha'^*, M^*). \tag{6.D5}$$

[17] Ultimately, this is a consequence of the Bolzano-Weierstrass theorem.

This also relates the associated dimensionless quantities:

$$I^*_\infty = FM^*. \tag{6.D6}$$

We could have chosen a different scaling for I_∞, but this is of secondary importance, as any other combination leads to the same result in the end. For example, choosing μ instead of M as dimensional parameter amounts to $I_\infty = F'\mu$ with $F'(\sigma^*, \alpha'^*, \beta'^* M^*) = F(\sigma^*, \alpha'^*, \beta'^* M) \times (M/\mu)$, because M/μ is a function of σ^*.

6.D.3. Mean value theorem result as a Gompertz function of scaled median income

The objective of this section is to relate $V'^*(I^*_\infty)$ to a Gompertz function of M^*. The relation is not exact but rather precise. More specifically, we show in a stylized way the following property:

Property

For a given country, I^*_∞ can be expressed as a function of M^* (this statement is exact). One can therefore always find a Gompertz function of M^*:

$$V(M^*) = c \exp[-a \exp(-bM^*)], \tag{6.D7}$$

that best approximates $V'^*(I^*_\infty)$ in the least square sense, for an arbitrary but limited range in M^*. This best Gompertz fit provides an accurate model of $V'^*(I^*_\infty)$.

For a given country, α'^* is constant while M^* and σ^* vary in time. For all countries of interest M increases with time (although M might be a decreasing fraction of GDP per capita y for some range of y, as shown on Fig. 6.5). Thus, one could use M^* as a time variable and characterize the variations of σ^* as a function of M^*: $\sigma^* = \sigma^*(M^*)$. From Eq. (6.D5), this establishes that I^*_∞ can be expressed as a function of M^* only for any given country (the dependence on α'^* can be ignored as it is constant for a single country).

Furthermore, generally speaking, σ^* varies on average much less for major countries than μ^* over historical data (see Appendix 6.C). Thus, in first approximation, one is motivated to assume that σ^* is also approximately constant for a given country.

In light of this discussion, we expect that

$$F(\sigma^*, \alpha'^*, M^*) \simeq F(M^*), \tag{6.D8}$$

is a sufficiently precise characterization of the time-dependence of I^*_∞ and therefore of $V'^*(I^*_\infty)$. We will comment again on the neglect of the variation of σ^* with M^* at the end of this section.

To characterize further the dependence on M^*, let us first rewrite Eq. (6.D3) as

$$g'(I^*) = \frac{1}{(2\pi)^{1/2}\sigma^* I^*} \exp\left(-\frac{1}{2}\left(\frac{\log(I^*/M^*)}{\sigma^*}\right)^2\right), \tag{6.D9}$$

$$\int_{-\infty}^{+\infty} V'^*(I^*) g'(I^*) dI^* \equiv V'^*(I^*_\infty). \tag{6.D10}$$

Note that the shift from I to I^* makes g' dimensionless whereas g is not. For definiteness, we set $\gamma'^* = 1$ (as this scaling factor plays no role in the argument), $\alpha'^* = 6$ (a typical value for α), and $\sigma^* = 0.6$ (also a typical value for this quantity).

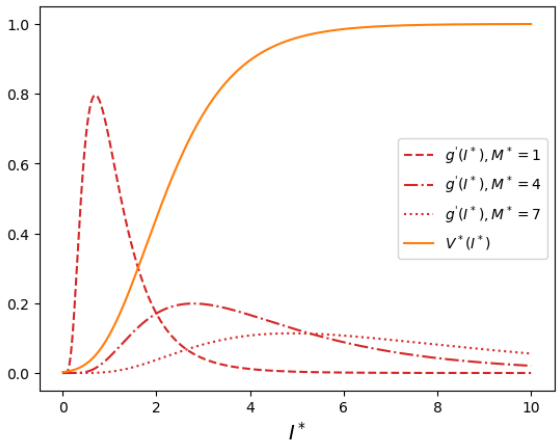


FIGURE 6.D1: Gompertz function of income $V'^*(I^*)$ for $\alpha'^* = 6$ and $\gamma'^* = 1$, and three examples of $g'(I^*)$ for $\sigma^* = 0.6$ and different M^*. The vertical axis is dimensionless for both quantities.

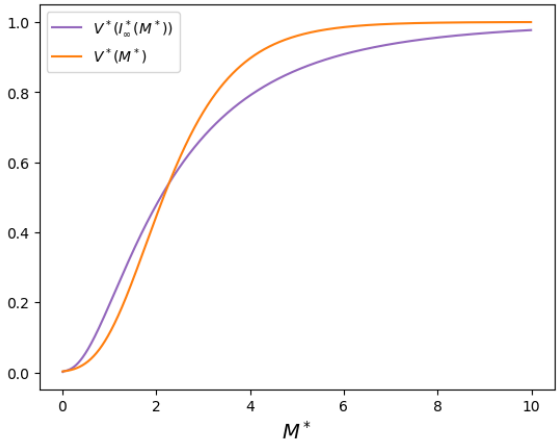


FIGURE 6.D2: Gompertz function $V'^*(M^*)$ and the function $V'^*(I^*_\infty(M^*))$ as a function of $M^* \in [0, 10]$, for $\alpha'^* = 6$ and $\gamma'^* = 1$.

Fig. 6.D1 shows the income Gompertz function and three examples of the income distribution (differing by the choice of the dimensionless median income M^*) for this choice of parameters. The displayed behavior allows us to capture in a graphic way the meaning of Eqs. (6.D6) and (6.D8): the integral giving $V'^*(I^*_\infty)$ is dominated by contributions from the (possibly not so narrow) vicinity of the maximum of g', which itself is closely related to M^*.

The form of $F(M^*)$ in this illustrative example is not particularly informative (it decreases from ~ 1.5 to ~ 0.5 for $I^* \in [0, 10]$). It is more relevant to compare $V'^*(I^*_\infty(M^*))$ and $V'^*(M^*)$. These are displayed on Fig. 6.D2. Not surprisingly, $V'^*(I^*_\infty(M^*))$ is not very different from $V'^*(M^*)$, and does look like a Gompertz function itself. However the parameters of $V'^*(M^*)$ do not seem to provide a good match of $V'^*(I^*_\infty(M^*))$.

The behavior of these two curves is directly related to the behavior of $F(M^*)$. A given ordinate obtains for two different abscissae — one for each curve — say M^*_g for $V'^*(I^*_\infty)$ and M^* for the $V'^*(M^*)$. By construction, $I^*_\infty = M^*_g$ so that $F(M^*) = M^*_g/M^*$. This illustrates the behavior of F indicated at the beginning of the paragraph, and shows that $F = 1$ obtains for $M^* \simeq 2$.

Requiring F to be always very close to unity would be too stringent a constraint for $V'^*(I^*_\infty)$ to be Gompertz-like or nearly so. In particular, for $M^* \gtrsim 5$, the horizontal difference between

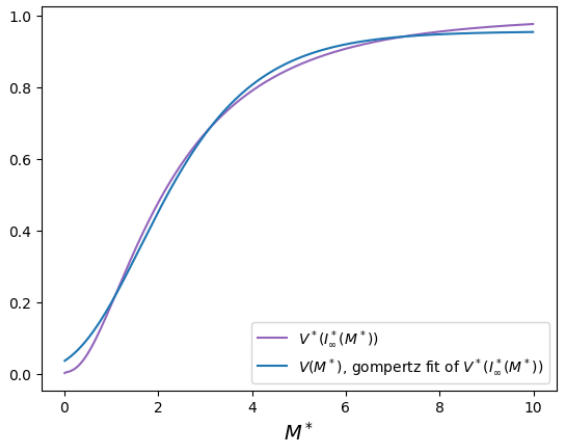


FIGURE 6.D3: Gompertz function fit $V(M^*)$ to the function $V'^*(I^*_\infty(M^*))$ for $M^* \in [0, 10]$, $\alpha'^* = 6$ and $\gamma'^* = 1$.

M^*_g and $M^* = I^*_\infty$ is large, but does not indicate a substantial difference in vehicle ownership between the two curves as their amplitude differs by $< 10\%$ (and converges to 0 at large M^*); this follows because the curves become asymptotically flat.

In fact, a better test of the deviation from a Gompertz shape of $V'^*(I^*_\infty)$ is to find its best match by some Gompertz function, Eq. (6.D7). The quality of the fit indicates whether $V'^*(I^*_\infty)$ is sufficiently precisely approximated by a Gompertz function or not.

Fig. 6.5 indicates that the median income M differs from GDP per capita y by a factor of order unity. We have already mentioned that F itself is of order unity. These facts, combined with Eq. (6.D3) suggest that a, b and c (the parameters of $V(M^*)$) and α'^*, β'^* and γ'^* are related by factors of order unity.

This expectation is borne out when fitting these three parameters a, b, c in the least square sense by minimizing $(V'^*(I^*_\infty(M^*)) - V(M^*))^2$. The result is shown on Fig. 6.D3, and obtains for $a = 3.29$, $b = 0.74$ and $c = 0.96$. As visible on the figure, $V'^*(I^*_\infty(M^*))$ is rather precisely approximated by a Gompertz function of M^*, and conversely, one expects that any Gompertz function of M^* can be adequately fitted by an appropriately chosen function $V'^*(I^*_\infty(M^*))$ obtained from the mean value theorem in integral form. This requires to fit $(\alpha'^*, \beta'^*, \gamma'^*)$ instead of (a, b, c), but follows in exactly the same way (this point is explicitly shown in the more realistic context of the next subsection).

To conclude this section, let us briefly discuss to which extent the result obtained for a specific parameter choice and in the limit of constant σ^* may be expected to be of general validity and application. This hinges on the deviations of F from a constant. Indeed, if F is constant, $V'^*(I^*_\infty)$ is a an exact Gompertz function of M^*. This is however too crude a requirement, and a more complete discussion of this point will be provided at the end of the next section.

6.D.4. MEAN VALUE THEOREM RESULT AS A GOMPERTZ FUNCTION OF SCALED GDP PER CAPITA

The objective of this section is to investigate the following property, which closely mirrors the property stated in the previous section:

PROPERTY

For a given country, I^*_∞ can be expressed as a function of y (this statement is exact). One

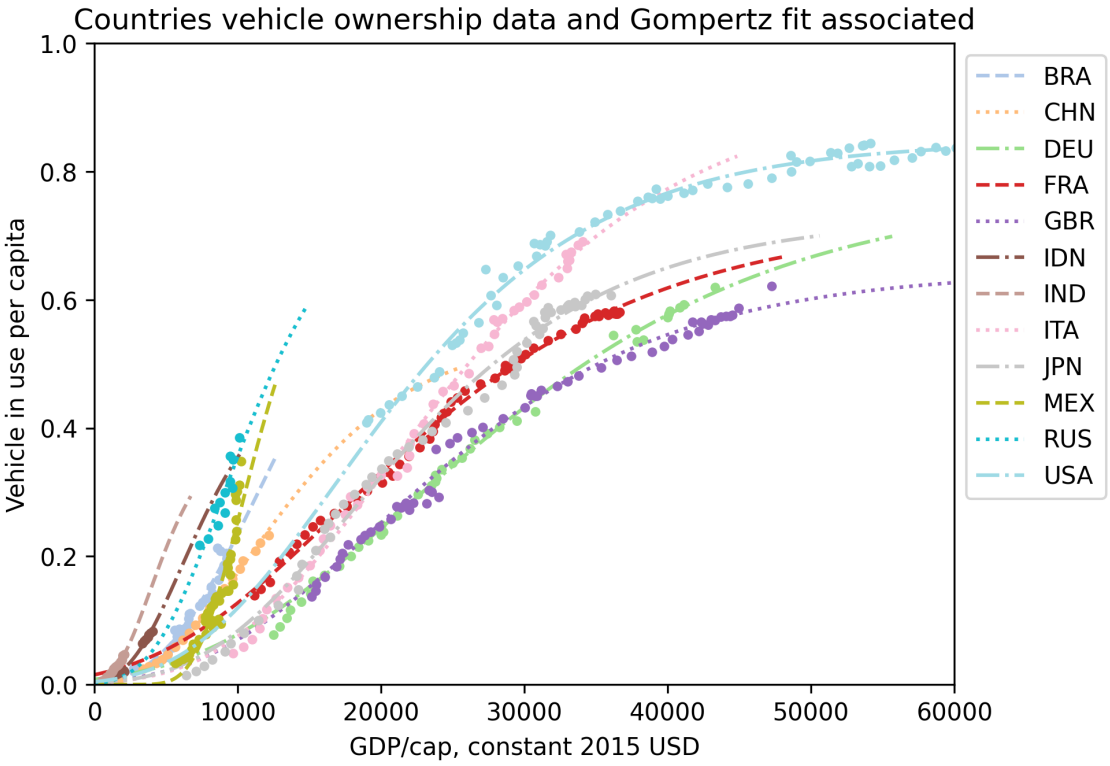


FIGURE 6.D4: Major countries' Gompertz fits (number of 4Ws per capita as a function of GDP per capita). Points represent historical data and lines show their fits. The curve ends when the GDP per capita reaches its 2050 value. Countries are labeled by their alpha-3 code. Note that the type of vehicles represented is 4W, which includes PVs and CVs (PVs represent about 90% of the 4W stock, see section 6.2).

can therefore always find a Gompertz function of $y^* = \beta'^* y$:

$$V(y^*) = c \exp[-a \exp(-by^*)], \tag{6.D11}$$

that best approximates $V'^*(I^*_\infty)$ in the least square sense, for an arbitrary but limited range in y. This best Gompertz fit provides an accurate model of $V'^*(I^*_\infty)$.

This is achieved in what follows by relating M^* to y and relying on the results of the previous section.

6.D.4.1. RELATING $V'^*(I^*)$ TO $V(y)$

The relation between $V'^*(I^*)$ and $V(y)$ follows from the fact that M is related to y as shown on Fig. 6.5 for historical data. Furthermore, Fig. 6.D4, reproduced from Chapter 4, indicates that for GDP per capita smaller than $y = 5,000$ 2015$/yr/cap, PV ownership is very limited. This allows us, in the present stylized exercise, to ignore lower incomes, and therefore to focus on the right part of Fig. 6.5.

This part of this figure suggests that M/y can be represented in a stylized way as a logistic

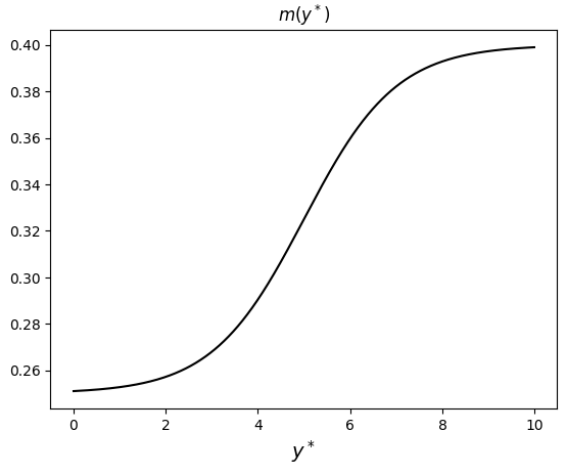


FIGURE 6.D5: Stylized model of median income fraction of GDP per capita M/y as a function of scaled GDP per capita y^*. To be compared with Fig. 6.5.

function of y as

$$y^* = \beta'^* y, \tag{6.D12}$$

$$m(y^*) \equiv \frac{M}{y} = \frac{M^*}{y^*} = L_1 + \frac{L_2}{1 + \exp[-(y^* - y_0^*)]}. \tag{6.D13}$$

We have set $L_1 = 0.25$, $L_2 = 0.4 - 0.25 = 0.15$ and $y_0^* = 5$ (corresponding to an inflection point — largest slope — at $y = 50,000$ yr.cap/2015\$, but any value in the range $30,000$ — $50,000$ could be realistically selected instead). We have chosen $\beta'^* = 10^{-4}$ yr.cap/2015\$ in order to map the initial range in y (5,000 to 100,000 2015\$/yr/cap) to the range of y^* $[0.5, 10]$. This value of β'^* is typical of the values of β for the Gompertz functions displayed in Fig. 6.D4.

The resulting function is shown on Fig. 6.D5. This function has been only loosely adjusted to resemble Fig. 6.5 in a semi-quantitative and stylized way. In particular, y_0^* is chosen to place the inflection point in the middle of the range $[10^4, 10^5]$ in linear scale in y (instead of the middle of $\log(y)$). Working in linear scale makes it easier to test the Gompertz function approximation of $V'^*(I_\infty^*)$, but has no impact on the quality of the results, as shown country by country in section 6.4.3. Also, this makes us test a significant range of $m(y^*)$ values.

This specification allows us to relate M^* and $V'^*(I_\infty^*)$ to y^* in a stylized but realistic way, through

$$M^*(y^*) = m(y^*)y^*, \tag{6.D14}$$

$$V'^*(I_\infty^*(y^*)) = V'^*(I_\infty^*(M^*(y^*))). \tag{6.D15}$$

We are now in position to carry through the procedure of the previous section, in order to compare first $V'^*(I_\infty^*(y^*))$ and $V'^*(M^*(y^*))$. This is performed on Fig. 6.D6. Again the functions are similar and the result of the mean value theorem $V'^*(I_\infty^*(y^*))$ does indeed also appear to be very similar to a Gompertz function of y^*, albeit not with the same parameters as $V'^*(M^*(y^*))$.

This leads us again to look for a least square fit of $V'^*(I_\infty^*(y^*))$ with a Gompertz function $V(y^*)$, Eq. (6.D11). The fit is remarkably good — a partial consequence of the fact that the domain of fit is still somewhat fat from saturation, and this will be looked at more precisely in

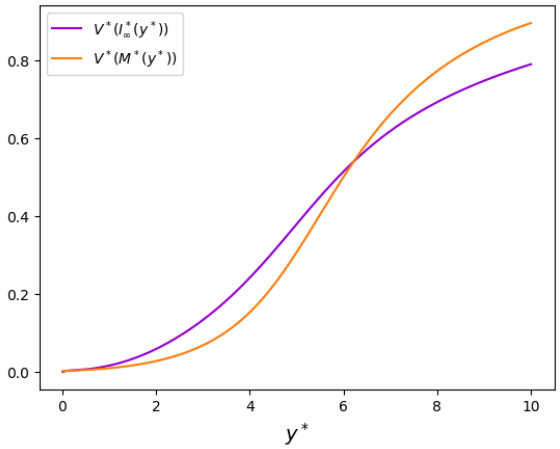


FIGURE 6.D6: Gompertz function $V'^*(M^*(y^*))$ and the function $V'^*(I^*_\infty(y^*))$ as a function of $y^* \in [0, 10]$, for $\alpha'^* = 6$ and $\gamma'^* = 1$.

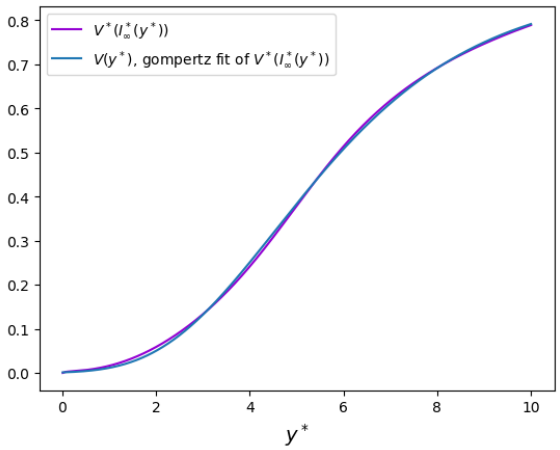


FIGURE 6.D7: Gompertz function fit $V(y^*)$ to the function $V'^*(I^*_\infty(y^*))$ for y^* for $\alpha'^* = 6$ and $\gamma'^* = 1$.

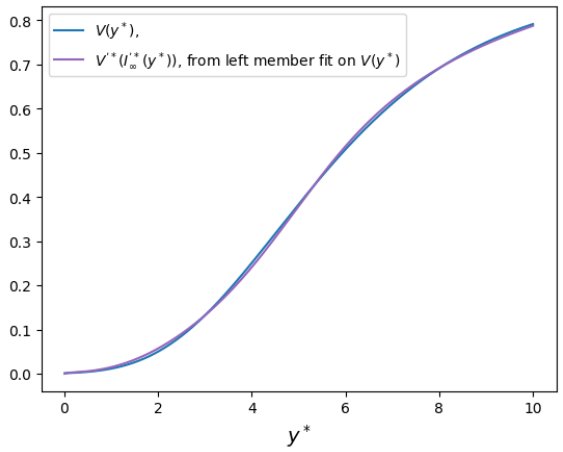


FIGURE 6.D8: Gompertz function fit $V'^*(I'^*_\infty(y^*))$ to the function $V(y^*)$; see text for details.

section 6.D.4.2. The fit parameters are $a = 6.56$, $b = 0.41$ and $c = 0.88$. Note finally that $V(y)$ (with parameters α, β and γ) is related to $V(y^*)$ by $\alpha = a$, $\beta = b\beta'^*$ and $\gamma = c\gamma'^*$ (upon restoring the scaling of V'^* with γ'^*). This completes, at least in the context of this stylized exercise, the relation between the mean value theorem result $V'^*(I^*_\infty)$ and its associated $V(y)$.

The actual problem is the converse one: starting with $V(y^*)$, we wish to obtain $V'^*(I^*)$. This requires to find $V'^*(I^*) = \gamma'^* \exp[-\alpha'^* \exp(-\beta'^* I^*)]$ such that $V'^*(I'^*_\infty(y^*))$ fits best a given $V(y^*)$. In practice, the exercise requires the knowledge of $M^*(y^*)$ historically associated to this specific Gompertz function of GDP per capita. This will be looked at in detail in section 6.4.3 for individual countries, as not having this information (or choosing M^* more or less randomly) may result in a poor fit or even in no fit at all if the optimization algorithm is ill-conditioned.

Here, we circumvent this problem by looking for V'^* that best fits the function $V(y^*)$ just found from our our assumed V'^* and M/y behavior. By construction this ensures a form of (pseudo-)historical consistency between $M^*(y^*)$ and $V(y^*)$. We thus start with $V(y^*) = c\exp[-a\exp(-by^*)]$, with $a = 6.56$, $b = 0.41$ and $c = 0.88$. The guess of V'^* is initiated with $\alpha'^* = a$, $\beta'^* = b$ and $\gamma'^* = c$. The best fitting V'^* obtains for $\alpha'^* = 6.21$, $\beta'^* = 1.03$ and $\gamma'^* = 0.99$ (to be compared to the initial $\alpha'^* = 6$, $\beta'^* = 1$ and $\gamma'^* = 1$). The resulting $V'^*(I'^*_\infty(y^*))$ is compared to $V(y^*)$ on Fig. 6.D8.Quite clearly, this strongly suggests that fits of V'^* on V are good results as the converse, at least if $M(y)$ and $V(y)$ are historically consistent.

6.D.4.2. THE RELATION BETWEEN γ'^* AND γ

Up to now, Gompertz fits have been performed by relaxing the constraint $\gamma'^* = \gamma$. This constraint is unavoidable if the fit domain is extended arbitrarily far in the direction $y \to \infty$. This can be seen directly on Eqs. (6.D9) and (6.D10) and taking into account the fact that $M^* \to \infty$ when $y \to \infty$, and is illustrated on Fig. 6.D9, which shows the result of the best Gompertz fit $V(y^*)$ on $V'^*(I^*_\infty)$ for a domain in GPD per capita extended by a factor of 5. The parameters of V'^* are unchanged ($\alpha'^* = 6$, $\beta'^* = 10^4$ yr.cap/2015\$, $\gamma'^* = 1$) and the best fit obtains for $a = 4.5$, $b = 0.31$ and $c = 0.98$. This last number in particular implies that $\gamma = c\gamma'^*$ differs by less than 2% from γ'^*.

Such a large range in GDP per capita is of course unrealistic (even our 2050 projections lead to limited or nonexistent foray of the ownership distribution in the saturation regime, except, to a limited extent, for the USA). Still, one may ask why it is reasonable to relax the constraint

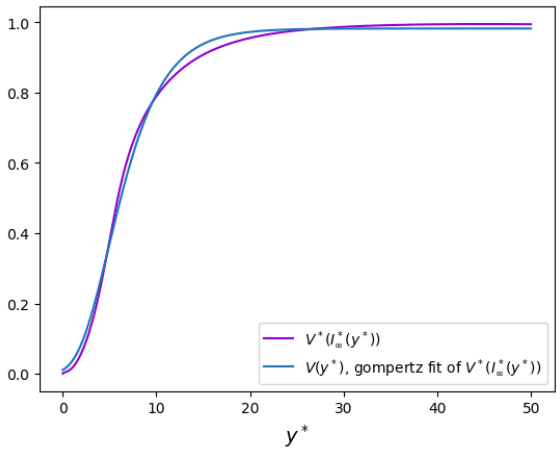


FIGURE 6.D9: Gompertz function fit $V(y^*)$ to the function $V'^*(I^*_\infty(y^*))$ for y^* for $\alpha'^* = 6$ and $\gamma'^* = 1$ (same as Fig. 6.D7 for a domain in y^* extended by a factor of 5).

$\gamma'^* = \gamma$ when performing fits.

The answer lies in the choice of the fit range in y^*. When relaxing the $\gamma'^* = \gamma$ constraint, one must fit over the range that will be used in projections. This implies to exceed historical data. The rationale of this rule lies in the fact that one wishes to find the overall best Gompertz function of income V'^* for a given $V(y)$ at the country level. In particular, for future projections, which may be extrapolated rather far away from historical data, fitting beforehand the future projections of $V(y)$ to obtain $V'^*(I^*)$ will clearly ensure that the saturation level of the latter (for optimal results on the fitting range) will be better captured, albeit at the cost of a small degradation of the fit at intermediate GDP per capita, as exemplified on Fig. 6.D9. As the saturation level of Gompertz functions is critical to correctly extrapolate future PV fleets, even in the non-saturated range, relaxing the constraint when fitting only on historical data may lead to non negligible errors in projections. If reliable extrapolations of $V(y)$ are not available or if the modeler does not wish to use them, then the contraint $\gamma'^* = \gamma$ must be enforced to find the most relevant $V'^*(I^*)$ from $V(y)$ on the projection range based on this more limited information.

Whether extrapolations of $V(y)$ are available beforehand depends on the type of problem at hand. Thus, it is of some interest to have a look at the quality of the fit when $\gamma'^* = \gamma$ is enforced. This is realized by imposing $c = 1$ when fitting $V(y^*)$ on $V'^*(I^*_\infty)$ and conversely, maintaining $\gamma'^* = c$ when looking for the best fitting $V'^*(I^*)$ to a given $V(y^*)$. This is illustrated on Figs. 6.D10 , which mirror Figs. 6.D8 when these constraints are imposed in the fitting procedure.

One can see that even in this case, the best Gompertz fits are still a reasonably accurate representation of the original functions.

6.D.4.3. FROM STYLIZED EXAMPLES TO GENERIC CONCLUSIONS

Thus far, the main property of interest in this work (accurate representation of PV ownership as a function of income as a Gompertz function inasmuch as PV ownership is accurately represented as a function of GDP per capita as a Gompertz function) has been shown through stylized examples. The question of the generality of this property therefore remains. The most direct argument is provided through the country level fits of section 6.4.3. Nevertheless, it is possible to give some generic arguments as to why this property applies so effectively:

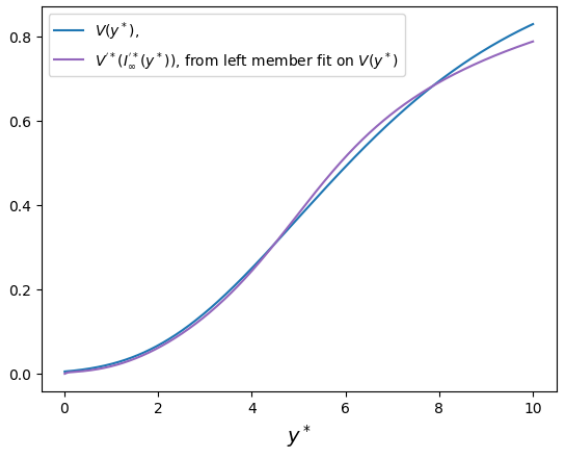


FIGURE 6.D10: Gompertz function fit $V'^*(I'^*_\infty(y^*))$ to the function $V(y^*)$, imposing $\gamma'^* = c = 1$; see text for details.

- First, and rather tautologically, the major factor making $V'^*(I^*_\infty)$ Gompertz-like (S-shaped) is the fact that V'^* is a Gompertz function. In such a context, as long as F is a sufficiently smoothly varying function of M^*, the S-shape form can hardly be lost.
- This requirement on F is shown in the example above, but there is very little that is specific in this example. This strongly suggests that the result is more or less generic.
- This feature is clearly reinforced by two secondary elements:
  - The fact that σ^* — and more specifically, the ratio of $\sigma/M = \exp(\sigma^{*2}) - 1$ varies little for a number of countries.
  - The range of relevant values of M^* over which a Gompertz fit of $V'^*(I^*_\infty)$ is needed is intrinsically limited. This feature allows us to relax the $\gamma'^* = \gamma$ asymptotic requirement, and this definitely helps to find an accurate Gompertz fit.

These arguments give a strong support to the fact that the number of PVs per capita at a given time can be modeled as a Gompertz function of income, in relation to the fact that the time evolution of PV ownership can be modeled as a Gompertz function of GDP per capita.

These arguments also indicate when the fit will be less successful. In particular, in the case of Brazil and Mexico (see main text), the sharp drop of σ^* induces a related sharp variation in F. This is the mathematical root of the less good fits observed for these two countries. This also indicates that although σ^* varies less than μ^*, its variations must be checked with caution for the model to be precise. We argued in section 6.5 that when this condition on σ^* was not satisfied, the resulting function is most likely explicitly time-dependent.

CHAPTER 7 | MODELING THE ADOPTION OF ELECTRIC VEHICLES AMONG WORLDWIDE HOUSEHOLDS UNDER THE AFFORDABILITY BARRIER

This chapter finally seeks to model the deployment of EVs at the country level and over time, considering affordability as a barrier for households.

The models developed in this chapter are not complete — but has required a significant amount of work during the PhD — and require further work. The present chapter gathers elements paving the way towards this objective.

7.1. Introduction

The deployment of electric vehicles (EVs), particularly in private vehicles (PVs), is crucial for two reasons. Firstly, it serves the energy transition by replacing oil with electricity — which would be produced by renewable energy sources in this context — without requiring significant transformation in mobility demand and patterns[1].

Secondly, the deployment of electric private vehicles is crucial in the context of peak oil. Oil supply is expected to decline soon due to geological limits (Laherrère et al. 2022; Delannoy et al. 2021a and see also data from Rystad[2] and Globalshift[3]) as discussed in Chapter 2. Meanwhile, whether oil demand will increase or decrease heavily relies on the future deployment of EVs. Chapter 4 indeed concludes that oil demand would increase in all scenarios in which the penetration level of EVs in the PV stock is lower than 50%. In such scenarios, the oil demand of a

[1]Note that, in turn, this would not foster changes in mobility, while significant changes to mobility structures and patterns would be required to reduce long-term energy consumption in the transport sector.

[2]`https://www.rystadenergy.com/news/discovered-recoverable-oil-resources-increased-by-5-billion-barrels-despite-produ`

[3]`https://www.globalshift.co.uk/glooprcharts.html`

BAU scenario would be limited by oil supply, which is likely to result in economic crises (Tverberg, 2012a; Murphy and Hall, 2011; Sorrell et al., 2009; Brandt, 2017). Indeed, oil represented 95% of the energy consumed by the transport sector in 2022 according to IEA (2024b). Consequently, supply chains would be impacted by tension in the oil market, which would in turn affect the economy, on top of the direct impact on households driven by energy inflation.

Nevertheless, EVs only accounted for only 4% of the vehicle stock in 2024 (IEA, 2024d, 2025b). While the stock still grows exponentially at the global level, the EV share of PV sales saturates in many Western countries. China is leading the deployment of EVs, concentrating a little over half of the global EV stock.

There are multiple reasons for this saturation, the most important of which is higher purchasing prices (Virmani et al., 2023; Muratori et al., 2021; Rajper and Albrecht, 2020; Zhuge and Shao, 2019; Fevang et al., 2021; Purwanto and Irawan, 2024; Naseri et al., 2024; Soszynska et al., 2024; Pulido-Sánchez et al., 2022; IEA, 2024d, 2025b). Indeed, the purchase prices of EV are higher due to the costs of electric batteries, which can account for 40% of the price of a car (see section 7.2). The adoption of EVs by households is therefore expected to be limited, particularly in poorer households.

Modeling the affordability barrier to EV deployment is therefore important, but has never been assessed. Firstly, this requires modeling how higher purchasing price influence the purchase decision of households, considering that part of this overcost can be compensated by savings due to the lower cost of electricity compared to oil for the same transport service. Secondly, this requires to consider the distinct behavior of richer and poorer households. Thirdly, this requires modeling the distribution of PV stocks as a function of household income, for which Chapter 6 developed a new and convenient mathematical model. Fourthly, poorer household tend to buy secondhand cars, indicating that the effect of secondhand sales must be considered. Finally, it is also necessary to forecast the future price of EVs thus of batteries, which are uncertain and are still evolving rapidly. Some articles provide useful information and models regarding this issue, however none of them integrated all the steps needed to model EV deployment under the affordability barrier (Bento et al., 2009; Choi and Koo, 2019; Berkovec, 1985; Gavazza et al., 2014; Yurko, 2008; Glerum et al., 2013).

The present chapter therefore seeks to address this issue. The approach is the following: we seek to model the maximum possible EV deployment, considering the affordability as the only barrier to their deployment.

Section 7.2 discusses the overcost of EVs and how it would evolve. Section 7.3 computes the distribution of the PV stock as a function of income in countries and over time based on Chapter 6. Section 7.5 then disaggregates this distribution between new and secondhand vehicles. Finally, section 7.6 gives modeling elements required to model the households behaviour towards EV adoption as a function of income, based on previous information. Section 7.7 concludes the chapter.

7.2. THE OVERCOSTS OF EVS

7.2.1. EV PURCHASING OVERCOSTS

In 2023, the stock of EVs was distributed among China (54%), Europe (27%), the United States (12%) and the rest of the world (RoW, 7%)(IEA, 2024d). The 2024 IEA "Global Elec-

tric Vehicle Outlook"(IEA, 2024d) was marked by a focus on the affordability of EVs. It indicated that EVs were priced 10% to 50% higher than equivalent internal combustion engine vehicles (ICVs) in Europe and in the United States. In particular, IEA (2025b) indicates that the overprice is higher in small EVs than in other segments in these countries. This increases the affordability constraint for poorer households, i.e. those for whom overprices are less or not acceptable.

However, in China, EVs are sold at similar prices to equivalent ICVs. Pages 47—56 of IEA (2025b) indicate that EV costs are still higher than equivalent ICV costs in most cases, except for Chinese small EVs which were priced at around 40% less than equivalent ICVs in China, but represented 10% of the sales in 2024. This indicates that the affordability constraint is less of an issue in China, where the PV stock is expected to account for approximately 25% of the global total between 2030—2050 in a BAU scenario.

Since 2008, China's industrial strategy has been to develop electric cars[4]. Indeed, China, in the midst of massive industrialization, lagged far behind the United States and Europe in terms of industrial maturity in combustion engine cars. It also lagged behind Japan in the development of hybrid cars. China therefore took the risk of betting on the development of electric cars at a time when these vehicles were still in the prototype stage. The development of electric cars — in addition to being a gamble to gain an industrial advantage over the rest of the world — also supported two national objectives, which were (and still are) the reduction of air pollution in cities and the reduction of oil imports. The development of this industrial sector was therefore a national priority.

China's support for the development of the industry took several forms. While the government was able to adapt the legislative system to promote the deployment of these industries and invest significant resources in them, China also introduced a system of subsidies and tax exemptions from 2010 to 2023 to offset the difference in purchase price compared to combustion engine cars. These subsidies amounted to approximately 30 billion dollars [5]. In addition to direct purchase subsidies, electric cars benefited from a 10% purchase tax exemption until the end of 2023[6]. Obtaining a license plate, which is difficult and expensive in some cities, is made easier and free for electric cars[7]. Car manufacturers are subject to a "dual credit" system[8]: the weighted average fuel consumption of cars sold must be below a target set by the government; if it exceeds this target, manufacturers must pay a fine. China has also supported the deployment of charging stations to accompany the deployment of electric cars.

All these incentives have led to two mutually reinforcing phenomena: electric car sales have been high in China (accounting for 50% of sales in 2024 according to IEA 2025b), and industries have been able to achieve technological maturity and a scale of production unmatched anywhere else in the world. This partly explains the low prices of entry-level cars available in China.

Furthermore, China controls a large part of the electric car supply chain. In terms of raw materials, China refines around 70% of the world's lithium, 80% of cobalt, and 15% of nickel (but 50% of Nickel is refined in Indonesia), produces 70% of graphite (for anodes) of which it refines

[4] See https://www.technologyreview.com/2023/02/21/1068880/how-did-china-dominate-electric-cars-policy/

[5] Various sources were found:
https://www.reuters.com/world/europe/eu-launches-anti-subsidy-investigation-into-chinese-electric-vehicles-2023-09-13/
https://www.technologyreview.com/2023/02/21/1068880/how-did-china-dominate-electric-cars-policy/, and https://www.sixthtone.com/news/1012221 from the Chinese Ministry of Industry and Information Technology.

[6] https://chinadialogue.net/en/digest/china-ends-electric-vehicle-subsidies/

[7] https://energy5.com/examining-the-impact-of-financial-incentives-on-electric-car-adoption-in-china

[8] https://www.iea.org/policies/14779-dual-credit-system

50% (IEA, 2023b). It also owns numerous mines abroad, facilitating its supply need. In 2022, 70% of cathodes, 85% of anodes, and three-quarters of batteries worldwide were manufactured in China (IEA, 2022). The price of batteries represents about 40% of the price of electric cars (König et al., 2021), and the price of raw materials represents about 70% of the price of batteries (Pillot and Renard, 2022) — although this is of course subject to fluctuations in raw material prices and variations in the penetration of different technologies. China's stranglehold on raw materials therefore logically has an impact on the prices of the electric cars it can produce. Some Chinese manufacturers (CATL, BYD) produce their own batteries.

Some Chinese companies sell their electric cars abroad, but there is often a significant markup (at least $10,000) compared to the prices of the same models in China[9]. This is because exporting cars involves significant logistical costs, and production abroad would mean moving away from the advantageous context in China[10]. Added to this are export and import taxes, given that Europe and the United States are seeking to protect their automotive industries from Chinese competition[11]). For example, the tax on chinese EV imports was raised from 25% to 100% in 2024 in the United States[12] Thus, if a MiniEV were sold in Europe, its cost would probably make it unattractive compared to other combustion engine models available in Europe.

In conclusion, EVs and especially smaller EVs in Europe and United States are expected to remain more expensive than ICVs except in a case in which the battery prices drop significantly, which is not expected to be the case as discussed in section 7.2.2. However, the affordability constraint may be quite reduced in China, and also lower in South-East Asian countries due to the proximity to China than in Europe and in the United States.

7.2.2. Battery technologies and prices

The costs of the batteries depends also on the autonomy and is the main (and nearly only) source of price difference with ICVs.

Lithium-ion technology has been used for a decade in portable devices (phones and computers). However, its specific use in electric cars comes with its own characteristics (power, energy storage, power variations) and constraints, particularly in terms of stability (lower risk of ignition). The batteries used are therefore less energy-dense but more stable. Thus, heavy investment in research and development around 2015, at the beginning of the industrial development of electric cars (IEA, 2022), led to considerable efficiency gains (Mauler et al., 2021; Schmidt et al., 2017; Muratori et al., 2021; König et al., 2021). Electric car batteries accounted for 71% of Li-Ion battery sales in 2021.

As a result, the price per kWh of electric cars has fallen significantly in recent years. It is generally described that the price decrease follows a learning curve, or Wright's law, i.e., the price per kWh decreases by the same coefficient as soon as the number of units produced (counted in kWh) doubles[13] (Mauler et al., 2021).

At the same time, battery prices rose strongly in 2022. This follows because raw materials account for a significant portion of the cost of batteries, about 70% (Pillot and Renard, 2022; Bernhart, 2022), a result varying with the scope of the transformations taken into account in this calculation. Changes in raw materials prices will therefore strongly affect this fraction, and

[9] See `https://europe.autonews.com/automakers/dacias-spring-beats-all-china-evs-price-europe`

[10] https://en.pingwest.com/a/10934

[11] `https://www.reuters.com/world/europe/eu-launches-anti-subsidy-investigation-into-chinese-electric-vehicles-2023-09-13/`

[12] `https://www.carscoops.com/2025/04/how-one-man-outsmarted-us-tariffs-to-legally-import-a-chinese-ev/`.

[13] See also `https://about.bnef.com/blog/behind-scenes-take-lithium-ion-battery-prices/`

the overall cost of batteries. Raw material supply constraints in 2020-2022, coupled with strong demand for batteries for electric vehicles, have led to sharp increases in the prices of these raw materials (IEA, 2022; Bernhart, 2022). These supply constraints are of three different types. First, the consequences of policy measures in response to the Covid-19 pandemic led to a slowdown in economic activity. The rebound in demand in 2022 could not be met by production, causing prices to rise. Second, Russia's military attack on Ukraine has raised fears about the supply of Class 1 nickel (the purity required for the manufacture of Li-Ion batteries), 20% of which comes from Russia. Finally, lithium prices were low during the three years preceding the Covid outbreak, which structurally led the mining sector to underinvest in its production infrastructure.

It should be remembered that lithium is irreplaceable in current battery technologies, and that its use in batteries accounted for 50% of its annual production in 2021. While 25% of annual cobalt production is dedicated to the production of electric car batteries, manufacturers are now tending to reduce its content in batteries in favor of nickel in order to improve energy density and reduce costs.

Faced with these price increases, manufacturers are increasingly turning to LFP technology which, despite lower performances compared to NMC, is less sensitive to fluctuations in raw material prices as it does not contain nickel or cobalt. As a result, in 2024, LFP batteries accounted for 70% of batteries sold in China and 50% worldwide (IEA, 2025b).

One of the major questions is whether significant changes in battery prices could occur, making electric cars more affordable. In the literature, Muratori et al. (2021) provides an overview of the deployment of electric cars. The authors expect battery prices to fall. The authors anticipate cost savings through changes in the chemical composition of batteries (increased performance through the addition of active materials, reduction in the quantity of expensive materials), through improvements in battery pack optimization, and through economies of scale with production volumes. König et al. (2021) also anticipate an increase in battery energy densities. Mauler et al. (2021) reviews the literature on methods for forecasting battery cost trends. The authors list the types of technological improvements that can be expected at the cell level, adding that efficiency gains can also be expected at the pack level, particularly with the "Cell to pack" design. The authors expect battery prices to fall even if raw material prices rise. It should be noted, however, that the article was published before the sharp price increases of 2021-2022 and that it is difficult to identify the assumptions behind this assertion regarding raw material price increases. According to them, the lowest price estimates for Li-Ion technologies for NMC 811 technology (the cheapest) would be around $84/kWh at the pack level in 2050, compared to $115/kWh in 2024[14]. However, real values are found lower than the projections from Mauler et al. (2021).

As for the price of raw materials, trends are uncertain. It is difficult to predict their short-term trends. Following the rise in lithium prices, operators have been able to reactivate production capacities that had been set aside in previous years (due to low lithium prices). However, the time between the decision to invest in a mining operation and the start of production can range from 6 to 19 years for lithium and 4 to 19 years for nickel (IEA, 2022). Strong demand for electric vehicles could lead to continued pressure on mining in particular.

IEA (2025b) indicates that the prices of the battery raw materials went back to stable pre-2021 values, and that the 2024 value of the price of the battery packs was back in the trend given by the learning curve fitted on historical data. Battery prices may be likely to still slowly decrease following the learning curve, as long as there is no disruption on the supply chains of

[14]See `https://about.bnef.com/insights/commodities/lithium-ion-battery-pack-prices-see-largest-drop-since-2017-falling-to-115-per-kilowatt-hour-bloombergnef/`

raw materials.

7.2.3. Other EV costs

Apart from batteries, electric vehicles have other differences compared to combustion engine vehicles. While some wear parts are common (brakes, tires, suspension, on-board electronics, etc.), the reduction in the number of mechanical parts required for the engine to function reduces the likelihood of these parts malfunctioning (belt, clutch, injectors, etc.)[15].

Additionally, one should also consider the costs of financing the purchase — expected to be around 5% of the price of the vehicle[16] — the cost of insurance and the cost of maintenance. The cost of finance may increase slightly due to EV overcosts, however this may be offset by a decrease in the cost of insurance if EVs turn out to be more reliable than ICVs due to the lower amount of mechanical elements. This is neglected in the model.

7.2.4. Leasing

In recent years, there has been media coverage in France of electric car leasing deals available for a monthly price of €100. This section investigates if these offers are advantageous and, ultimately, whether leasing could be a way of making cars accessible to the lower income households.

Car leasing consists in renting a car for a fixed period, with the option to purchase it at the end of the contract. Otherwise, the cars are sold on the used car market. Leasing is currently most developed in the United States and Europe, where it accounts for 30% and 20% of new car sales respectively[17], and only 5% the Asia-Pacific region. A report by a market research company[18] indicates that leasing is more common among businesses (representing around 75% of end users) than individuals. This report forecasts revenue growth for the sector of around 7% per year between 2022 and 2027, i.e. a doubling time of 10 years.

Although leasing could make it easier to own a vehicle by limiting the initial cost, few articles actually mention this benefit and practice. The integrated cost over the period of ownership is also logically similar to the integrated cost of owning a purchased vehicle. Given that this practice is not widespread in the Asia-Pacific region, where incomes are lower than in the United States or Western Europe, we can deduce that leasing does not, or only slightly, facilitate car ownership.

Nevertheless, the concept of social leasing has emerged in France. This is supposed to enable low-income households to own an electric car for around €100/month. Some manufacturers already offer this type of deal[19]. However, this is conditional on obtaining the eco-bonus and the conversion bonus. The eco-bonus credits €5,000 for electric cars, increased by €2,000 for lowst income households (reference taxable income <€14,000). The €2,500 conversion bonus is conditional on scrapping an old combustion engine car that is still in working order. In France, cars covered by this leasing scheme have a purchase price of around €20,000. These conditions

[15] See, for example: https://www.fiches-auto.fr/articles-auto/fiabilite/s-267-duree-de-vie-des-pieces-d-usure-moteur.php

[16] See https://en.wikipedia.org/wiki/Car_costs or https://en.wikipedia.org/wiki/Car_finance

[17] See https://www.frost.com/frost-perspectives/a-deep-dive-into-asia-pacifics-leasing-market-shift-towards-vehicle-outsourcing/

[18] https://www.technavio.com/report/car-leasing-market-industry-analysis

[19] https://www.largus.fr/actualite-automobile/voiture-electrique-a-100-e-mois-pour-qui-pour-quand-et-pour-quels-modeles-30000210.html,
https://www.capital.fr/auto/voiture-electrique-a-100-euros-par-mois-des-offres-existent-deja-1475799

are quite restrictive.

Based on the modeling presented in section 7.3, we can also say that a household spending $100/month on car ownership has a budget that allows it to purchase a used car costing $14,400 (with secondhand ownership duration τ_s=12 years) and therefore has an initial new value of around €28,800, equivalent to an entry-level compact car (taking new ownership duration $\tau_n = 6$ and depreciation $d(\tau_n) \approx 0.5$) or a new car costing €14,400, equivalent to a mini-compact car, i.e., a model equivalent to the electric model offered for leasing. We also know from the initial results of results obtained from the first, static model presented below, that in France (see section 7.5), households with these budgets purchase around 90% of secondhand PV.

The various subsidies make the offer potentially attractive to households wishing to replace their vehicle. However, assuming that the incentives are zero, leasing simply smooths out the cost of ownership by reducing the initial purchase price — bearing in mind that leasing offers involve an initial cost without incentives of €7,000—9,500. We can therefore assume that the proportion of new buyers corresponding to these budgets (10%) would change little.

7.2.5. Economy savings in the fuel costs

Fueling a car with electricity is cheaper than with oil.

Data[20] indicate that the average price of oil was about 1.3—1.4$/liter. Assuming a fuel consumption of 6liter/100km for oil vehicles amounts to a price of 8$/100km. In comparison, the average price of electricity is around 0.16$/kWh[21]. Assuming a 0.20 kWh/km consumption[22], this amounts to 3.2$/100km. Assuming an overcost due to the fact that the cost of the charge increases compared to the usual cost of electricity, this result in a 4$/100km charge.

Therefore, there is a factor ≈2 between the price of ICV and EV fuel. Considering an average 15 000 km/year distance driven by PVs, this leads to a 600$/yr saving, or 3600$ of savings over 6 years (mean duration of the new PV ownership). This is roughly half of the overcost of an EV compared to a 20 000$ ICV.

7.2.6. Car segments

PVs can be splitted in several price segments. These indicative prices may vary from country to country. Minicompact cars which are generally small cars measuring about 3.4—3.7m (e.g. Renault Twingo, Fiat 500 or Fiat Panda), are sold around $15000. Subcompacts cars are sold around $20000 and can serve multiple purposes (examples: Peugeot 208, Ford Fiesta, Volkswagen Polo). Compact cars cost around $30000, are larger and have better performance (examples: Peugeot 2008, 308, Audi A3, Citroen C4). Beyond these prices, mid-size car are sold around $40000 and SUVs and some pickups are sold around $50000 and are both composed or cars serving multiple and different purposes, including social status.

This information is important for understanding household's car purchase as a function of their income, and for forecasting their behavior towards EVs.

[20] The data were retrieved from a website gathering oil prices of countries. The retained values represent the 2023—2025 trend, evolving with the global price of oil.
See `https://www.globalpetrolprices.com/gasoline_prices/`.

[21] The data were found at `https://www.globalpetrolprices.com/electricity_prices/`.

[22] This assumption was made over `https://www.iea.org/data-and-statistics/charts/electricity-demand-from-the-electric-vehicle-fleet-by-country-and-region-2030`, and
`https://ev-database.org/cheatsheet/energy-consumption-electric-car`.

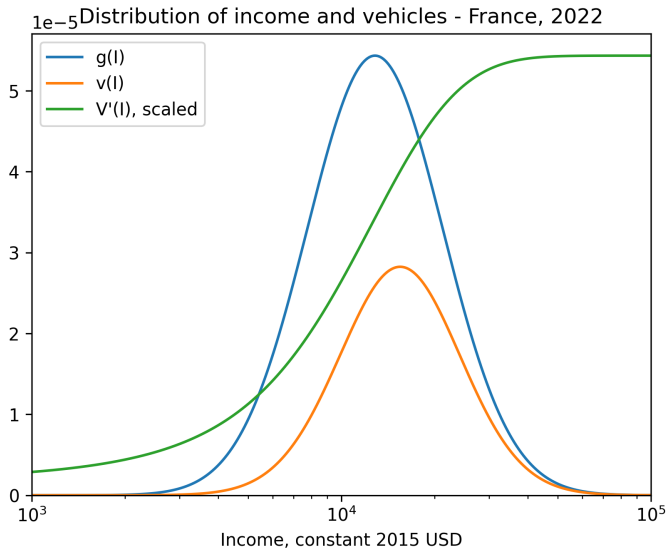


FIGURE 7.1: PV distribution $v(I)$ (see eq. 7.1) shown along income distribution $g(I)$ and the scaled PV ownership as a function of income $V'(I)$, scaled to match $g(I)$, for the readability of the figure. The data are shown for France in 2022, which is typical in Western countries.

7.3. DISTRIBUTION OF THE PV STOCK AS A FUNCTION OF INCOME

Chapter 6 directly allows the derivation of the distribution of the stock of PVs within a country and at a given time. We define:

$$v^c(I,t) = g^c(I,t)V'^c(I), \tag{7.1}$$

with $v^c(I,t)$ being the PV stock density function (in 1 / constant $ 2015 unit) for income I in country c and year t. Thus $v^c(I,t)$ is the PV stock distribution. $g^c(I,t)$ is the income distribution among the population, and $V'^c(I)$ the PV ownership associated with income I. These two last quantities are defined in Chapter 7. The superscript c designating the country and the parameter t designating the year are dropped in the remainder of the Chapter for simplicity. Figure 7.1 shows theses parameters in the case of France.

The vehicle distribution $v(I)$ often takes the form of a log-normal shaped curve with a richer median income than in the case of the income distribution $g(I)$.

7.4. DATA ON SECONDHAND VEHICLES

$v^c(I,t)$ provides the information on the distribution of the PV stock as a function of income in a country at a given time. The idea is then to add information on the behavior of household when purchasing a PV in order to deduce the distribution of the PV stock as a function of purchasing price. This will ultimately allow to differentiate households behavior towards electric private vehicle choice as a function of the class of the PV.

This section first discusses major assumptions and parameters to take into account for modeling the distribution of the PV stock as a function of purchasing price. Particularly, it is nec-

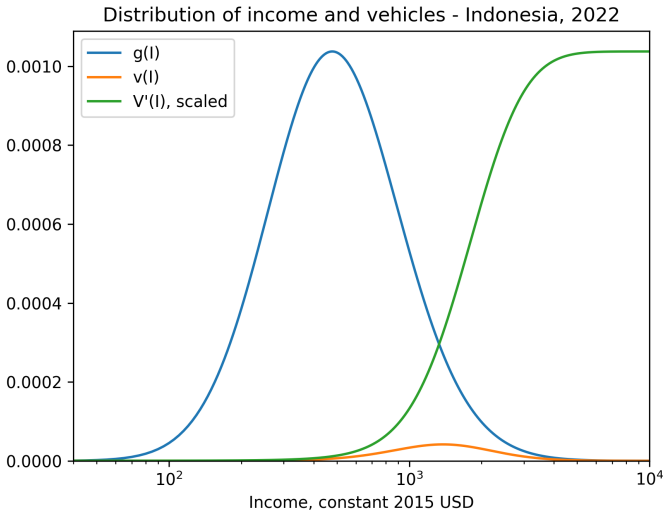


FIGURE 7.2: PV distribution $v(I)$ (see eq. 7.1) shown along income distribution $g(I)$ and the scaled PV ownership as a function of income $V(I)$, scaled to match the maximum of $g(I)$ for the readability of the figure. This is in the case of Indonesia in 2022, which best depicts trends in low to middle GDP per capita countries of south-east asia.
Note that these data are less certain due to the low robustness of $g(I)$ for higher income levels, see Chapter 6.

essary to differentiate the patterns towards the purchase of new or secondhand PV.

7.4.1. LIFETIME OF PV, AND OWNERSHIP DURATION OF NEW AND SECONDHAND PV

Held et al. (2021) study the cumulative survival probability of European cars as a function of their age based on european data, taking into account imports and exports. From this work, the average lifetime of a vehicle in Europe is 22 years, with a 7 years standard deviation. Higher GDP per capita and the presence of a local automobile industry is associated with lower car lifetimes. The lifetime of cars in France and Germany are 15 years.

The Chinese automobile industry has evolved quickly around 2010, and the lifetimes of cars in China was 13 years in 2016 (Zheng et al., 2019). Extrapolating the trend in the evolution of this data would lead to a 14—15 years car lifetime in 2025. Otherwise, the lifetime of cars are 14 years in Japan[23], 16 years in United States and 19 years in Brazil (Oguchi and Fuse, 2015).

The remaining question is how this lifetime is distributed between first- and secondhand owners. The European commission (2014) indicates — based on surveys — that the average age of cars sold secondhand in Europe was 6.2 years in 2010—2014, and increases to 7.1 years in lower income countries. This is in agreement with Vanherle and Vergeer (2017), who provide additional information on the lifetime distribution. A survey[24] conducted in 2022 found that the average age at which cars were bought secondhand was 6.5 years in the United States.

No data on third-hand PV were found. It is thus assumed that there is no third-hand purchasers but only secondhand ones that will keep the cars until scrappage, which is considered as a reasonable neglect. Also, because the ultimate aim is to analyze the speed of penetration of EVs, the most important factor is how fast new buyers will sell them secondhand, and their overall lifetimes. In this respect, whether a used car is sold only once or several times is unessential, and conflating together second-, third or higherhand owners has no influence on the correctness of the model

[23] See `https://www.statista.com/statistics/679614/japan-passenger-car-average-lifespan/`
[24] `https://www.valuepenguin.com/used-car-ages-study`

In this model, it is finally considered that the ownership duration of a new car is 6 years. The ownership duration of secondhand cars is considered to be 12 years, or the average lifetime of a car minus 6 years in countries in which the average lifetime of cars is known (Held et al., 2021; Zheng et al., 2019; Oguchi and Fuse, 2015). Denoting τ_n^c, τ_s^c the ownership duration of a new and secondhand car, and τ_{PV}^c the lifetime of PV in country c, one can write:

$$\tau_n^c = 6\text{yr}, \tag{7.2}$$

$$\tau_s^c = \tau_{PV}^c - \tau_n^c. \tag{7.3}$$

Due to the lack of data, imports and exports were neglected in the model.

7.4.2. Limitations on the battery lifetimes

The previous section actually discusses the lifetime of ICVs, but not of EVs as their deployment in the fleet is very recent. The EV stock only reached 1% of the global PV stock in 2021. However, the lifetime of batteries becomes a critical element regarding the lifetime of the vehicle.

Due to the similarity of EVs compared to ICVs, with the exception of the lack of major mechanical elements of ICVs causing failures when ICV get old, the battery is expected to be the limiting factor of EV lifetimes because of its price.

The lifetime of a battery is generally expressed in cycles. König et al. (2021) mentions a lifetime of around 1,000 cycles. According to a discussion with a Renault expert on battery chemistry (April 2023), the lifespan is expected to be now much longer, of at least 2,000 cycles. It is difficult to obtain accurate data on these lifespans today. In fact, there is little literature on the lifespan of electric vehicle batteries, as these technologies are emerging[25] and have been developing rapidly in recent years. It is therefore not possible to rely on statistical data on the lifespan of electric vehicle batteries, as the battery technologies used in used vehicles are now obsolete and do not reflect current technologies. In addition, the fleet of vehicles over 5 years old is relatively small (10 million vehicles worldwide according to IEA 2024d).

It is observed that depreciation of EVs is greater than for ICVs, with the vehicle worth only 20% of its initial cost after 6 years[26] (Schloter, 2022), while it is around 50% for ICVs (see section 7.4.3). However, it is difficult to know to what extent this is due to battery depreciation, as this is also a result of these vehicles to be early models in EV developments.

The capacity of lithium-ion batteries decreases during use. This reduction is mainly dependent on the number of usage cycles, the range of use (it is recommended to use them between 20% and 80% of their capacity to preserve their lifespan), the age of the battery, charging speeds, and operating temperatures.

The end of a battery's life is generally determined when its capacity reaches 80-70% of its initial capacity. Capacity loss accelerates beyond this point and displays a cliff effect at around 60%[27]. If we estimate the range of an electric vehicle to be around 200 km[28], the associated battery pack would have a lifespan of 200,000 km for 1,000 full cycles, which would correspond

[25] Li-ion batteries have been used in computers and smartphones for 15 years, however the technology used in EV batteries is different due to different technical constraints, and the total production volume increased significantly with the deployment of EVs since around 2020.

[26] `https://www.bloomberg.com/news/newsletters/2021-05-18/hyperdrive-daily-nobody-wants-china-s-used-evs`

[27] See `https://www.geotab.com/blog/ev-battery-health/` and `https://www.automobile-propre.com/voiture-electrique-quelle-garantie-pour-la-batterie/`

[28] See classical ranges at `https://theicct.org/publication/update-on-electric-vehicle-costs-in-the-united-states-through-2030/`

to a lifespan of around 13 years, assuming that a vehicle travels an average of 15,000 km/year (König et al., 2021; European commission, 2014; Schloter, 2022). Assuming the lifetime to be 2,000 full cycles would lead lifetimes of about 25 years. However, manufacturers now guarantee a battery life of 8 years[29], and batteries are generally expected to last between 10 and 15 years[30].

Used batteries could have a second life as stationary storage for grid balancing. Neubauer et al. (2015) estimates that the maximum repurchase price for second-life batteries would be between $20 and $40/kWh for the system to be economically viable, which is lower than the current price of batteries (around $120/kWh). In any case, the cumulative effect of battery health degradation limits the economic appeal of second-hand batteries. Moreover, due to the fact that battery capacity is expected to be the limiting factor in the lifetime of EVs, it is very likely that EVs will use the battery until it becomes unusable.

Let us assume that the battery will last 15 years. The value of ICVs at this age is around 15% of their initial price (see section 7.4.3). It is likely that a buyer would prefer to scrap its car and buy a secondhand one at 50% of its initial value rather than to buy a new battery (at 40% the cost of the initial vehicle) for its old vehicle.

The end of life of the batteries of electric vehicles will therefore very probably mark the end of life of the vehicle. Depending on the effective lifetime of the batteries, this could be a major barrier to the purchase of secondhand EV. The model developed in this Chapter would thus have to account for the uncertainty on the battery lifetime.

7.4.3. Depreciation of PVs

From Storchmann (2005), the depreciation $d(\tau)$ of a PV of age τ could be approximated by the following function:

$$d(\tau) = \exp\left(-\frac{\tau}{\tau_0}\right), \tag{7.4}$$

with τ_0 the time constant.

Based on Storchmann (2005) and several data found online on the price depreciation of cars[31], the time constant has been defined to $\tau_0 = 8\text{yr}$. Particularly, the depreciation of several segments has been studied. Generally, the price of secondhand cars is around 50% (30%) of the initial price of the car when it is 6 (10) years old.

7.4.4. Share of household spending in transport and car purchase

Valenzuela-Levi (2018), Mainaud (2021) and Eurostat (2025) inform us that the average share of household expenditures dedicated to transport is about 12%, with a share dedicated purchase of vehicles purchase around 4%[32] is around 4%, for OECD and European countries, and is relatively stable over time.

However, Gandelman et al. (2019b) indicates that these shares are higher in the case of Latin America. Indeed, in the case of the purchase of vehicles, Valenzuela-Levi (2021) and Hussain et al. (2025) indicate that the share of the expenditures dedicated to private transports tends to

[29] See `https://batteryuniversity.com/article/bu-1003a-battery-aging-in-an-electric-vehicle-ev`, `https://www.automobile-propre.com/voiture-electrique-quelle-garantie-pour-la-batterie/`

[30] See `https://batteryuniversity.com/article/bu-1003a-battery-aging-in-an-electric-vehicle-ev`

[31] `https://www.themoneycalculator.com/vehicle-finance/calculators/car-depreciation-by-make-and-model/` gave information based on data they retrieved, `https://www.largus.fr/` and `https://www.edmunds.com/` were used in order to see real data on secondhand car prices.

[32] This figure is the results of the total expenditures in new and secondhand vehicles, of which the earnings of the individual selling its car to a secondhand buyer have been subtracted.

be higher in countries in which the level of income inequalities is high, because these countries tend to invest less in collective infrastructure thus in public transport.

Chinese households devote a higher share of their expenditure to the purchase of vehicles at around 8% (Liu et al., 2023), although that could be due to some extent to the fact that the fleet of vehicles is growing quickly (+60% between 2017 and 2023). Indeed, as the fleet grows, the number of second-hand vehicles sold is lower than the number of new vehicles purchased, which decreases the overall benefits obtained by households from reselling their used car.

Finally, Gandelman et al. (2019b), Kauppila (2011) and the data from Eurostat (2025) indicate that the share of household expenditures dedicated to the purchase of vehicles is increasing with income quintiles within a country at a given year. This makes sense as low-income household tend to spend more on public transport than on private vehicles that require a high initial investment. Moreover, Schanzenbach et al. (2016); RAC Foundation (2008) show that low-income household tend to spend a greater share of their expenditures to basic needs such as food and housing.

The observed metric is often the share in total expenditures. On the other side, the income data we use are fitted on PIP data, which seek to "measure disposable income defined as the sum of labor and non-labor income (including transfers) less taxes and contributions"[33], which correspond grossly to the sum of expenditures and savings of the households. Saving rates of household increase with their income level. In the absence of data on the saving rates of household as a function of their income levels, it is thus not possible to derive the actual PV expenditures level of each household. We neglect this source of error in our modeling, which creates a systematic error.

7.5. Modeling the new and secondhand PV stock distribution as a function of income

The model presented below assumes that the total stock of vehicles (new and secondhand) is given by the modeling of $v(I)$ resulting from Chapter 6. Because of this we do not adopt the most common stock-flow modeling through differential equations for the stocks of new and secondhand vehicles. Instead, we use the vehicle number conservation constraints in a different way, explained below.

7.5.1. Models

Let us consider that the distribution of the PV stock $v^c(I,t)$ disaggregates between the new and secondhand PV stocks $v_n^c(I,t)$ and $v_s^c(I,t)$.

$$v^c(I,t) = v_n^c(I,t) + v_s^c(I,t). \tag{7.5}$$

The superscript c referring to the country is dropped in the remainder of the section. Indeed, as long as the imports and exports are neglected (which is the case here), the model does not contain inter-country dynamics.

The distribution of the PV stock as a function of income evolves with time in a country.

[33] https://datanalytics.worldbank.org/PIP-Methodology/welfareaggregate.html#incomeorconsumption

Generally, GDP per capita increases, which implies the distributions grow in size due to the increase of the PV stock, and slides towards higher incomes as the population get richer. We thus define the entering ("+") and leaving ("−") flow of PVs each year in the stock of new ("n")and secondhand ("s") PV: $\phi_{n,+}(I,t)$, $\phi_{n,-}(I,t)$, $\phi_{s,+}(I,t)$ and $\phi_{s,-}(I,t)$. The stock-flow balance can be written:

$$v_n(I,t) = v_n(I,t-1) + \phi_{n,+}(I,t) - \phi_{n,-}(I,t), \tag{7.6}$$

$$v_s(I,t) = v_s(I,t-1) + \phi_{s,+}(I,t) - \phi_{s,-}(I,t). \tag{7.7}$$

We then assume that there is a static equilibrium, or a stationary regime between entering and leaving flows at each year. This is reasonable as the PV stock distribution as a function of income evolves slowly for most countries. The uncertainty resulting from this hypothesis in the case of China — the country in which the PV stock as well as the GDP/cap are growing very rapidly — is studied in section 7.7. Ideally, modeling the evolution of the new and secondhand PV stocks would require modeling precisely the time evolution of all flows. However, the lack of data limits the precision of the model in any cases. Moreover, this would add mathematical complexity to the model and lead to an overdetermined mathematical problem.

This static equilibrium implies that:

$$\phi_{n,+}(I,t) = \phi_{n,-}(I,t) = \frac{v_n(I,t)}{\tau_n}, \text{and} \tag{7.8}$$

$$\phi_{s,+}(I,t) = \phi_{s,-}(I,t) = \frac{v_s(I,t)}{\tau_s}. \tag{7.9}$$

The sale of a PV converting from new to secondhand PV can be written:

$$\phi_{n,-}(I_n,t) = \phi_{s,+}(I_s,t), \tag{7.10}$$

with I_n the income of the seller and I_s the income level of the buyer. This also implies that:

$$\frac{v_n(I_n,t)}{\tau_n} = \frac{v_s(I_s,t)}{\tau_s}. \tag{7.11}$$

The correspondence between these two quantities must now be found.

We assume that the share $S(I)$ of the budget allocated to the purchase of vehicles as a function of income is proportional to $V'(I)$ the vehicle ownership as a function of income: $S(I) \propto V'(I)$. This empirical proportionality is observed to be reasonable for a number of countries, including France (Kauppila, 2011; Gandelman et al., 2019b), as depicted on figure 7.3 and considerably simplifies the algebra of the model. Due to the lack of data, we also assume that $S_n(I) = S_s(I) = S(I)$. From section 7.4.4, we also assume the average share of the budget allocated to the purchase of vehicles for households to be $S_0 = 4\%$.

The definition of $S(I)$ implies that:

$$\int S(I)g(I)dI = S_0. \tag{7.12}$$

Finally, Chapter 6 yields the following equation:

$$\int V'(I)g(I)dI \approx V(y), \tag{7.13}$$

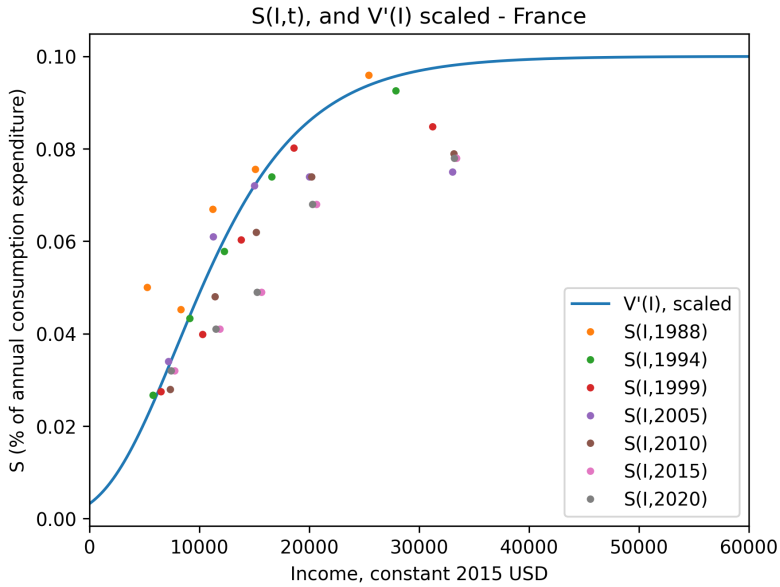


FIGURE 7.3: Data on $S^{FRA}(I,t)$ shown with the theoretical scaled $V'^{FRA}(I)$.
The $S(I,t)$ data represent the data on quintiles, retrieved from Eurostat (2025).

with $V(y)$ the national vehicle ownership level for a given GDP per capita y. Chapter 6 shows that this is valid to a good degree of approximation in most countries.

This leads to the following equation:

$$S(I) = V'(I)\frac{S_0}{V(y)}. \tag{7.14}$$

We denote $C_x(I_x)$ with $x \in \{n, s\}$ the average price of the PV new or secondhand bought by a buyer of income I. The definition of the average share of the annual budget allocated to the purchase of vehicles as a function of income yields:

$$S(I_s) = V'(I_s)\frac{C_s(I_s)}{I_s\tau_s}, \tag{7.15}$$

$$S(I_n) = V'(I_n)\frac{C_n(I_n) - C_s(I_s)}{I_n\tau_n}. \tag{7.16}$$

Note that the t parameter can only be removed due to the stationary condition.

Finally, the depreciation relation Eq. 7.17 leads to:

$$C_s(I_s) = d(\tau_n)C_n(I_n). \tag{7.17}$$

Combining Eqs. 7.14 7.15, 7.16 and 7.17 yields:

$$C_n(I) = I\frac{\tau_n S_0}{(1 - d(\tau_n))\,V(y)}, \tag{7.18}$$

$$C_s(I) = I\frac{\tau_s S_0}{V(y)}. \tag{7.19}$$

The following correspondence between the income of the seller I_n and the buyer I_s at the sec-

ondhand sale is deduced:

$$I_s = I_n \frac{d(\tau_n)\tau_n}{(1 - d(\tau_n))\,\tau_s}. \tag{7.20}$$

7.5.2. Disaggregating new and secondhand PV distributions

$v_n(I)$ and $v_s(I)$ must simultaneously respect 7.5, 7.11 and 7.20. The principle of the method used in the problem is the following:

Firstly, the income range is split in discrete intervals. It is evident that only new PVs are associated with higher incomes, and only secondhand cars are associated with lower incomes. Both computations are designed to produce a series of income values connected to each other through Eq.7.20 in a recursive fashion. The first one starts from a high income I^0, and chains discrete income values with $I^1 = I_s$ deduced from this equation from $I^0 = I_n$. The process is repeated from I^1 to I^n until the lowest possibly income of the distribution is reached (the next iteration then ending outside the range of incomes). The second one mirrors the first one. A small income value $I^0 = I_s$ is set, with $I^1 = I_n$ deduced from Eq.7.20. The process is repeated until the highest income of the distribution is reached. The first series (starting from the right-side of the distribution) is indexed by r, the second (starting from the left-side of the distribution) is indexed by l.

Next $v_s(I^i)$ and $v_n(I^i)$ are obtained from Eqs.7.5 and 7.11. For the right series, this starts with $v_{s,r}(I^0) = 0$ and $v_{n,r}(I^0) = v(I^0)$. For the left one, this starts with $v_{n,l}(I^0) = 0$ and $v_{s,l}(I^0) = v(I^0)$.

More precisely, for the right series, this gives:

$$\begin{cases} v_{n,r}(I) = v(I) - v_{s,r}(I) \text{ if } v_{s,r} \leq v(I)\,, v_{n,r}(I) = 0 \text{ else;} \\ I_s = I \frac{d(\tau_n)\tau_n}{(1-d(\tau_n))\tau_s} \text{ (see equation 7.20),} \\ v_{s,r}(I_s) = v_{n,r}(I) \frac{\tau_s}{\tau_n} \text{ see equation 7.11.} \end{cases} \tag{7.21}$$

Similarly, for the left series:

$$\begin{cases} v_{s,l}(I) = v(I) - v_{n,l}(I) \text{ if } v_{n,l} \leq v(I)\,, v_{s,l}(I) = 0 \text{ else;} \\ I_n = I \frac{(1-d(\tau_n))\tau_s}{d(\tau_n)\tau_n} \text{ (see equation 7.20),} \\ v_{n,l}(I_s) = v_{s,l}(I) \frac{\tau_n}{\tau_s} \text{ see equation 7.11.} \end{cases} \tag{7.22}$$

Each of this series allows us to use in a simple manner the constituting equations of the model, while respecting the income relation between secondhand buyers and firsthand owners. Several such pairs of series of income can be produced to sample finely enough the income distribution.

However, as seen on Fig.7.4, the right series starts to develop unphysical oscillations on the left, while the left series does the same on the right. These oscillations are produced by the simplifications introduced in the model (including the stationary hypothesis). The simplest way to achieve a more realistic result while keeping the present model is to fade one solution into the other. In the end, the final PV stock is chosen as a weighted average of the left and right quantities with weights $a(I)$ (for the left series) and $1 - a(I)$ (for the right series). With $v_{n,th}(I)$ and $v_{s,th}(I)$ the new and secondhand PV stock distribution retained, we can write:

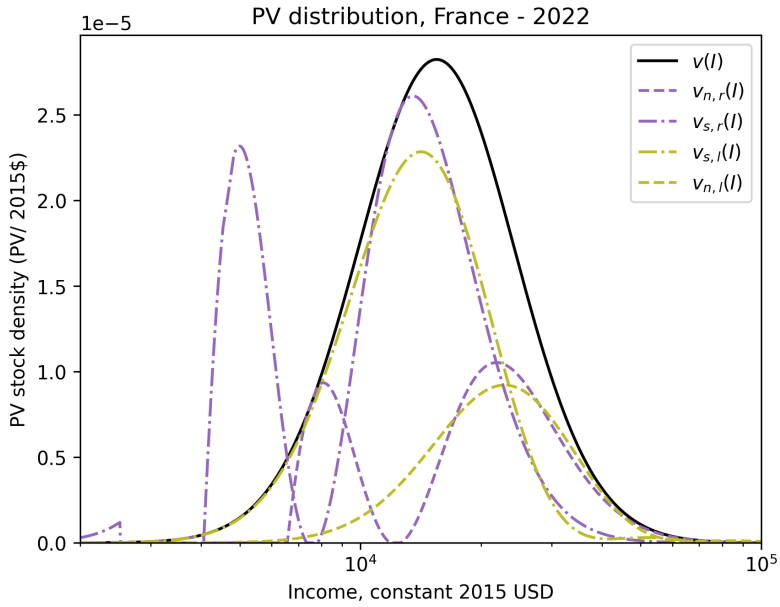


FIGURE 7.4: PV distributions computed with the method described. Purple curves represent the distribution resulting from the method beginning at highest incomes, while green curves begin at the lowest. Dashed curves represent the new PV stocks, while dash-dotted curves represent the secondhand stocks. The oscillations are a result of the method.

$$v_{n,th}(I) = a(I)v_{n,l} + (1 - a(I))\, v_{n,r}, \tag{7.23}$$

$$v_{s,th}(I) = a(I)v_{s,l} + (1 - a(I))\, v_{s,r}, \tag{7.24}$$

with:

$$a(I) = \begin{cases} 1 & \text{for } I < I_l \\ K_1 \ln(I) + K_2 & \text{for } I_l \leq I \leq I_r \\ 0 & \text{for } I > I_r \end{cases}, \tag{7.25}$$

I_l and I_r being income thresholds, defined as the first income value at which $v(I) = max\left(v(I)\right)/K_l$ and the last value at which $v(I) = \max\left(v(I)\right)/K_r$ respectively. Empirically, we set $K_l = 1.1$ and $K_r = 2$. K_1 and K_2 are 2 constants found in order for $a(I)$ to be log-linear between I_l and I_r.

Figure 7.5 finally show $v_{n,th}(I)$ and $v_{s,th}(I)$ resulting from the process, along with $a(I)$, in the case of France in 2022.

The distribution of the PV stocks as a function of the purchase price of the PV $v_n(C_n(I))$, and $v_s(C_s(I))$ can also be computed. This is an important information for the remainder of the model. The result in the case of France in 2022 is depicted in Fig. 7.4.

Note that this last $v_n(C_n(I))$ is actually the distribution of the PV stock sold at a given years. For example, we deduce that 30 000$ cars were the most common segment sold in France in 2022. This information is crucial in the model of section 7.6. This result seems consistent with the reality, but note that no real data on the distribution on the vehicles sold as a function of their price were found.

The results indicate that the PV stock distribution evolves slowly with time for most advanced economies. In these cases, the stationary condition is quite correct. However, China and South-East Asian countries depict a strong increase in yearly GDP per capita, consequently

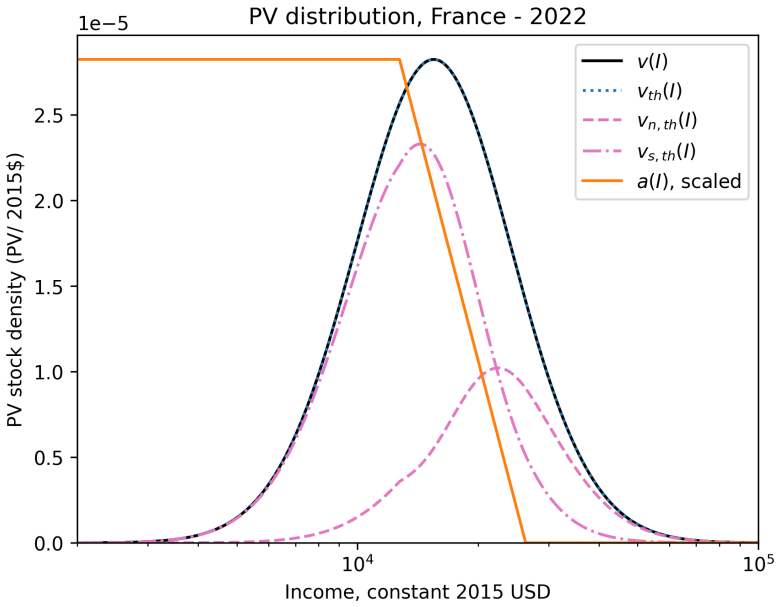


FIGURE 7.5: PV stock distributions and $a(I)$. v_{th} is mixed with $v(I)$. $a(I)$ have been scaled.

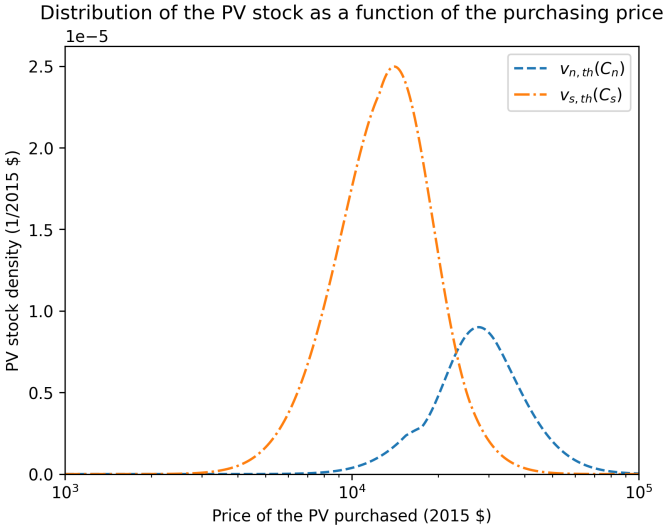


FIGURE 7.6: Distribution of PV stock as a function of purchasing prices $C_n(I)$ and $C_s(I)$ in the case of France in 2022. $C_s(I)$ is the price of the secondhand purchase, which is lower than the price payed for buying it new.

in the distribution of income $g(I)$, and also in the total PV stock. This implies that the PV stock distribution as a function of income would probably increase strongly with time. Therefore, the error induced by the stationary condition would have to be quantified for these countries. Note however that the case of China is not important in our study as EV affordability is not expected to be a main barrier to Chinese EV deployment.

7.6. MODELING THE BEHAVIOUR OF HOUSEHOLD TOWARDS EV PURCHASE AS A FUNCTION OF THEIR INCOME

Having devised methods to obtain the number of new and secondhand PV in the countries and world fleets, we are now in position to make projections of (partial) EV substitution for the future. To this effect, we split new PV inflows into an internal ICV $\phi_{n+,ICV}(I,t)$ and EV $\phi_{n+,EV}(I,t)$ sub-flows. We have:

$$\phi_{n+}(I,t) = \phi_{n+,ICV}(I,t) + \phi_{n+,EV}(I,t) \tag{7.26}$$

The issue revolves around modeling $\phi_{n+,EV}(I,t)$. This is envisioned through the elaboration of a series of more and more sophisticated scenarios, by income categories. Different categories of cars were defined in section 7.2.6, and represent different level of service or quality, which are strongly correlated to PV prices. In this, we follow a common practice in the PV market.

For each category of income, we define a new purchasing behavior. It is assumed that each potential buyer, when renewing his PV, can choose between a new or second-hand ICV, or a new or second-hand EV. Lower-income earners may also choose not to buy PVs, satisfying their mobility needs in other ways.

If a buyer chooses to switch to an EV, (s)he faces a cost overhead $A(I,t)$ of an electric car compared with an equivalent (same category) ICV, i.e. the purchase price of an equivalent car increases: $C_{EV} = A(I,t)C_{ICV}$. Part of the savings made by the household on their car use and maintenance budget are assumed to be reinvested in the purchase budget (see section 7.2.5). To simplify things, we have chosen to include this directly in the overhead cost calculation.

A buyer then has several choices:

1. A buyer may first accept the cost overhead without changing her/his behavior (i.e., choose a PV in the category he is used to and not changing the PV ownership duration), in which case (s)he increases her/his annual budget $S(I)$. However, this implies at first sight that associated second-hand buyers must also have a higher budget than initially envisioned.

2. A buyer may instead increase his ownership duration in order to buy an equivalent electric car without increasing his annual budget. In terms of modeling, if the buyer is a new PV purchaser, this would result in higher depreciation, since this depends directly on the duration of the PV ownership. The associated second-hand buyer will therefore have a lower budget. If a second-hand car is purchased, the ownership duration may be limited by the lifetime of the PV (and the most constraining point on this front may possibly be the battery lifetime for EVs).

   In both cases, changes in ownership duration will have an influence on the flow of PV, and therefore on stocks. For example, for a stationary solution, Eq. (7.11) implies that an

increase in τ_n would imply an increase in $v_n(I)$, accompanied by a decrease in $v_s(I)$ as a consequence of Eq. (7.5).

3. A buyer may choose to switch from a new to a second-hand PV (or vice-versa).

   In this case, we can expect to see an imbalance between supply and demand for new and second-hand PVs, whether EV or ICV. In the case of an imbalance for second-hand PV sales, we can assume that depreciation will evolve, for the same ownership duration τ_n: PVs would lose value less quickly if supply is lower than demand. The second-hand income associated with the new income would then evolve. We can also assume that buyers will vary the ownership duration to adapt to these price variations. This would have the same effects as in the previous case.

4. A buyer may accept a downgrade.

   In this case, the purchase price remains the same, but the car model will be downgraded from the original ICV category.

In all cases, except for downgrading, the effects of changes in behavior will modify the market. The modeling exercise will have to take this into account.

The options listed below are in all likelihood presented in order of decreasing preference. Indeed, generically speaking, potential buyers have a preference to maintain their level of comfort or increase it (Choi and Koo, 2019; Glerum et al., 2013), and this applies when they change their vehicles (at least in the type of BAU scenario of interest in this thesis; degrowth scenarios imply fundamental behavior changes towards sufficiency that are not within the scope of this study). Thus they will prefer to maintain or improve the category of vehicles they use, and prefer newer vehicles over older or aging ones; in this logic, a downgrade will be the last fallback option. Taking into account that a change of vehicle is operated under a budget constraint, the option that will in the end be chosen in the above list will depend on the available budget.

It was not possible within the time frame of this thesis to pursue this investigation to its conclusion. Some indications on the modeling required are hereby discussed. The difficulty lies in the fact that all decisions influence subsequent new or the secondhand markets.

In the case of buyers purchasing new vehicles: 1/increasing their budget implies that these electric vehicles will be sold at higher prices on the secondhand market, or that vehicles will depreciate more rapidly; 2/increasing ownership duration reduces the flow of EVs for secondhand buyers. The price is also affected by the effects of the initial overcosts, which are partially offset by greater depreciation. The equilibrium between both phenomena would have to be found; 3/Switching to secondhand EVs would reduce future stocks of secondhand PVs (EVs and PVs), and increase demand for secondhand PVs; 4/Accepting a downgrade is not possible for the lowest incomes that are already purchasing lowest segment cars.

In the case of buyers purchasing secondhand vehicles: 1/extending secondhand ownership duration reduces the pressure on demand for secondhand PVs. However, this is critically limited by the battery lifetime; 2/Downgrading or increasing the budget is unlikely for lowest income households.

Some consequences of these modeling principles and remarks can be anticipated. Firstly, only the highest income households are in position to increase their car ownership budget. We could assume that households purchasing secondhand EVs from first-hand households increasing their budget for new electric PVs will also increase their budget. This will not affect the rest of the market. In practice, one may assume that the probability of increasing the budget increases with income, and when the difference between ICVs and EVs prices reduces.

Secondly, uncertainties on battery lifetimes may be handled through scenarios. Indeed, this is the most uncertain parameter, and it limits the maximum ownership duration. The assumption about the lifetime of EVs will be reflected in the depreciation function: a shorter lifetime will result in a faster EV depreciation.

Thirdly, the ICVs depreciation function will also be changed to account for the differences in the demand and supply of secondhand PVs. This is because buyers deciding to extend the ownership of new electric PVs will reduce the stock of secondhand cars. In cases where the EV lifetime is low, owners will probably keep their vehicle quite long due to their faster depreciation (due to the limited battery lifetime), or even keep their EVs until the end of their lives. In these cases, secondhand buyers would probably keep their ICVs longer. This may create a tension on the secondhand market. One may take this into account through the depreciation functions for ICVs and EVs: depreciation will slow down when secondhand demand falls short of supply. In turn, the required budget of new ICVs buyers will decrease, accentuating the overcosts of new EVs compared to new ICVs.

The amount of new ICV buyers opting for secondhand EVs will thus depend on the demand-supply tension of secondhand EVs and ICVs (thus on depreciation functions). Their number is likely to be negligible in scenarios with a short battery lifetime. Similarly, households opting for a downgrade will be strongly influenced by EV and ICV depreciation: rapid EV depreciation alongside slow ICV depreciation would increase the comparative overcosts of EVs, resulting in a reduction the proportion of these households.

The market evolution described will be dynamic, taking into account the delay for new EVs to become secondhand (τ_n). In this model, EV and ICV depreciation functions will therefore be important parameters, influencing the decisions of households that initially buy new ICVs.

Building a model based on these principles will require significant work to adjust parameters and functions to ensure consistency.

7.7. Discussion

This chapter presents steps involved in building a model of EV deployment under the affordability constraint.

Firstly, it provides relevant elements that frame the problem. These elements are necessary in order to refine the assumptions of the model, but it should be noted that some of these are uncertain and will require updating, as EVs are still in their early stages of deployment. Particularly, 1) the evolution of the overcost of EVs compared to equivalent ICVs over time (partly due to the evolution of battery prices) and over regions mainly due to trade with China (IEA, 2025b); 2) the lifetime of batteries is still speculative and real-world data would be really useful.

One of the main conclusions of these considerations is that the Chinese market is not much affected by affordability as a barrier to EV deployment (50% of the PV sales were EVs in China in 2024 IEA 2025b while this figure increases by around 10% per year), whereas Western countries will still be strongly affected, along with other countries. Proximity to the Chinese market tends to lower the overcost of EVs. The results of Chapter 4 indicate that the Chinese PV fleet will represent around 25% of the global PV stock between 2030 and 2050.

Secondly, based on the models of Chapter 6, we modeled the distribution of new and secondhand PVs as a function of income in a country at a given time, and as a function of the purchasing price of the vehicle. This is an important result of this chapter. This result is also

crucial for the next step of the model. The error induced by the stationary condition must be computed for countries in which the PV stock and GDP per capita are expected to grow significantly. However, the lack of information on the dynamics of the PV fleet may prevent the elaboration of more refined models.

Thirdly, section 7.6 defines leading guidelines for modeling the impact of EV overcosts on EV deployment. Completing such a model requires however a significant amount of additional work.

Conclusion

Aim of the thesis

Industrialized societies generate environmental pressures that lead to threats such as climate change, biodiversity loss and resource scarcity. Moreover, their development has led to a high level of complexity, interdependence as well as vulnerabilities. This is likely to induce more systemic crises in the future and possibly at an increased pace, of which the 2008 great recession and the 2019 COVID pandemic are examples.

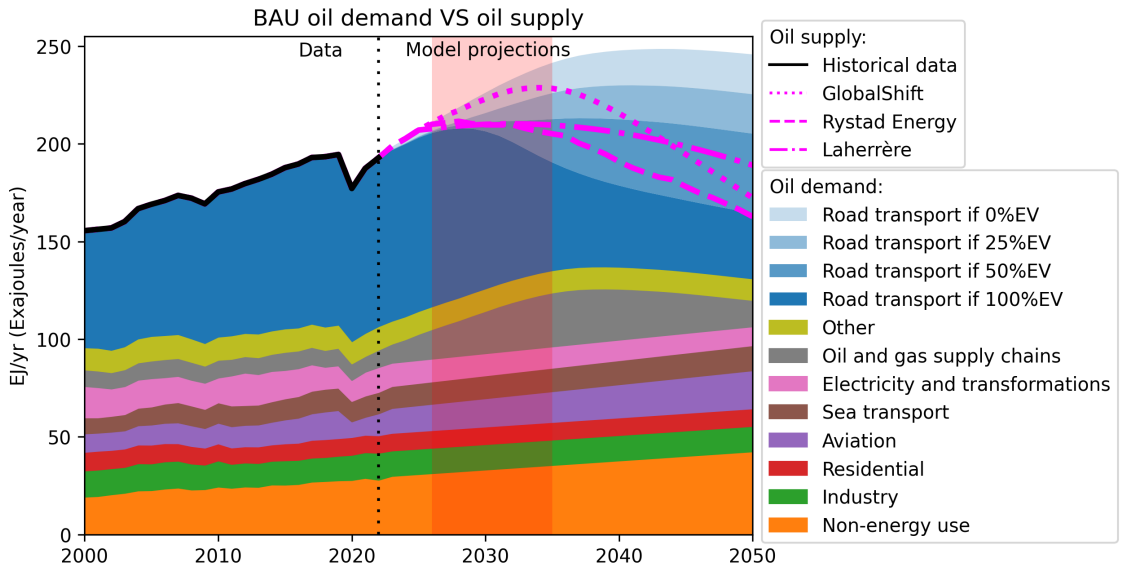
In particular, the energy supply is expected to come under pressure, due to the anticipated peak in oil and gas supply around 2030—2035 and 2035—2040 respectively. Consequently, this thesis investigates whether energy supply could be able to match energy demand up to 2050 in a business as usual (BAU) scenario. The ability of the oil supply to meet oil demand is investigated particularly due to the criticality of oil in the economy and its early supply peak.

BAU scenarios are often considered as reference scenarios in models (particularly in IAMs). Although it is clear that fossil fuels should be phased out before their supply peaks in order to limit climate change and other irreversible threats to human societies, this thesis instead examines the limits of BAU scenarios with regard to energy supply in order to discuss their relevance.

Will energy supply be able to meet energy demand of a business as usual (BAU) scenario by 2050?

Chapter 1 first concludes that wind turbines and photovoltaic panels (PV) are the only two energy technologies that could be deployed at high rates. However, many barriers are expected to their large-scale deployment. Electric grids must expand quickly in order to connect these distributed sources. Moreover, high levels of wind and PV penetration in the grid result in increased costs due to required storage and grid balancing capacities. The electrification of oil usage is also expected to face technical and economic barriers. The limited electrification rate of consumption technologies, combined with lock-ins in fossil fuel consumption, is expected to limit the large-scale deployment of wind and PV.

Secondly, Chapter 2 concludes that oil and gas gross energy supplies are expected to peak around 2035 and 2040 respectively, with limited uncertainty, and coal around 2067. Addi-



Result from Chapter 5. Cumulative oil demand in a Business as Usual (BAU) scenario, confronted to different projections on future oil supply representing the amplitude of ultimate recoverable resources (URRs). Oil demand in the road transport sector is shown according to different scenarios of electric vehicle (EV) deployment. The legend ("0%EV", "25% EV", "50%EV", "100%EV") indicates the saturation of the share of EVs in the total stock of private vehicles in 2050. The total oil demand in each of these scenarios corresponds to the upper limit of the associated colored zone.
The red area is the 2026—2035 time area at which oil demand is more likely to fall short of oil supply.

tionally, regarding only the maximum expected industrial deployment rate, the required exponential deployment rate of wind and PV in order to compensate for future declines in oil and gas supply would theoretically be feasible. In any case, it is also noted that consuming all available fossil fuels resources would lead to a global warming of around 3°C at the end of the 21^{st} century.

Thirdly, Chapter 3 shows that the energy investments required in the oil and gas supply chains will increase significantly towards 120 EJ/yr for oil in 2035 and 100 EJ/yr for gas in 2040, which respectively represent a +75% and a +100% increase compared to 2022. These investments are expected to slightly increase the tension between oil and gas supply and demand, and significantly increase the required energy investment from other energy sources in the oil and gas supply chains. The societal EROI is thus expected to decline.

Chapter 4 then models oil demand and finds that it is expected to increase in all scenarios in which private electric vehicles account for less than 50% of the total vehicle stock. This is primarily driven by the development of cars in China and India, as well as by increasing petrochemical demand and the oil demand of the oil and gas supply chains computed in Chapter 3. The uncertainties are dominated by the uncertainty surrounding the future deployment of electric private vehicles.
This is then compared to oil supply in Chapter 5. It is found that oil supply could be lower than BAU oil demand as soon as in 2026, and would probably be between 2026 and 2035, as shown in the figure above. This final conclusion is all the more robust that in the process of this investigation, oil supply has been somewhat overestimated when in doubt, and oil demand underestimated by choosing a very moderate BAU growth scenario.

Chapter 6 found a model for the evolution of PVs ownership in countries as a function of household income. The distribution of private vehicles as a function of households income is

then deduced. Chapter 7 finally distributes new and secondhand PV stocks as a function of household income, or as a function of PV prices, in countries and over time. It is also found that EVs battery lifetime, together with the future evolution of EVs purchasing price overcosts compared to ICVS, are critical in the deployment of EVs. Further work is required in order to achieve the model of households behavior towards the EV market, allowing the computation of the deployment of EVs under their affordability barriers.

The main conclusion of this thesis is that oil supply will not be able to meet the oil demand of a BAU scenario up to 2050, probably falling short as soon as between 2026—2035 (which is quite soon). This is mainly discussed in Chapter 5.

Implications

This implies that, in the case of a BAU scenario, oil consumption will be constrained around 2026—2035, likely resulting in a crisis. However either massive efforts toward the energy transition, or voluntary early decline in GDP by refocusing production towards satisfaction of the population needs through much less energy and material intensive technologies, could avoid this widespread recession scenario.

In the first case, states would have to invest massively in the energy transition as well as to tax fossil fuels in order to foster energy transition technologies. This would likely impair GDP growth for at least a transitory period considering that increases in fossil fuel prices would spread to the prices of all commodities, and that the activities of some sectors would be likely displaced towards efforts in the energy transition. However, this would enable a higher long-term energy supply than in the absence of any investments, and a lower climate change level[34]. This seems in any case more desirable than BAU scenarios of whatever type (understood as unimpaired GDP growth scenarios with related energy demand growth). Indeed, BAU scenario will inevitably result in energy crises — thus economic crises — as well as high levels of climate change, as shown in this thesis. Better than just an ambitious energy transition scenario, an anticipated degrowth scenario seeking maximum welfare for citizens while decreasing the environmental footprint and other societal vulnerabilities would be more effective on social and environmental fronts.

The second case — an early GDP decline — is a more likely scenario. Indeed, the disruptions observed in the 2020's, such as Covid-19 pandemic and Russian aggression war on Ukraine have had major effects on the global economy and supply chains. Moreover, there has been a rise in global conflicts and tensions, such as the Israeli invasion of Gaza and subsequent rise in tensions in the Middle East, the international law is being more frequently violated, defense spending rise globally and authoritarian political regimes arise worldwide. These can be seen as the signs of the growing significance of global vulnerabilities, which lead to more frequent crises. Tainter (1988) has shown that this has historically led to constant competition between states, resulting in collapses or gradual disintegrations.

Energy issues are therefore eminently political, and not just technical. Political lock-ins[35]

[34] The long-term effects on climate change could in fact be discussed. Indeed, in the case in which the societies seek maximum energy supply despite climate effects — which has historically been the case — the energy supply from renewable sources may enable to partially offset oil and fossil peaks, allowing the economic conditions for fossil fuel extraction to last longer than in a scenario of economic crises produced by the mismatch between oil supply and demand. On the other side, a massive energy transition would hopefully seek to phase out fossil fuels.

[35] I personally think of the pursuit of maximum power by states, the growth ideology and the influence of the capitalist class on media and

currently prevent massive efforts towards an ambitious energy transition as well as towards voluntary degrowth, even though these scenarios can be argued to be more desirable (in light of the impending and unanticipated energy crisis demonstrated in this thesis as well as of the environmental damages that put pressure on industrialized societies). Political and institutional failure to solve issues has been identified in Tainter (1988) and Diamond (2005) as a common characteristic of societies that have faced disintegration. This calls for study and action on these lock-ins and at a systemic level.

Relevance and limitations

The remainder of the conclusion only reflects my personal view.

This work provides a reasonably robust proof of the impossibility of BAU scenarios in the next decade, due to energy limits. The objective of this approach is to encourage the academic community and stakeholders to move away from BAU scenarios, and to recognize the near-future related limits to growth. The ethics and the possible societal effects of this thesis are further discussed in Appendix B (in French) and C (in English).

This work however does not attempt to model future pathways, which are likely to diverge from BAU scenarios earlier than the time imposed by the energy limits quantified in this work. It also does not describes how energy limits would affect the global economy. Finally, it does not attempt to propose desirable scenarios. Moreover, the energy tension modeled in this work is on a global scale. This hides disparities between countries. Typically, countries with lower GDP/cap are likely to suffer more than high-GDP/cap ones[36] from the future tension between oil supply and demand, whatever the form it will take.

Finally, I find it a bit strange to talk about industrialized societies without discussing the social, political and economic systems it has led to. The tremendous growth achieved since the Industrial Revolution has led to significant progress in human health indicators; but this has also led to economic systems in which companies are encouraged to maximize profit rather than societal benefits. This has led to value consumerism and material wealth, of which the interests for our communities are controversial, and that are harmful for the environment and thus to future living conditions, at the expense of social values. This also currently leads to societies in which people are less and less encouraged to emancipation. This leads, as observed nowadays, to the rise of authoritarian regimes with domination values.
This society has also grown upon power relationships. Future scenarios are not necessarily exempt of this logic and may exacerbate them[37]. Every study proposing future scenarios should therefore critically discuss the implications on social and political structures.

politics.

[36] The access of the population of low to mid-GDP countries to basic needs relies more on the price of commodities and on the price of energy.

[37] For example, if not designed with social and political implications in mind, scenarios depicting rapid top-down changes may induce authoritarian decisions. Additionally, there are energy transition scenarios in which advanced economies would seek to exploit countries with high raw material resources and low income levels at the expense of benefits from the designated countries and local communities.

Perspectives

To better identify the closest limits to growth, one could refine the models developed in this work; or model how economic and financial instability are likely to trigger crises, influenced by and influencing oil supply tensions.

In the context of a degrowth scenario, it would be interesting to model the minimum amount of energy and minimum complexity required to achieve material living conditions that allow for high levels of health and well-being in future societies. While some studies have attempted to quantify this (Millward-Hopkins et al., 2020; Grubler et al., 2018), their assumptions are based on the current energy and industrial systems, which would be significantly different in a significant degrowth scenario. Modeling a future industrial system with a far lower level of complexity is not straightforward. Moreover, designing such scenarios require defining health and well-being goals, as well as creating scenarios for alternative societal organizations — particularly for housing and transport — which implies mobilizing several social science disciplines and the democratic implications of citizens and civil society organizations in such a project.

Such scenarios can be seen as utopian and impossible to achieve as long as stakeholders and States seek maximum wealth and power. On the other hand studying lock-ins to voluntary degrowth scenarios and how they could be overcome seems to be of higher-priority. Still, some elements answering these issues are already identified[38]. In any case, providing relevant answers to these questions requires political, interdisciplinary, and systemic work.

[38] Among these: constructing groups to deal with political subjects at the community level, changing what is socially valued, permanently questioning state of affairs and collectively building political visions.

APPENDIX A | RÉSUMÉ DÉTAILLÉ EN FRANÇAIS

This appendix answers the requirements imposed on theses written in English at the University of Grenoble Alpes by providing a substantial description of its content in French. The english reader is invited to skip this appendix.

Cette annexe répond aux contraintes imposées aux thèses de l'Université Grenoble Alpes rédigées en langue anglaise en proposant une description substantielle de son contenu en français.

Elle propose une traduction de l'introduction, des conclusions des chapitres 1 et 7, des abstracts de chaque chapitre ainsi que de la conclusion. Cela permet ainsi au lecteur Français d'avoir un bon aperçu des enjeux et des conclusions de cette thèse.

A.1. Introduction

A.1.1. Énergies fossiles, entre bénédiction et malédiction

En 2022, l'approvisionnement énergétique mondial était de 622 exajoules (EJ) d'énergie primaire, dont 81% était fourni par les énergies fossiles (IEA, 2024b). C'est 30 fois plus que l'approvisionnement énergétique de 1800, qui n'était alors constitué que de biomasse.

Les sociétés industrielles modernes dans lesquelles nous vivons reposent et dépendent de cette consommation énergétique. Tous les produits consommés ont subi de multiples étapes de fabrication et de transformation, dont la plupart sont réalisées par des machines, et la chaîne d'approvisionnement demande souvent plusieurs étapes de transport. L'énergie investie dans la chaîne d'approvisionnement d'un produit est appelée "empreinte énergétique". De la même manière, toutes les activités réalisées dans les sociétés industrielles impliquent une consommation d'énergie, soit directement (le pétrole par les voitures par exemple), soit indirectement via l'empreinte énergétique des produits.

Les sociétés industrielles modernes se sont développées depuis 1850 sur la base du co-développement des technologies et de l'extraction d'énergie. L'extraction de charbon a d'abord permis le développement des premières industries et de technologies, en se basant notamment sur la production d'acier et sur les machines à vapeur. Plus tard, l'extraction du pétrole a permis le développement des véhicules (principalement les voitures et les camions), essentiels aux chaînes d'approvisionnement.

Il faut noter que l'extraction d'énergie et le développement technologique sont étroitement liés. L'extraction d'énergie alimente les technologies, qui permettent alors le développement d'autres technologies, consommant à leur tour d'autant plus d'énergie. Cela a permis de réduire l'intensité en travail humain dans la production industrielle et l'agriculture, et s'est accompagné d'une croissance de la demande en de nouveaux produits. Ces processus constituent la base des sociétés industrielles. (Carrey, 2020; Fressoz, 2024; Smil, 2018).

Sans surprise, on observe que la croissance du PIB (produit intérieur brut) — indicateur communément utilisé pour mesurer l'activité économique — est très fortement corrélée à la consommation d'énergie (Haberl et al., 2020).

Du fait de l'interdépendance entre l'extraction énergétique et l'économie, une diminution de la consommation d'énergie [1] — volontaire ou non — entraînerait très probablement une diminution du PIB par habitant et donc un déclin économique.

L'énergie est donc essentielle au fonctionnement des sociétés industrielles. Cependant, le système énergétique actuel est confronté à de multiples défis : il faudrait sortir rapidement des énergies fossiles afin de limiter les effets du changement climatique, l'approvisionnement en pétrole et en gaz devrait atteindre leur pic au cours de la prochaine décennie, et leur taux de retour énergétique (TRE ou EROI) devrait diminuer. Enfin, des risques systémiques menacent de plus en plus les sociétés modernes.

A.1.1.1. Risques systémiques globaux et limites planétaires

Pressions environnementales

Le développement des sociétés industrielles s'accompagne d'une augmentation des pressions environnementales. La « Grande Accélération », expression utilisée par Steffen et al. (2015b, 2004), illustre la corrélation entre le développement industriel et socio-économique exponentiel avec certaines pressions environnementales telles que les émissions de dioxyde de carbone, l'acidification des océans et la dégradation de la biosphère terrestre. Parallèlement, le défrichage et la déforestation, la surpêche, la pollution et le changement climatique entraînent une perte massive de biodiversité, conduisant à la sixième extinction de masse (Ceballos et al., 2015). Par ailleurs, l'érosion des sols, combinée à la pollution, à la surexploitation des ressources et au changement climatique, érode directement et de manière irréversible les capacités agricoles de nos sociétés et l'accès à l'eau douce (IPBES, 2019; Pereira et al., 2024; Dirzo et al., 2014; Scheffer et al., 2001; Lenton et al., 2008; Morgan, 2005; Wang-Erlandsson et al., 2022). Cela a conduit Rockström et al. (2009) à définir des « limites planétaires », dont certaines sont déjà dépassées(Steffen et al., 2015a).

Quand la quête d'efficacité mène à la vulnérabilité

Les sociétés industrielles ont atteint un haut niveau d'efficacité, principalement grâce à l'optimisation des chaînes d'approvisionnement, ce qui a créée des vulnérabilités. En effet, le prix de cette optimisation est une faible robustesse face aux perturbations ou à des chocs. Ces vulnérabilités ont été révélées, par exemple, lors des répercussions économiques de la pandémie de Covid-19 et la hausse consécutive des prix de nombreux produits et matières premières, lors des perturbations de chaînes d'approvisionnements causées par l'obstruction du canal de Suez en 2021, ou lors de la pénurie de semi-conducteurs qui a débuté en 2020 favorisée par la concentration de la production de semi-conducteurs en Asie du Sud-Est (92% des semi-conducteurs avancés étant produits à Taïwan en 2021 Varas et al. 2021). En dehors des chaînes d'approvisionnement, des

[1] La corrélation observée est en fait celle entre le PIB et l'énergie utile, comme l'a souligné Haberl et al. (2020). Cette subtilité est en fait particulièrement importante dans le cadre de la transition énergétique, où la conversion entre énergie primaire et énergie utile a un meilleur rendement pour l'éolien et photovoltaïque (PV) que les énergies fossiles.

coupures d'électricité prolongées auraient des répercussions socio-économiques majeures dans les pays occidentaux (Petermann et al., 2011). L'économie s'est également révélée très sensible aux flambées des prix du pétrole (Hamilton, 1983, 2009). Enfin, la spécialisation a conduit les économies de certains pays à dépendre de la production d'un nombre limité de matières premières, ce qui a déjà entraîné des crises économiques majeures spécifiques à certains pays [2].

La combinaison des pressions environnementales, des vulnérabilités et des interdépendances.

Les réseaux globaux sont complexes et interconnectés, ce qui les rend interdépendants, vulnérables et sensibles à la possibilité de défaillances en cascade (Helbing, 2013; Homer-Dixon et al., 2015; Mignan and Wang, 2020). Le terme « risque systémique mondial » a donc été utilisé pour décrire les risques découlants de ces caractéristiques (Centeno et al., 2015).

La combinaison des pressions environnementales, des vulnérabilités et des interdépendances entraîne donc des risques élevés pour les sociétés industrielles. Certains de ces risques, ainsi que des phénomènes émergents du développement et de la croissance, ont été étudiés assez tôt par le Club de Rome, et cela a finalement conduit Meadows et al. (1972) à modéliser certains de ces risques en concluant que la société s'effondrait et ce dans tous les scénarios de croissance considérés. Le "Global Risk Report" du World Economic Forum (2025) tente également d'illustrer les principaux risques et leurs interconnexions, sur la base d'enquêtes menées auprès des responsables politiques et des experts. Le terme « polycrise » a récemment été défini par Lawrence et al. (2024), qui appelle à mener des recherches sur le sujet.

Une autre approche utilisée par Tainter (1988) s'appuie sur le concept de complexité pour étudier les effondrements sociétaux. Il soutient que les sociétés ont tendance à accroître leur complexité afin de résoudre des problèmes, ce qui entraîne un effondrement sociétal en raison de la diminution des rendements marginaux de cette complexité au cours du temps.

Si les risques systémiques mondiaux sont souvent étudiés de manière conceptuelle, ils sont difficiles à modéliser. Cela s'explique par la multitude de facteurs à modéliser, la difficulté de modéliser quantitativement les phénomènes sociaux, mais aussi par le fait que l'occurrence de chocs comporte un certain niveau d'aléatoire et que certains phénomènes sont non linéaires, voire soumis à des effets de seuil déclenchant des points de basculement. De tels modèles sont par nature interdisciplinaires.

Conclusion sur les risques systémiques globaux

Les risques systémiques mondiaux découlent du développement des sociétés industrielles, qui n'auraient pas étés possible sans de nouvelles sources d'énergie importantes. Cependant, ces risques ne résultent pas directement de la consommation d'énergie (sauf dans quelques cas, comme le changement climatique), mais plutôt des impacts de l'accroissement des activités de ces sociétés. Cela signifie que la transition énergétique à elle seule n'aurait pas d'impact sur la plupart de ces risques, à l'exception évidente du changement climatique.

Néanmoins, en raison de la corrélation entre la consommation d'énergie et le développement des sociétés industrielles, une réduction importante et durable de la consommation d'énergie conduirait à terme à une réduction de la complexité et des pressions environnementales. Il convient de noter que cela pourrait se produire assez rapidement si les risques systémiques conduisaient à un effondrement global. Même en l'absence d'effondrement, les phénomènes irréversibles se produisant depuis des décennies impliquent que le système terre ne reviendra jamais à son état pré-industriel.

[2] Quelques exemples sont présentés dans les supplementary materials du chapitre 4

A.1.1.2. Premier enjeu du mix énergétique : le changement climatique

Le changement climatique est causé par les émissions de gaz à effet de serre (GES), dont les trois quarts sont du CO2 émis par les énergies fossiles[3] (IPCC, 2023). Selon les données de HadCRUT5 (Morice et al., 2021)[4], cette augmentation moyenne des températures terrestres et océaniques mondiales a atteint 1,5 °C en 2024 par rapport aux températures pré-industrielles (moyenne de 1850 à 1900) (mais il faudra attendre encore quelques années avant que le seuil de 1,5 °C ne soit définitivement franchi par la moyenne glissante). Le changement climatique est une menace majeure bien connue pour les sociétés du XXIe siècle, car il dégrade l'habitabilité de certaines régions (en raison d'inondations ou de vagues de chaleur), accélère la perte de biodiversité, perturbe les systèmes hydrologiques, l'accès à l'eau douce et le cycle de l'eau, ainsi que les systèmes agricoles (principalement en raison des impacts précédents). Cela est bien documenté dans les rapports du GIEC (IPCC, 2023).

Il convient de noter que les énergies fossiles ont une responsabilité directe majeure dans le changement climatique. La limitation du réchauffement climatique est le plus souvent l'argument principal utilisé pour plaider en faveur d'une transition énergétique vers des sources à faible émission de CO_2.

A.1.1.3. Deuxième enjeu : les pics pétroliers et gaziers

L'approvisionnement en pétrole devrait atteindre son pic vers 2030-2035 (Laherrère et al., 2022; Delannoy et al., 2021a), puis se stabiliser avant de décliner. L'évolution historique de l'approvisionnement en pétrole aurait alors suivi une courbe en cloche. Après ce pic, l'approvisionnement en gaz devrait également atteindre son maximum vers 2040 (Delannoy et al., 2021b; GGR, 2024). Ce sujet est abordé plus en détail au chapitre 2.

Si cela peut être considéré comme positif pour le changement climatique, le pétrole et le gaz représentent actuellement 53% du mix énergétique. Le pétrole est essentiel pour les transports, donc pour les chaînes d'approvisionnement et, par conséquent, pour l'économie mondiale, et sa substitution reste difficile, comme nous le verrons plus en détail au chapitre 5. Ces pics d'approvisionnement à venir menacent donc l'économie mondiale.

A.1.1.4. Troisième enjeu : le métabolisme

Le taux de retour énergétique (TRE ou EROI) d'un système de production d'énergie est défini comme le rapport entre l'énergie brute totale produite et la quantité d'énergie investie dans le processus. En raison des valeurs d'EROI élevées du charbon, du pétrole et du gaz, les investissements dans les secteurs de la production d'énergie ne représentaient qu'une petite partie (Delannoy et al., 2021a,b) des activités mondiales. Cependant, l'EROI du pétrole et du gaz devrait diminuer considérablement dans les années à venir en raison de leur accessibilité décroissante et de leur qualité moindre (en particulier pour le pétrole). Cela a deux effets principaux.

Premièrement, des investissements énergétiques supplémentaires seront nécessaires dans les secteurs de la production énergétique, ce qui augmentera la demande énergétique. Deuxièmement, d'un point de vue métabolique, ce déclin pourrait impacter la société en raison de l'échelle de son économie et de son niveau de complexité Tainter (1988); Hall et al. (2009); Brandt (2017); Fizaine and Court (2016).

L'EROI de l'éolien et du photovoltaïque (PV) est incertain, mais Aramendia et al. (2024)

[3] Voir `https://www.wri.org/insights/4-charts-explain-greenhouse-gas-emissions-countries-and-sectors`

[4] Des données mises à jour ont été trouvées à l'adresse `https://www.eea.europa.eu/en/analysis/indicators/global-and-european-temperatures/global-and-european-annual-average`.

affirme qu'il est probablement supérieur à celui du pétrole et du gaz. Néanmoins, cela pourrait être au moins partiellement compensé par les investissements dans le stockage électrique et l'équilibrage du réseau électrique nécessaires à une forte pénétration des énergies renouvelables dans le mix électrique. En outre, les investissements énergétiques temporaires nécessaires à la construction d'infrastructures éoliennes et photovoltaïques pourraient réduire temporairement l'EROI global du système énergétique (Capellán-Pérez et al., 2019; Slameršak et al., 2022).

A.1.1.5. Disparités territoriales

Il existe également des enjeux géopolitiques importants en matière d'approvisionnement énergétique. Les États-Unis, la Russie et le Moyen-Orient concentrent une part importante de la production de pétrole et de gaz. L'Europe, par exemple, ne produisait qu'environ 5% du pétrole et du gaz en 2024, alors qu'elle consommait 10 à 15% de la production mondiale (Energy Institute, 2025). Plus important encore, la Chine, bien qu'elle consomme 27% de l'approvisionnement énergétique mondial, ne produisait respectivement que 4% (un quart de sa consommation) du pétrole et 6% (la moitié de sa consommation) du gaz produits dans le monde en 2024. Cela explique en partie pourquoi la Chine a choisi de s'appuyer sur le charbon plutôt que sur le pétrole et le gaz pour ses activités : le charbon représentait 58% de son mix énergétique en 2024, alors que cette valeur est de 28% à l'échelle mondiale. En fait, la Chine a produit la moitié (52%) et consommé 56% de l'approvisionnement mondial en charbon en 2024. Il est intéressant de noter que cette dépendance de la Chine à l'égard des importations de pétrole explique également en partie pourquoi elle a investi dans le développement des véhicules électriques (EV) dès 2010[5].

Dans un contexte où l'approvisionnement mondial en pétrole et en gaz risque d'être soumis à des tensions à l'avenir, les disparités géographiques dans leur production joueront un rôle de plus en plus important dans la géopolitique.

A.1.2. Trajectoires possibles vis-à-vis de ces enjeux

Face à ces problèmes, plusieurs réponses sont souvent avancées. Premièrement, il est possible de réduire la consommation énergétique, mais cela entraînerait une décroissance économique. Deuxièmement, certains affirment que les gains d'efficacité entraîneraient une réduction de la consommation d'énergie sans réduire le PIB, mais ces analyses ignorent les effets de rebond et exemples historiques. Troisièmement, la transition énergétique vise généralement à réduire la consommation d'énergies fossiles sans réduire l'approvisionnement total en énergie, seulement cela est rendu difficile voire impossible par de nombreux verrous.

Ces trois points sont abordés dans les sous-sections suivantes.

A.1.2.1. Le choix difficile de la décroissance

Réduire l'approvisionnement en énergies fossiles serait un moyen simple et efficace de lutter contre le changement climatique, ainsi que d'éviter de futures tensions entre un approvisionnement en déclin et une demande en croissance.

Millward-Hopkins et al. (2020) a calculé l'énergie finale minimale nécessaire pour fournir "des conditions matérielles décentes et des services de base pour tous", estimée à environ 15-

[5] Il y avait au moins deux autres raisons principales à cet investissement. Premièrement, la Chine visait à devenir un leader sur le marché des EV à une époque où l'industrie automobile thermique chinoise était en retard par rapport aux pays occidentaux. Deuxièmement, la pollution atmosphérique était un problème dans les grandes villes.

20 GJ/an/habitant. Cela se traduirait par une consommation d'énergie finale de 160 EJ pour une population de 8 milliards d'individus, soit près de trois fois moins que la consommation d'énergie finale actuelle, à un moment où des milliards de personnes dans le monde n'ont toujours pas accès aux biens matériels de première nécessité.

Cependant, il n'existe aucun exemple historique d'un pays ayant satisfait à la fois aux indicateurs de bien-être social et aux indicateurs écologiques (Fanning et al., 2022). Ranjan and Kanitkar (2025) indique en effet qu'une consommation énergétique d'environ 70 GJ/habitant/an était historiquement nécessaire pour que les individus atteignent des niveaux suffisants d'espérance de vie, de scolarisation, d'accès à l'eau douce et à un air non pollué. Enfin, Tamberg et al. (2024) indique qu'un niveau de revenu d'environ 10 000 $/cap/an serait suffisant pour garantir un niveau élevé de satisfaction des besoins. Bien que tous ces niveaux d'énergie et de revenus soient inférieurs à la moyenne mondiale actuelle, il convient de noter qu'ils s'appuient sur des exemples historiques et ne reflètent pas nécessairement les trajectoires de décroissance futures. En effet, la réorganisation des activités sociétales afin de prioriser le bien-être mondial et la réduction des inégalités tout en diminuant la consommation d'énergie pourrait permettre l'émergence de sociétés dont les niveaux de consommation énergétiques seraient inférieurs à ceux des sociétés industrielles du XXIe siècle.

Néanmoins, en raison du couplage PIB/énergie (Haberl et al., 2020), une réduction de la consommation énergétique entraînerait une baisse du PIB. Si les scénarios de décroissance et de post-croissance font l'objet d'études de plus en plus nombreuses dans la littérature scientifique, comme l'évoque Kallis et al. (2025), ils sont ignorés par les institutions et les partis politiques[6].

A.1.2.2. L'efficacité énergétique : la chasse aux fantômes

Les gains d'efficacité énergétique consistent à réduire la consommation d'énergie d'une activité tout en maintenant la même production. Ils sont parfois considérés comme une solution importante pour réduire les émissions de CO2 (IEA, 2024d; BP, 2024). Cependant, les cela omet les effets de rebond. En effet, Brockway et al. (2021) affirment que les gains d'efficacité énergétique sont toujours partiellement ou totalement compensés par des effets rebond, les économies d'énergie réalisées dans un processus étant réinvesties ailleurs par le biais de divers mécanismes. En fait, la robustesse du couplage PIB/énergie suggère que les gains d'efficacité ont toujours été compensés à l'échelle mondiale et à l'échelle de l'économie.

Par conséquent, il est illusoire de compter sur l'efficacité énergétique pour réduire la consommation d'énergie de manière importante tout en menant des politiques promouvant la croissance, compte tenu notamment de l'énorme réduction des émissions de CO2 nécessaire pour limiter le changement climatique.

A.1.2.3. La transition énergétique et ses limites

La transition énergétique est la solution la plus largement envisagée pour lutter contre le changement climatique. Les sources d'énergie à faible émissions de CO_2, principalement les éoliennes et les panneaux photovoltaïques (PV), devraient remplacer les énergies fossiles afin que le système énergétique puisse maintenir des niveaux d'approvisionnement stables tout en réduisant les émissions de CO_2. En effet, la production d'énergie éolienne et photovoltaïque se développe rapidement, la production photovoltaïque étant notamment encore exponen-

[6]Cette invisibilisation peut s'expliquer par plusieurs facteurs. Parmi ceux-ci, je pense aux politiques étatiques visant à concentrer le maximum de pouvoir, ce qui se traduit par la poursuite de la croissance du PIB, aux verrous institutionnels (notamment idéologiques et réglementaires) et aux tensions sociales dues à la lutte de la classe capitaliste pour maximiser sa richesse tandis que les plus pauvres luttent pour atteindre et maintenir un niveau de vie décent. Ces verrous devraient toutefois être étudiés plus en détail.

tielle. Ces sources d'énergie sont actuellement également moins chères que les énergies fossiles (IRENA, 2025; NEA and IEA, 2020).

Cependant, la production d'énergie éolienne et photovoltaïque ne représente actuellement que 3 à 4% de l'approvisionnement en énergie primaire (Energy Institute, 2025). Plusieurs barrières à leur déploiement à grande échelle sont à prévoir. Par exemple, les coûts d'investissement élevés des projets, l'opposition sociale et le raccordement au réseau entravent actuellement le déploiement de l'éolien. Le réseau électrique doit également être étendu afin de raccorder ces sources d'énergie distribuées. De plus, à long terme, l'intermittence de l'éolien et du photovoltaïque nécessitera le déploiement de systèmes de stockage et d'équilibrage, qui ajoutent des coûts non linéaires à l'électricité lorsqu'un certain seuil est atteint (environ 30 à 40% de pénétration de l'éolien et du photovoltaïque dans le réseau). En outre, les infrastructures de production d'énergies fossiles ainsi que les infrastructures de leur consommation doivent être progressivement supprimées, ce qui entraîne des coûts économiques et se heurte à des barrières techniques.

Toutefois, ces barrières peuvent être surmontés dans une certaine mesure, par exemple grâce à des taxes sur les énergies fossiles combinées à des subventions en faveur des sources d'énergie à faible émissions de CO_2 et des équipements de consommation électrique. Cependant, la taxation des énergies fossiles nécessite une volonté politique importante, car elle aurait un effet négatif sur l'économie en raison de la répercussion des taxes sur les prix.

A.1.2.4. Les scénarios business-as-usual (BAU), l'option par défaut

Opter pour une décroissance volontaire ou accélérer la transition énergétique tout en éliminant progressivement les énergies fossiles nécessite une volonté politique forte et un engagement à long terme. Il est possible qu'aucune de ces options ne soit choisie. C'est ce qu'on appelle le scénario "business-as-usual" (BAU).

Dans ce scénario, les sociétés industrielles continueront à rechercher une consommation énergétique maximale et seront confrontées à des pics d'approvisionnement en pétrole et en gaz sans anticipation, ce qui entraînera une déstabilisation et des tensions au sein des pays et entre eux. En outre, elles seront également confrontées aux effets désastreux et durables du changement climatique.

A.1.3. Questions de recherche

À ce stade, il est possible de réduire la consommation énergétique de nos sociétés. Cependant, il est très probable que les sociétés aient tendance à suivre des scénarios BAU plutôt que des scénarios de décroissance/post-croissance ou de transition énergétique, comme expliqué précédemment. En raison des pics d'approvisionnement en pétrole et en gaz prévus et des barrières à la transition énergétique (abordés dans les sections précédentes), l'approvisionnement énergétique pourrait être limité. Cette thèse vise donc à répondre à la question suivante :

Principale question de recherche : **L'approvisionnement énergétique sera-t-il en mesure de répondre à la demande énergétique d'un scénario BAU jusque 2050 ?**

Une réponse négative à cette question indiquerait que les scénarios BAU, qui représentent les tendances futures les plus probables, entraîneront des perturbations, rendant le scénario BAU impossible par la suite.

Pour répondre à cette question de recherche principale, il est utile de la décliner en plusieurs sous-thèmes et questions connexes.

A.1.3.1. Le système énergétique et les barrières à la transition énergétique

Le rythme auquel une transition énergétique pourrait se produire est très incertain. En effet, on attend beaucoup d'une telle transition (voir par exemple IEA 2024d; BP 2024), mais de nombreuses barrières sont ignorés. Bien que bon nombre de ces barrières soient identifiés dans la littérature, ils ont peu étés modélisés et ils restent incertains. Le chapitre 1 étudie les barrières attendues à la transition énergétique et leur importance. Cela permettra d'obtenir des informations sur le rythme de la transition énergétique dans un scénario de croissance BAU, et sur ce qui serait nécessaire pour surmonter ces barrières, partiellement ou complètement. Cela contraindra donc les futurs possibles en ce qui concerne le remplacement des énergies fossiles par des sources d'énergie à faible émissions de CO_2.

> Question de recherche n°1 : Quels sont les barrières biophysiques à la transition énergétique ? Comment ces barrières limitent-ils le rythme maximal de la transition énergétique ?

A.1.3.2. Approvisionnement énergétique brut VS demande à l'horizon 2050. La transition énergétique peut-elle compenser le déclin du pétrole et du gaz ?

Si les pics d'approvisionnement en pétrole et en gaz sont identifiés, les projections de leur approvisionnement sont quelque peu incertaines. C'est également le cas pour le charbon. Comme ces trois sources d'énergie représentent actuellement 80% du mix énergétique, il est important de discuter des projections d'approvisionnement possibles ainsi que de leurs incertitudes. En utilisant les informations du chapitre 1 pour élaborer des scénarios sur le déploiement des panneaux éoliens et photovoltaïques (PV) ainsi que des projections pour les autres sources d'énergie, on peut analyser les conditions dans lesquelles l'approvisionnement énergétique brut pourrait répondre à la demande énergétique mondiale d'un scénario BAU. Le chapitre 2 est donc dédié à la question suivante :

> Question de recherche n°2 : Quelle serait l'approvisionnement énergétique brut d'un scénario BAU ? Sous quelles conditions l'approvisionnement énergétique brut peut-il répondre à la demande énergétique dans un scénario BAU ?

A.1.3.3. Désagréger l'investissement énergétique par source dans l'approvisionnement net en pétrole et gaz au point d'utilisation

Les EROI du pétrole et du gaz sont également déjà en baisse. Cela signifie que l'énergie issue de l'extraction du pétrole et du gaz restante après l'autoconsommation diminue plus rapidement que leur approvisionnement brut. Ce phénomène est étudié dans le chapitre 3, qui désagrège les investissements énergétiques dans les chaînes d'approvisionnement en pétrole et en gaz par source d'énergie, étendant les analyses classiques au périmètre auxiliaire et au point d'utilisation.

Question de recherche n° 3 : Comment l'approvisionnement énergétique net en pétrole et en gaz va-t-il diminuer d'ici 2050 ? Comment les investissements nécessaires en pétrole, gaz et en autres sources pour leu chaînes d'approvisionnement vont-ils augmenter ? Comment cela se traduira-t-il au niveau de l'EROI ?

A.1.3.4. Pic pétrolier VS transition énergétique: qui ira le plus vite ?

L'étape précédente néglige toutefois les barrières au déploiement des technologies de consommation énergétiques. Les technologies de consommation de pétrole sont notamment difficiles à remplacer en raison de barrières technico-économiques (voir section 1.4.4). De plus, le pic d'approvisionnement en pétrole est le plus tôt de toutes les énergies fossiles, vers 2030-2035. La question de la possibilité de répondre à une demande BAU en pétrole est donc la plus pressante. Le reste de la thèse se concentre donc sur la question de savoir si l'approvisionnement en pétrole sera en mesure de répondre à la demande de pétrole dans le scénario BAU.

Question de recherche n° 4 : L'approvisionnement en pétrole sera-t-il en mesure de répondre à la demande de pétrole dans un scénario BAU jusqu'en 2050 ? Sous quelles conditions ?

En effet, la demande en pétrole devrait augmenter dans certains secteurs. Outre les investissements pétroliers dans les chaînes d'approvisionnement en pétrole et en gaz, le nombre de véhicules devrait augmenter en Chine et en Inde, ce qui entraînera une hausse de la demande énergétique pour le transport routier, dont 90% est actuellement satisfaite par le pétrole. Les hausses prévues de la demande en produits pétrochimiques, dans l'aviation et le transport maritime devraient également faire augmenter la demande en pétrole. D'un autre côté, le déploiement des véhicules électriques (EV) remplacera une partie de cette demande en pétrole, mais leur déploiement reste très incertain. Cette question est étudiée au chapitre 4, qui se concentre sur la modélisation de l'évolution du parc automobile au fil du temps dans différents pays, permettant ainsi de comparer la demande BAU en pétrole avec l'approvisionnement dans un scénario BAU au chapitre 5.

Question de recherche n°4.1 : Quelle serait la demande de pétrole d'un scénario BAU ? En particulier, quelle serait l'évolution de la demande énergétique du transport routier dans un scénario BAU ?

A.1.3.5. Modéliser la barrière d'accessibilité économique au déploiement des voitures électriques parmi les foyers.

Les principales incertitudes de ce modèle concernent le déploiement des EVs. En effet, le prix d'achat des voitures électriques reste supérieur à celui des voitures à essence ou diesel classiques. Cela constitue une barrière majeure à leur déploiement à grande échelle et lève la question de savoir si les ménages seraient prêts à investir dans un EV (neuf ou d'occasion) compte tenu de ce surcoût à l'achat.

Question de recherche n° 5 : Comment les ménages de différentes catégories de revenus se comporteraient-ils en matière d'achat de véhicules électriques privés, compte tenu du surcoût d'achat ? Comment ces comportements influenceraient-ils le déploiement mondial des véhicules électriques privés ?

Le chapitre 6 développe d'abord des outils de modélisation qui permettent de calculer la répartition du parc automobile actuel dans les pays en fonction du revenu des acheteurs. Le chapitre 7 modélise ensuite la répartition des véhicules privés neufs et d'occasion en fonction du revenu des ménages, et ouvre la voie à un modèle de diffusion des véhicules électriques sous contrainte de leur accessibilité économique.

Les chapitres 2, 3, 4, 5 et 6 sont des articles qui ont été ou seront soumis à des revues.

A.1.4. Contributions aux articles

Cette thèse a été réalisée sous la direction de Pierre-Yves Longaretti. Les analyses présentées dans les articles de cette thèse ont été menées conjointement avec Pierre-Yves.

Pierre-Yves a notamment estimé les réserves d'énergies fossiles du chapitre 2, formalisé les modèles initiaux du chapitre 3, les principaux calculs mathématiques du chapitre 6 et aidé à formaliser le modèle du chapitre 7. J'ai développé la majeure partie du reste, j'ai mis en œuvre et calculé toutes les données, les modèles et les résultats de cette thèse.

A.2. CHAPITRE 1 : LE MIX ÉNERGÉTIQUE ET LES BARRIÈRES À LA TRANSITION ÉNERGÉTIQUE

Ce chapitre examine les barrières à la transition énergétique d'ici 2050. Tout d'abord, les éoliennes et les panneaux photovoltaïques (PV) — qui ont produit 3% de l'énergie en 2024 — ont été identifiés comme les seules sources d'énergie à faible émissions de CO_2 capables de croître rapidement pour atteindre des niveaux de production significatifs. Cependant, plusieurs barrières sont à prévoir : le potentiel de l'éolien et du photovoltaïque ainsi que leurs taux de croissance pourraient être limités, le déploiement des réseaux électriques pourrait limiter les niveaux de pénétration de l'éolien et du photovoltaïque, certains secteurs de consommation devraient être techniquement et économiquement difficiles à décarboner, il y a des phénomènes de verrous dans les systèmes fossiles, des barrières financiers, institutionnelles et liés à la main-d'œuvre qui pourraient ralentir et limiter la transition énergétique. En outre, les implications métaboliques de la transition énergétique doivent être prises en compte lors de sa planification.

Bien que certaines études aient abordé quantitativement certaines de ces barrières (par exemple dans Dupont et al. 2018, 2020 pour les potentiels éolien et photovoltaïque), la littérature sur les barrières présentées dans ce chapitre est généralement rare. Cela s'explique en partie par deux raisons : 1/ le déploiement de l'éolien, du photovoltaïque et des technologies à faibles émissions de CO_2 telles que les véhicules électriques (EV) est assez récent et évolue rapidement, ce qui signifie que les articles peuvent rapidement devenir obsolètes. 2/ La modélisation de ces barrières est incertaine en raison de l'évolution rapide des technologies, de l'évolution du contexte économique et politique et, dans une certaine mesure, du manque de données. Néanmoins, l'absence de littérature sur ces barrières ne signifie pas qu'elles n'existent pas.

Les limites, principalement techniques et économiques, abordées dans ce chapitre sont pour la plupart valables dans un scénario BAU. En effet, un engagement politique fort, des investissements substantiels dans la transition énergétique et une taxation importante des énergies fossiles pourraient éliminer certaines des barrières économiques aux technologies à faible émissions de CO_2 et favoriser leur déploiement. Cependant, aucune de ces mesures n'est actuellement mise en œuvre. Le déploiement actuel de la production d'électricité éolienne et photovoltaïque s'explique par leurs coûts (LCOE) inférieurs par rapport à la production fossile et nucléaire. À l'inverse, les investissements dans la transition énergétique risquent d'être encore plus limités dans un monde en crise. Des investissements ambitieux dans la transition énergétique ainsi que la taxation des énergies fossiles (entraînant une hausse des prix des matières premières) seraient très improbables dans un tel contexte. Il convient d'être prudent quant aux conclusions de ce chapitre. Celui-ci ne suggère pas que la transition énergétique doive être évitée. Il présente plutôt les limites biophysiques à la transition énergétique d'ici 2050 et affirme qu'une transition énergétique ambitieuse d'ici cette date dans un scénario BAU peut être impossible.

S'engager dans la transition énergétique serait un moyen efficace de réduire les émissions de CO_2 et la dépendance à l'égard des ressources fossiles limitées tout en limitant la décroissance énergétique. Dans le cadre de scénarios de transition énergétique ambitieux, il pourrait même être possible de maintenir le niveau actuel d'approvisionnement en énergie utile tout en limitant le réchauffement climatique à +2 °C, bien que cette affirmation doive être étudiée à la lumière des barrières mentionnées dans le contexte d'un scénario de transition énergétique ambitieux.

Ce chapitre comporte deux messages principaux. D'abord, la faisabilité de scénarios de transition énergétique ambitieux dans des conditions BAU doit être remise en question. Tout scénario supposant une transition énergétique ambitieuse doit justifier la cohérence de ses hy-

pothèses, notamment par rapport aux barrières biophysiques évoquées. Deuxièmement, les barrières identifiées dans ce chapitre pourraient être considérablement réduites grâce à un engagement politique fort (les investissements et les actions nécessaires doivent être étudies en s'appuyant sur les informations contenues dans ce chapitre). La transition énergétique est donc une question économique et politique.

A.3. Chapitre 2 : Approvisionnement énergétique brut VS demande à l'horizon 2050. La transition énergétique peut-elle compenser le déclin du pétrole et du gaz après 2035 ?

Des points de vue optimistes et pessimistes sont souvent exprimés dans la littérature sur l'avenir de la production d'énergie primaire à l'échelle mondiale. En particulier, la question des réserves d'énergies fossile et de l'approvisionnement annuel est souvent considérée comme secondaire en raison de l'abondance des ressources, tandis que, d'autre part, un certain nombre d'auteurs insistent sur les limites de la conversion des ressources en réserves et sur les pics d'approvisionnement plus ou moins imminents du pétrole et du gaz. Cette dichotomie sous-tend également un désaccord sur la question de savoir si le déclin imminent du pétrole et du gaz est dû à un pic de la demande ou de l'approvisionnement.

Le présent travail vise à réexaminer cette question de l'approvisionnement et de la demande d'énergie, en analysant de manière critique les données sur les réserves récupérables ultimes (URR) et en utilisant des estimations réalistes du potentiel des énergies éolienne et solaire. En particulier, nous quantifions les conditions dans lesquelles ces sources d'énergie renouvelable peuvent faire face au déclin prévu du pétrole et du gaz tout en répondant à la demande énergétique attendue dans un scénario BAU modéré.

Nous constatons que les énergies renouvelables pourraient compenser le déclin des énergies fossiles et la hausse de la demande brute d'énergie si leurs taux de croissance normalisés étaient de 3 à 6% par an pour l'énergie solaire et de 4 à 5% par an pour l'énergie éolienne. Cela représente une capacité supplémentaire annuelle équivalente à près d'un tiers de la production mondiale actuelle d'électricité. De tels taux soutenus nécessitent des engagements majeurs à long terme.

A.4. Chapitre 3 : Désagréger l'investissement énergétique par source dans l'approvisionnement net en pétrole et gaz au point d'utilisation

Ce travail réexamine la question de l'approvisionnement énergétique net du pétrole et du gaz, en élargissant les analyses précédentes sur plusieurs fronts : 1/ du point d'extraction au point d'utilisation (une perspective désormais courante, en raison de sa plus grande pertinence)

; 2/ de la limite standard à la limite cumulative et auxiliaire (Murphy and Hall, 2011) ; 3/ en désagrégeant les investissements énergétiques dans leur chaîne d'approvisionnement par source d'énergie aux différents points et limites ; 4/ en introduisant un nouveau concept d'énergie nette se concentrant sur la source, pour compléter celui habituellement basé sur l'EROI.

Cette analyse confirme que, bien que les stocks de pétrole et de gaz soient abondants, leurs flux seront limités plus rapidement et à des niveaux inférieurs à ceux habituellement prévus. L'énergie nette du pétrole est déjà en baisse, et celle du gaz atteindra son pic d'ici 2035. D'ici 2050, les investissements énergétiques dans la chaîne d'approvisionnement pétrolière dépasseront 70% de son énergie brute. La demande énergétique annuelle en sources d'énergies renouvelables devra augmenter de 130 EJ/an en 15 ans, entre 2035 et 2050 (plus de la moitié de l'énergie nette maximale du pétrole et du gaz), rien que pour maintenir l'économie mondiale à un niveau stable.

Il reste à déterminer si les sources d'énergie renouvelables seront à la hauteur de ce défi. En outre, le remplacement du pétrole par d'autres sources d'énergie ou de matières premières est une question urgente. Nos résultats suggèrent qu'une transition énergétique rapide est plus urgente qu'on ne le pense généralement, non seulement pour lutter contre le changement climatique, mais aussi pour éviter une éventuelle récession économique structurelle mondiale.

A.5. Chapitre 4 : L'électrification du transport routier comme juge entre un accroissement ou un pic de la demande en pétrole

Il est essentiel de prévoir la demande mondiale de pétrole afin d'anticiper les potentielles tensions futures sur l'approvisionnement brute de pétrole, qui devrait atteindre son pic puis décliner au cours de la prochaine décennie. Cet article modélise l'évolution de la demande de pétrole dans un scénario BAU. Le secteur des transports (de loin le plus gros consommateur de pétrole) est notamment analysé en détail, en mettant l'accent sur la demande de pétrole des véhicules privés, et est désagrégé par pays.

L'analyse révèle que l'évolution de la demande de pétrole dépend principalement du rythme de déploiement des véhicules électriques (EV). En l'absence d'EV, la demande de pétrole augmenterait régulièrement pour atteindre +25% en 2050 par rapport à la valeur de 2024. À l'inverse, la poursuite du déploiement des VE en vue de l'électrification de tous les véhicules privés entraînerait une baisse de 18%. Il apparaît également que les incertitudes du modèle sont relativement faibles et que la demande de pétrole dans les secteurs autres que le transport routier fait l'objet d'un quasi-consensus dans les rapports institutionnels.

Cette étude appelle à poursuivre les recherches sur les barrières au déploiement des EV et à comparer les scénarios de demande de pétrole BAU avec ceux de l'approvisionnement de pétrole.

A.6. Chapitre 5 : Pic pétrolier VS transition énergétique: qui ira le plus vite ?

Un pic d'approvisionnement pétrolier est attendu vers 2035, en raison de la fin de vie de nombreux champs pétroliers. Parallèlement, la demande pétrolière devrait augmenter, principalement en raison :
1/de l'expansion du secteur du transport routier en Chine et en Inde ;
2/de la croissance de la production pétrochimique ;
3/l'augmentation de la demande dans les chaînes d'approvisionnement en pétrole et en gaz due à la baisse du taux de retour énergétique (EROI) ;
4/la croissance modeste dans d'autres secteurs.

Le déploiement des véhicules électriques (EVs) pourrait atténuer cette augmentation de la demande en pétrole. Afin d'évaluer les effets de ce problème imminent, l'approvisionnement et la demande de pétrole sont projetées dans un scénario BAU. Nous constatons que l'approvisionnement de pétrole pourrait ne pas répondre à la demande dès 2030 dans le scénario le plus probable, bien que nos résultats soient sensibles au déploiement des EVs et, dans une moindre mesure, à l'incertitude des projections de l'approvisionnement de pétrole.

Cette conclusion remet en question la possibilité et la cohérence des scénarios BAU à cet horizon temporel. En raison du rôle critique du pétrole dans les transports et, par conséquent, pour l'ensemble de l'économie, cette tension anticipée aura également des répercussions économiques négatives structurelles. Cela souligne la nécessité de réviser les hypothèses relatives à la croissance du PIB dans les scénarios de référence des modèles (y compris les modèles d'évaluation intégrée ou IAMs).

A.7. Chapitre 6 : Modéliser le taux de possession de véhicules privés en fonction des revenus et non pas du PIB/habitant

Le taux de possession de véhicules privés est souvent modélisée dans la littérature à l'aide de fonctions de Gompertz afin de caractériser le nombre moyen de véhicules par habitant en fonction du PIB par habitant.

Cependant, ce modèle ne tient compte que de manière indirecte du principal déterminant de la propriété d'un véhicule privé (PV), à savoir le revenu. Un modèle plus direct de la dépendance au revenu serait très utile pour produire de nouveaux modèles fiables de projections du parc automobile, en particulier dans la perspective de la modélisation de la transition énergétique dans le secteur des transports. Malheureusement, les données sur la relation entre le revenu réel et le taux de possession de PVs ne sont pas largement disponibles, et les modèles existants qui tentent de surmonter cette limitation ne sont ni suffisamment répandus ni assez simples pour être utilisés de manière généralisée.

Nous abordons ce problème en montrant que la distribution du nombre de véhicules privés par habitant en fonction du revenu peut, avec un niveau d'approximation raisonnable, être

représentée par une fonction de Gompertz dans la mesure où la possession d'un véhicule peut elle-même être représentée par une fonction de Gompertz (différente) du PIB par habitant, en vertu du théorème de la valeur moyenne. Nous produisons les paramètres du modèle qui en résultent pour un large éventail de pays. L'utilité potentielle de cette caractérisation du taux de possession de véhicules privés dans le contexte du déploiement des véhicules électriques est également brièvement soulignée.

A.8. Chapitre 7 : Modéliser l'adoption de véhicules électriques privées chez les foyers, sous la contrainte de leur accessibilité économique

Ce chapitre présente les étapes nécessaires à la construction d'un modèle de déploiement des EVs sous contrainte d'accessibilité financière.

Tout d'abord, il fournit les éléments pertinents qui encadrent le problème. Ces éléments sont nécessaires afin d'affiner les hypothèses du modèle, mais il convient de noter que certains d'entre eux sont incertains et devront être mis à jour, car les EV en sont encore à leurs débuts. En particulier, 1) l'évolution du surcoût des voitures électriques (EVs) par rapport aux voitures thermiques équivalentes au fil du temps (en partie due à l'évolution des prix des batteries) et selon les régions, principalement en raison des échanges commerciaux avec la Chine (IEA, 2025b) ; 2) la durée de vie des batteries reste hypothétique du fait du manque de recul.

L'une des principales conclusions de ces considérations est que le marché chinois n'est pas très affecté par le prix comme barrière au déploiement des EVs (50% des ventes de PV étaient des VE en Chine en 2024 IEA 2025b, et ce chiffre augmente d'environ 10% par an), alors que les pays occidentaux continueront d'être fortement affectés, tout comme d'autres pays. La proximité du marché chinois tend à réduire le surcoût des véhicules électriques. Les résultats du chapitre 4 indiquent que le parc de véhicules électriques chinois représentera environ 25% du parc mondial entre 2030 et 2050.

Deuxièmement, sur la base des modèles du chapitre 6, nous avons modélisé la distribution des véhicules privés neufs et d'occasion en fonction du revenu d'un pays à un moment donné et en fonction du prix d'achat du véhicule. Il s'agit d'un résultat important de ce chapitre. Ce résultat est également crucial pour la prochaine étape du modèle. L'erreur induite par la condition stationnaire doit être calculée pour les pays dans lesquels le parc de véhicules particuliers et le PIB par habitant devraient connaître une croissance significative. Cependant, le manque d'informations sur la dynamique du parc de véhicules particuliers peut empêcher l'élaboration de modèles plus précis.

Troisièmement, la section 7.6 définit les principales lignes directrices pour modéliser l'impact du surcoût des véhicules électriques sur leur déploiement. La mise en œuvre réelle n'est pas terminée et nécessite de nouvelles étapes de modélisation importantes.

A.9. Conclusion

A.9.1. Objectif de la thèse

Les sociétés industrielles génèrent des pressions environnementales qui entraînent des menaces telles que le changement climatique, la perte de biodiversité et la raréfaction des ressources. De plus, leur développement a conduit à un niveau élevé de complexité, d'interdépendance et de vulnérabilité. Cela risque d'entraîner à des crises systémiques de plus en plus fréquentes, comme la crise économique de 2008 et la pandémie de COVID-19 de 2019 en sont des exemples.

En particulier, l'approvisionnement énergétique devrait être soumis à des pressions, en raison du pic prévu de l'approvisionnement en pétrole et en gaz, respectivement vers 2030-2035 et 2035-2040. Par conséquent, cette thèse examine si l'approvisionnement énergétique pourrait être en mesure de répondre à la demande énergétique jusqu'en 2050 dans un scénario BAU. La possibilité pour l'approvisionnement en pétrole de répondre à la demande est particulièrement étudiée en raison du rôle crucial du pétrole dans l'économie et du pic précoce de son approvisionnement.

Les scénarios BAU sont souvent considérés comme des scénarios de référence dans les modèles (en particulier dans les IAMs). Bien qu'il faudrait sortir des énergies fossiles avant que leur approvisionnement n'atteigne son pic afin de limiter le changement climatique et d'autres menaces irréversibles pour les sociétés humaines, cette thèse examine plutôt les limites des scénarios BAU en matière d'approvisionnement énergétique, afin de discuter de leur pertinence.

A.9.2. L'approvisionnement énergétique sera-t-il en mesure de répondre à la demande énergétique d'un scénario BAU jusque 2050 ?

Le chapitre 1 conclut tout d'abord que les éoliennes et les panneaux photovoltaïques (PV) sont les deux seules technologies de production énergétique pouvant être déployées à grande échelle. Cependant, de nombreuses barrières à leur déploiement à grande échelle sont à prévoir. Les réseaux électriques doivent se développer rapidement afin de connecter ces sources distribuées. De plus, une forte pénétration de l'éolien et du photovoltaïque dans le réseau entraîne une augmentation des coûts en raison des capacités de stockage et d'équilibrage du réseau requises. L'électrification des applications du pétrole devrait également se heurter à des barrières techniques et économiques. Le taux d'électrification limité des technologies de consommation, combiné aux verrous à la consommation des énergies fossiles, devrait limiter le déploiement large de l'éolien et du photovoltaïque.

Deuxièmement, le chapitre 2 conclut que les approvisionnements bruts en pétrole et gaz devraient atteindre leur pic respectivement vers 2035 et 2040, avec une incertitude limitée, et ceux en charbon vers 2067. En outre, si l'on considère uniquement le taux de déploiement industriel maximal prévu, les taux de déploiement nécessaire de l'éolien et du photovoltaïque pour compenser les baisses futures de l'approvisionnement en pétrole et en gaz seraient théoriquement réalisable. Dans tous les cas, il convient également de noter que la consommation de toutes les ressources fossiles disponibles entraînerait un réchauffement climatique d'environ 3 °C à la fin du XXIe siècle.

Troisièmement, le chapitre 3 montre que les investissements énergétiques nécessaires dans les chaînes d'approvisionnement en pétrole et en gaz augmenteront considérablement pour atteindre 120 EJ/an pour le pétrole en 2035 et 100 EJ/an pour le gaz en 2040, ce qui représente

respectivement une augmentation de +75% et +100% par rapport à 2022. Ces investissements devraient légèrement accroître la tension entre l'approvisionnement et la demande de pétrole et de gaz, et augmenter considérablement les investissements énergétiques nécessaires provenant d'autres sources d'énergie dans les chaînes d'approvisionnement du pétrole et du gaz. Le taux de retour énergétique (EROI) sociétal devrait donc diminuer.

Le chapitre 4 modélise ensuite la demande de pétrole et constate qu'elle devrait augmenter dans tous les scénarios où les véhicules électriques privés représentent moins de 50% du parc automobile total. Cette évolution est principalement due au développement de l'automobile en Chine et en Inde, ainsi qu'à l'augmentation de la demande en pétrochimie et de la demande en pétrole des chaînes d'approvisionnement en pétrole et en gaz calculée au chapitre 3. Les incertitudes sont dominées par l'incertitude sur le déploiement futur des véhicules électriques privés. Ceci est ensuite comparé à l'approvisionnement en pétrole au chapitre 5. Il apparaît que l'approvisionnement en pétrole pourrait être inférieur à la demande en pétrole dans le scénario BAU dès 2026, et probablement entre 2026 et 2035. Cette conclusion est d'autant plus robuste que, dans le cadre de cette étude, l'approvisionnement en pétrole est légèrement surestimée dans les limites du BAU, et la demande de pétrole sous-estimée en choisissant un scénario de croissance BAU modéré.

Le chapitre 6 a permis de trouver un modèle d'évolution de la possession de véhicules particuliers dans les pays en fonction du revenu des ménages. La répartition des véhicules particuliers en fonction du revenu des ménages est ensuite déduite. Le chapitre 7 répartit enfin les stocks de véhicules particuliers neufs et d'occasion en fonction du revenu des ménages, ou en fonction des prix des véhicules particuliers, par pays et au fil du temps. Il apparaît également que la durée de vie des batteries des véhicules électriques, ainsi que l'évolution future du surcoût d'achat des véhicules électriques par rapport aux véhicules à moteur à combustion interne, sont des facteurs critiques pour le déploiement des véhicules électriques. Des travaux supplémentaires sont nécessaires afin d'aboutir à un modèle du comportement des ménages vis-à-vis du marché des véhicules électriques, permettant de calculer le déploiement des véhicules électriques en fonction de leurs barrières d'accessibilité financière.

La principale conclusion de cette thèse est que l'approvisionnement en pétrole ne sera pas en mesure de répondre à la demande de pétrole dans un scénario BAU jusqu'en 2050, et qu'elle sera probablement insuffisante dès 2026-2035 (ce qui est proche). Ce point est principalement abordé au chapitre 5.

A.9.3. Implications

Cela implique que, dans le cas d'un scénario BAU, la consommation de pétrole sera limitée entre 2026 et 2035, ce qui entraînera probablement une crise. Cependant, deux scénarios pourraient éviter ce scénario de récession généralisée : des efforts massifs en faveur de la transition énergétique, ou bien un déclin volontaire et anticipé du PIB en recentrant la production sur la satisfaction des besoins de la population grâce à des technologies plus sobres en énergie et en matières premières.

Dans le premier cas, les États devraient investir massivement dans la transition énergétique et taxer les énergies fossiles afin de favoriser les technologies de transition énergétique. Cela risquerait de nuire à la croissance du PIB pendant au moins une période transitoire, étant donné que les hausses des prix des énergies fossiles se répercuteraient sur les prix de toutes les matières premières et que les activités de certains secteurs seraient probablement déplacées vers des efforts

de transition énergétique. Toutefois, cela permettrait un approvisionnement énergétique à long terme plus élevé qu'en l'absence de tout investissement, et un niveau de changement climatique plus faible[7]. Cela semble en tout cas plus souhaitable que les scénarios BAU de quelque type que ce soit (entendus comme des scénarios de croissance du PIB sans entrave avec une croissance de la demande énergétique y étant adéquate). En effet, le scénario BAU entraînera inévitablement des crises énergétiques — et donc des crises économiques — ainsi que des niveaux élevés de changement climatique, comme le montre cette thèse. Mieux qu'un simple scénario de transition énergétique ambitieux, un scénario de décroissance anticipée visant à maximiser le bien-être des citoyens tout en réduisant l'empreinte environnementale et d'autres vulnérabilités sociétales serait plus efficace sur le plan social et environnemental.

Le deuxième cas, à savoir un déclin précoce du PIB, est un scénario plus probable. En effet, les perturbations observées dans les années 2020, telles que la pandémie de Covid-19 et la guerre d'agression menée par la Russie contre l'Ukraine, ont eu des effets majeurs sur l'économie mondiale et les chaînes d'approvisionnement. De plus, on assiste à une recrudescence des tensions et conflits mondiaux, tels que l'invasion israélienne de Gaza et la montée des tensions qui s'en est suivie au Moyen-Orient, les violations du droit international sont de plus en plus fréquentes, les dépenses de défense augmentent à l'échelle mondiale et des régimes politiques autoritaires apparaissent partout dans le monde. Ces phénomènes peuvent être considérés comme les signes de l'importance croissante des vulnérabilités mondiales, qui conduisent à des crises plus fréquentes. Tainter (1988) a montré que cela a historiquement conduit à une concurrence constante entre les États, entraînant des effondrements ou des désintégrations progressives.

Les questions énergétiques sont donc éminemment politiques, et pas seulement techniques. Des verrous politiques[8] empêchent actuellement les efforts massifs en faveur d'une transition énergétique ambitieuse et d'une décroissance volontaire, même si ces scénarios peuvent être considérés comme plus souhaitables (compte tenu de la crise énergétique imminente et imprévue démontrée dans cette thèse, ainsi que des dommages environnementaux qui exercent une pression sur les sociétés industrielles). L'incapacité politique et institutionnelle à résoudre les problèmes a été identifiée dans Tainter (1988) et Diamond (2005) comme une caractéristique commune des sociétés ayant connu une désintégration. Cela appelle à étudier et à agir sur ces verrous, et avec une vision systémique.

A.9.4. Pertinence des travaux et limites

Le reste de la conclusion reflète mon opinion personnelle.

Ce travail fournit une preuve raisonnablement robuste de l'impossibilité des scénarios BAU au cours de la prochaine décennie, en raison de limites énergétiques. L'objectif de cette approche est d'encourager la communauté universitaire et les institutions à s'éloigner des scénarios BAU et à reconnaître les limites de croissance liées à un avenir proche.

Ce travail ne tente toutefois pas de modéliser des trajectoires futures possibles, qui seraient susceptibles de s'écarter des scénarios BAU plus tôt que le délai imposé par les limites énergétiques quantifiées dans ce travail. Il ne décrit pas non plus comment les limites énergétiques affecteraient l'économie mondiale. Enfin, il ne tente pas de proposer des scénarios souhaitables.

[7] Les effets à long terme sur le changement climatique pourraient en fait être discutés. En effet, dans le cas où les sociétés recherchent un approvisionnement énergétique maximal malgré les effets climatiques — ce qui a été le cas historiquement —, l'approvisionnement énergétique à partir de sources renouvelables pourrait permettre de compenser partiellement les pics pétroliers et fossiles, permettant ainsi aux conditions économiques de l'extraction d'énergies fossiles de durer plus longtemps que dans un scénario de crise économique provoquée par l'inadéquation entre l'approvisionnement et la demande de pétrole. D'un autre côté, une transition énergétique massive permettrait, espérons-le, d'éliminer progressivement les énergies fossiles.

[8] Je pense à la recherche de la puissance maximale par les États, à l'idéologie de la croissance et à l'influence de la classe capitaliste sur les médias et la politique.

De plus, la tension énergétique modélisée dans ce travail est à l'échelle mondiale. Cela masque les disparités entre les pays. En général, les pays dont le PIB par habitant est faible ou modéré sont susceptibles de souffrir davantage que ceux dont le PIB par habitant est élevé de la tension future entre l'approvisionnement et la demande de pétrole, quelle que soit la forme qu'elle prendra, du fait de la plus grande sensibilité de l'accès aux besoins fondamentaux à leur prix et à l'accès à l'énergie.

Enfin, je trouve un peu étrange de parler des sociétés industrielles sans aborder les systèmes sociaux, politiques et économiques auxquels elles ont donné lieu. La croissance spectaculaire enregistrée depuis la révolution industrielle a entraîné des progrès significatifs en matière d'indicateurs de santé humaine, mais elle a également conduit à des systèmes économiques dans lesquels les entreprises sont encouragées à maximiser leurs profits plutôt que l'apport à la société. Cela a conduit à valoriser le consumérisme et la richesse matérielle, dont l'intérêt pour nos communautés est controversé et qui sont néfastes pour l'environnement et donc pour les conditions de vie futures, au détriment des valeurs sociales. Cela conduit également actuellement à des sociétés dans lesquelles les individus sont de moins en moins encouragés à s'émanciper. Cela conduit, comme on le constate aujourd'hui, à la montée de régimes autoritaires prônant des valeurs de domination.
Cette société s'est également développée sur la base de relations de pouvoir. Les scénarios futurs ne sont pas nécessairement exempts de cette logique et peuvent l'exacerber[9]. Toute étude proposant des scénarios futurs devrait donc discuter de manière critique des implications sur les structures sociales et politiques.

A.9.5. Perspectives

Pour mieux identifier les limites les plus proches de la croissance, on pourrait affiner les modèles développés dans ce travail ; ou modéliser comment l'instabilité économique et financière est susceptible de déclencher des crises, influencées par les tensions sur l'approvisionnement en pétrole et influençant celles-ci.

Dans le contexte d'un scénario de décroissance, il serait intéressant de modéliser la quantité minimale d'énergie et la complexité minimale nécessaires pour atteindre des conditions de vie matérielles permettant des niveaux élevés de santé et de bien-être dans les sociétés futures. Si certaines études ont tenté de quantifier cela (Millward-Hopkins et al., 2020; Grubler et al., 2018), leurs hypothèses reposent sur les systèmes énergétiques et industriels actuels, qui seraient très différents dans un scénario de décroissance significative. Modéliser un futur système industriel avec un niveau de complexité bien moindre n'est pas chose aisée. De plus, la conception de tels scénarios nécessite de définir des objectifs en matière de santé et de bien-être, ainsi que de créer des scénarios d'organisations sociales alternatives, en particulier dans les domaines du logement et des transports, ce qui implique de mobiliser plusieurs disciplines des sciences sociales et de prendre en compte les implications démocratiques pour les citoyens et les organisations de la société civile dans un tel projet.

De tels scénarios peuvent être considérés comme utopiques et impossibles à réaliser tant que les parties prenantes et les États recherchent un maximum de richesse et de pouvoir. D'autre part, il semble plus prioritaire d'étudier les verrous aux scénarios de décroissance volontaire et les moyens de les surmonter. Certains éléments permettant de répondre à ces questions ont

[9] Par exemple, s'ils ne sont pas conçus en tenant compte des implications sociales et politiques, les scénarios décrivant des changements rapides imposés par le haut peuvent induire des décisions autoritaires. En outre, il existe des scénarios de transition énergétique dans lesquels les économies avancées chercheraient à exploiter les pays riches en matières premières et à faible revenu, au détriment des avantages pour les pays désignés et les communautés locales.

toutefois déjà été identifiés[10]. Dans tous les cas, apporter des réponses pertinentes à ces questions nécessite un travail politique, interdisciplinaire et systémique.

[10]Parmi ceux-ci : la création de groupes chargés de traiter les questions politiques au niveau communautaire, la modification des valeurs sociales, la remise en question de l'état des choses et l'élaboration collective de visions politiques.

APPENDIX B | ÉTHIQUE ET EFFETS DE LA THÈSE SUR LA SOCIÉTÉ

Cette section est destinée à discuter des implications éthiques de la thèse et sur la société. En effet, cultiver une réflexivité éthique sur ses travaux de recherche me parait essentiel — d'autant plus sur un travail de thèse, où 3 à 5 années (ou plus) de recherche sont consacrées à un sujet de recherche — et en phase avec les invitations à la réflexivité éthique reçues lors d'un doctorat[1]. De plus, j'aimerais pouvoir lire dans toutes les thèses une discussion sur les implications éthiques et sociétales des travaux réalisés. J'aimerais donc inviter tous les doctorantes et doctorants à entreprendre une démarche similaire dans leur manuscrit de thèse.

B.1. POURQUOI CES TRAVAUX ? QUE SERVENT-ILS ? QUELS SONT LES EFFETS DÉSIRÉS SUR LA SOCIÉTÉ ?

Le sujet de cette thèse émerge des questionnements menés au sein de l'équipe STEEP[2] (Soutenabilité, Territoires, Économie biophysique, Environnement et Politiques territoriales), eux-mêmes issus de la vision de STEEP sur les enjeux socio-environnementaux du XXIe siècle. Le sujet de la thèse est d'abord motivé par la volonté de combler un manque de connaissance sur les risques systémiques globaux, en partant de l'intuition que les limites énergétiques (et notamment le pic pétrolier) pourraient limiter la croissance dans un futur proche. Le sujet de thèse est donc le fruit de questionnements internes plutôt que d'incitations d'acteurs externes.

Partant de cela, l'effet attendu des travaux de thèse est d'abord un apport de connaissances pour les travaux de recherche de l'équipe STEEP ainsi que pour la communauté scientifique discutant de ces enjeux. De même, ces sujets étant structurants pour le futur de nos sociétés industrielles, on peut s'attendre à un apport en connaissance pour le monde politique et pour les citoyens, pouvant aider à la décision. Néanmoins, l'ambition vers le monde politique est à tempérer du fait d'une certaine déconnexion entre le monde politique et le monde scientifique, mais surtout du fait des verrous aux changements structurels sur ce type d'enjeux, rendus visibles par le faible impact politique de la connaissance sur — par exemple — les effets du changement

[1] L'obligation de formation des doctorants à l'éthique de la recherche et à l'intégrité scientifique ainsi que le serment doctoral d'intégrité scientifique.

[2] `https://team.inria.fr/steep/fr`

climatique (exposés par le GIEC depuis au moins 1990 et largement reconnus depuis) ou sur les limites à la croissance (Meadows et al., 1972) depuis un demi-siècle.

L'apport principal de la thèse d'un point de vue sociétal est de donner une preuve quantitative et robuste de l'impossibilité de scénario BAU dès un horizon temporel proche (≈2030). Je suis évidemment conscient que ce résultat n'aura pas pour effet une volonté subite de la part des personnalités politiques, des institutions et des citoyens de remettre en question les scénarios BAU et de se tourner vers des scénarios de décroissance égalitaires (qui me paraissent bien plus désirables que des scénarios BAU, et qui sont étudiées dans la littérature scientifique, par exemple Kallis et al. 2025; Parrique 2019; Lauer et al. 2025). Le résultat n'est pas directement actionnable. Néanmoins, ce résultat a le mérite de remettre en question la possibilité même des scénarios BAU sur la base d'argument scientifiques quantitatifs robustes. Cela sert le débat public.

B.2. Quelles sont les implications des méthodes employées ?

Les analyses de cette thèse se basent sur de la modélisation mathématique et informatique, de complexité faible. Cela implique d'abord une distance avec les sciences sociales. Cette approche est renforcée de par ma formation d'ingénieur et des formations initiales de mes directeurs de thèse (astrophysique théorique, géologie, mathématiques). Un des risques de ce genre de modélisation est l'omission de tout types d'effets sociaux, aussi bien dans la conceptualisation des problèmes que dans la modélisation[3].

Cette thèse se place néanmoins à l'échelle globale et dans le cadre d'un scénario BAU, ce qui limite les effets politiques, sociaux ou culturels locaux. D'un autre côté, ce genre d'approche aggrégée et globale pourrait mener les modélisateurs à avoir une vision autoritaire des transformations qu'il "faudrait faire" plutôt que discuter de la désirabilité des scénarios produits par ce genre d'approche. Dans cette thèse nous ne proposons cependant pas de scénarios alternatifs et la désirabilité de scénarios BAU est discutée en introduction et en conclusion.

B.3. Quels peuvent être les effets non désirés de ces travaux sur la société ?

Je pars du principe que le principal effet de cette thèse sur la société se fera via la diffusion de connaissances. De ce fait, le principal risque est alors que les conclusions de cette thèse soient déformées et/ou utilisés pour justifier certains narratifs qui sortent du cadre de la thèse. Si l'on peut attendre que le message soit déformé, en partie du fait que les nuances qu'il contient ne peuvent être transmises en des communications courtes, j'ai néanmoins essayé de fournir des conclusions claires, limitant le risque de déformation des résultats. De plus, j'espère pouvoir participer à la diffusion de ces travaux une fois les publications scientifiques acceptées. La réu-

[3] A noter que les dynamiques sociales peuvent rarement être modélisées quantitativement de manière pertinente, mais peuvent par contre être prises en compte dans la conception des scénarios d'un modèle

tilisation des résultats de la thèse par divers acteurs est toutefois en partie hors de mon contrôle, la thèse — ainsi que les publications la composant[4] — étant publique.

Ainsi il est possible que le constat de futures tensions énergétiques dans un scénario BAU soit utilisé pour soutenir des projets impérialistes plutôt que de tendre vers l'émancipation des dépendances énergétiques. Il est aussi possible que les résultats soient interprétés comme une preuve inéluctable que le monde va rapidement s'effondrer dans la violence. S'il est possible que les sociétés industrielles subissent un déclin à long terme due à la combinaison de limites d'approvisionnement énergétique, d'effets climatiques, de l'érosion de la biodiversité ou de la perturbation des cycles biogéochimiques, j'ai pointé dans la conclusion que plusieurs scénarios hors BAU étaient possibles, notamment : un scénario ambitieux de transition énergétique, un scénario de décroissance choisie, ou plus probablement un scénario de ralentissement économique global impliquant une inflexion de la demande en pétrole. De plus, si l'on peut s'attendre à des crises économiques dans le cas d'un scénario BAU à partir du moment où l'approvisionnement serait insuffisant par rapport à la demande (Tverberg, 2012a; Murphy and Hall, 2011; Sorrell et al., 2009; Brandt, 2017; Hamilton, 2009), les travaux de thèse ne permettent pas ni d'inférer la situation énergétique future, qui dépend notamment de paramètres économiques et politiques, ni d'inférer comment cette crise se traduirait puisque cela dépend de nombreux paramètres sociaux et politiques.

Enfin, ces travaux mènent à parler de décroissance. Il est important de reconnaitre que de multiples scénarios de décroissance sont possibles — dont des scénarios égalitaires ainsi que des scénarios inégalitaires — cela afin d'éviter des faux dilemmes dans les débats sur l'élaboration de l'avenir, ou de se voir imposer certains scénarios et certaines mesures comme uniques solutions.

Finalement, j'estime que les apports des résultats de thèse pour la société outrepassent les risques que ces résultats impliquent.

B.4. Financements et valeurs

Cette thèse a été financée par un contrat doctoral (3 ans) de l'Université Grenoble Alpes (UGA) attribué par l'école doctorale de mathématiques, sciences et technologies de l'information, informatique (ED MSTII) dont les fonds proviennent du Ministère de l'Enseignement Supérieur et de la Recherche (MESRE), ainsi que de rallonges fournies par le laboratoire Jean Kuntzmann (LJK, 2 mois) et l'Institut national de recherche en sciences et technologies du numérique (INRIA, 3 mois). J'ai principalement été hébergé par l'équipe STEEP à l'INRIA Grenoble, ainsi qu'à ISTerre (Institut des sciences de la terre). Mes directeurs de thèse sont financés par le Centre National de la Recherche Scientifique (CNRS) et l'INRIA. Ces institutions n'ont pas été impliquées dans la conduite des travaux de recherche ni dans la préparation de la thèse. Je déclare n'avoir aucun conflit d'intérêt.

Enfin, il convient de noter que ma vision et mes valeurs (permises notamment par ma position privilégiée dans le monde et influencée par ma formation d'ingénieur) influent sur les objets de recherche ainsi que sur les approches choisies durant cette thèse. Il est néanmoins important de rappeler que cela n'affecte ni la conduite de ces travaux, menés conformément aux principes d'intégrité et à la rigueur scientifique (COMETS, 2023), ni la validité scientifique des résultats obtenus.

[4] Les preprints des articles composant la thèse seront publiés sur HAL en même temps que leur acceptation pour publication dans les journaux à revue par les pairs, et les versions définitives des articles seront publiées 6 mois après leur publication dans ledit journal, conformément à la loi française

APPENDIX C | ETHICS AND SOCIETAL EFFECTS

This section is intended to discuss the ethical implications of the thesis and for society. Indeed, cultivating ethical reflexivity in one's research work seems essential to me — especially in a thesis, where three to five years of research are devoted to a single research topic — and in line with the calls for ethical reflexivity received during a PhD[1] . In addition, I would like to see a discussion of the ethical and societal implications of the work carried out in all theses. I therefore would like to invite all current and future PhD students to take a similar approach in their thesis manuscripts.

C.1. WHY THIS RESEARCH? WHAT ARE THE DESIRED EFFECTS ON SOCIETY?

The subject of this thesis emerged from discussions within the STEEP team[2] (Sustainability, Territories, biophysical Economics, Environment, and local Policies), which in turn stemmed from STEEP's vision of the socio-environmental challenges of the 21st century. The subject of the thesis is primarily motivated by the desire to address a lack of knowledge on global systemic risks, based on the intuition that energy constraints (and in particular peak oil) could limit growth in the near future. The thesis subject is therefore the result of internal discussions rather than of external incentives.

On this basis, the expected outcome of the thesis work is primarily to bring new knowledge and understanding to the STEEP team and to the scientific community discussing these issues. Similarly, as these topics are fundamental to the future of our industrialized societies, we can expect them to bring new knowledge and understanding to political leaders and to citizens, which could aid decision-making. Nevertheless, ambitions in the political sphere must be tempered by the fact that there is a certain disconnect between the political and scientific worlds, but above all by the barriers to structural change on these types of issues, made visible by the weak political impact of knowledge on — for example — the effects of climate change (reported by the IPCC since at least 1990 and widely recognized since then) or on the limits to growth (Meadows et al., 1972) for half a century.

The main contribution of the thesis from a societal point of view is to provide quantitative

[1] The obligation for doctoral students to undergo training in research ethics and scientific integrity, as well as the doctoral oath of scientific integrity.

[2] `https://team.inria.fr/steep/`

and robust evidence of the impossibility of a BAU scenario in the near future (≈2030). I am obviously aware that this result will not suddenly prompt politicians, institutions, and citizens to question BAU scenarios and turn to egalitarian degrowth scenarios (which I find much more desirable than BAU scenarios, and which are studied in the scientific literature, e.g. Kallis et al. 2025; Parrique 2019; Lauer et al. 2025). The result is not directly actionable. Nevertheless, this result has the merit of questioning the very possibility of BAU scenarios on the basis of robust quantitative scientific arguments. This serves the public debate.

C.2. What are the implications of the methods used?

The analyses in this thesis are based on mathematical and computer modeling of low complexity. This implies, first of all, a distance from social sciences. This is reinforced by my engineering background and the training of my thesis supervisors (theoretical astrophysics, geology, mathematics). One of the risks of this type of modeling is the omission of all kinds of social effects, both in the conceptualization of problems and in modeling[3].

Nevertheless, this thesis is global in scope and based on a BAU scenario, which limits local political, social, or cultural effects. On the other hand, this type of aggregated and global approach could lead modelers to take an authoritarian view of the transformations that "would be required" rather than discussing the desirability of the scenarios produced by this type of approach. In the case of the thesis, we do not propose alternative scenarios, and the introduction and conclusion discuss the desirability of BAU scenarios.

C.3. What could be the undesirable effects of this work on society?

I assume that the main effect of this thesis on society will be through dissemination of knowledge. Therefore, the main risk is that the conclusions of this thesis will be distorted and/or used to justify certain narratives that fall outside the scope of the thesis. While we can expect the message to be distorted, partly because the nuances it contains cannot be conveyed in short communications, I have nevertheless tried to provide clear conclusions, limiting the risk of distortion of the results. In addition, I hope to be able to participate in the dissemination of this work once its related scientific publications have been accepted. However, the reuse of the thesis results by various actors is beyond my control, as the thesis itself — as well as the publications that comprise it[4] — being public.

Thus, it is possible that the observation of future energy tensions in a BAU scenario could be used to support imperialist projects rather than to move towards reducing the reliance of society on abundant energy. It is also possible that the results could be interpreted as irrefutable proof that the world is rapidly heading towards violent collapse. While it is possible that industrial

[3] It should be noted that social dynamics can rarely be mathematically modeled in a relevant way, but can, however, be taken into account in the design of model scenarios

[4] The preprints of the articles comprising the thesis will be published on HAL at the same time as their acceptance for publication in peer-reviewed journals, and the final versions of the articles will be published 6 months after their publication in the said journal, in accordance with french law

societies will experience long-term decline due to a combination of energy supply constraints, climate effects, energy dynamics, biodiversity erosion, and disruption of biogeochemical cycles, I pointed out in the conclusion that several non-BAU scenarios are possible, including: an ambitious energy transition scenario, a scenario of planned degrowth, or more likely a scenario of global economic slowdown involving a decline in oil demand. Furthermore, while economic crises can be expected in a BAU scenario once supply falls short of demand (Tverberg, 2012a; Murphy and Hall, 2011; Sorrell et al., 2009; Brandt, 2017; Hamilton, 2009), the thesis work does not allow us to infer the future energy situation, which depends in particular on economic and political parameters, nor to infer how this crisis would play out, as this depends on many social and political parameters.

Finally, this work leads us to discuss degrowth. It is important to recognize that multiple degrowth scenarios are possible — including both egalitarian and unequal scenarios — in order to avoid false dilemmas in debates about shaping the future, or having certain scenarios and measures imposed as the only solutions.

I believe that the benefits of the thesis results for society outweigh the risks that these results entail.

C.4. Funding and values

This thesis was funded by a doctoral contract (3 years) from the Université Grenoble Alpes (UGA) attributed by the doctoral school of mathematics, information science and technology, and computer science (ED MSTII), whose funds come from the French Ministry of Higher Education and Research (MESRE), as well as extensions provided by the Jean Kuntzmann Laboratory (LJK, 2 months) and the French National Institute for Research in Digital Science and Technology (INRIA, 3 months). I was mainly hosted by the STEEP team at INRIA Grenoble, as well as at ISTerre (Institute of Earth Sciences). My thesis supervisors are funded by the National Center for Scientific Research (CNRS) and INRIA. These institutions were not involved in conducting the research or preparing the thesis. I declare that I have no conflicts of interest.

Finally, it should be noted that my vision and values (shaped by my privileged position in the world and by my engineering education) influence the research topics and approaches chosen during this thesis. Nevertheless, it is important to note that this does not affect the conduct of this work, which was carried out in accordance with the principles of scientific integrity and rigor (COMETS, 2023), nor the scientific validity of the results obtained.

APPENDIX D | SUPPLEMENTARY MATERIALS: ROAD TRANSPORT ELECTRIFICATION IS THE ARBITER BETWEEN INCREASING AND PEAKING OIL DEMAND

D.1. CODES FOR COUNTRIES AND REGIONS

In the figures presented below, countries are referenced by 3 letters corresponding to their ISO 3166-1 alpha-3 code. Table D.1 lists these codes for all modeled countries. Codes for other countries can easily be found elsewhere, for example at `https://en.wikipedia.org/wiki/ISO_3166-1_alpha-3`.

The regional grouping of countries is shown in table D.2.

D.2. VEHICLES STOCK RESULTS: ADDITIONAL FIGURES

Figs.D.1, D.2 and D.3 show the past and projected evolution of the world 4-Wheeled vehicles (4Ws) stock. We recall that private vehicles (PVs) constitute approximately 85-90% of the stock of 4Ws.

Code	Country
ARE	United Arab Emirates
ARG	Argentina
AUS	Australia
AUT	Austria
BEL	Belgium
BGR	Bulgaria
BLR	Belarus
BRA	Brazil
CAN	Canada
CHE	Switzerland
CHL	Chile
CHN	China
COL	Colombia
CZE	Czech Republic
DEU	Germany
DNK	Denmark
DZA	Algeria
ECU	Ecuador
EGY	Egypt
ESP	Spain
FIN	Finland
FRA	France

Code	Country
GBR	United Kingdom
GRC	Greece
HRV	Croatia
HUN	Hungaria
IDN	Indonesia
IND	India
IRL	Ireland
IRN	Iran
IRQ	Iraq
ISR	Israel
ITA	Italy
JPN	Japan
KAZ	Kazakhstan
KOR	South Korea
LBY	Libya
MAR	Morocco
MEX	Mexico
MYS	Malaysia
NGA	Nigeria
NLD	Netherlands
NOR	Norway
NZL	New Zealand

Code	Country
PAK	Pakistan
PER	Peru
PHL	Philippines
POL	Poland
PRT	Portugal
ROU	Romania
RUS	Russia
SAU	Saudi Arabia
SRB	Serbia
SVK	Slovakia
SWE	Sweden
SYR	Syria
THA	Thailand
TUR	Turkey
UKR	Ukraine
USA	United States
VNM	Vietnam
WLD	World
ZAF	South Africa

TABLE D.1: Alpha-3 codes of modelled countries.

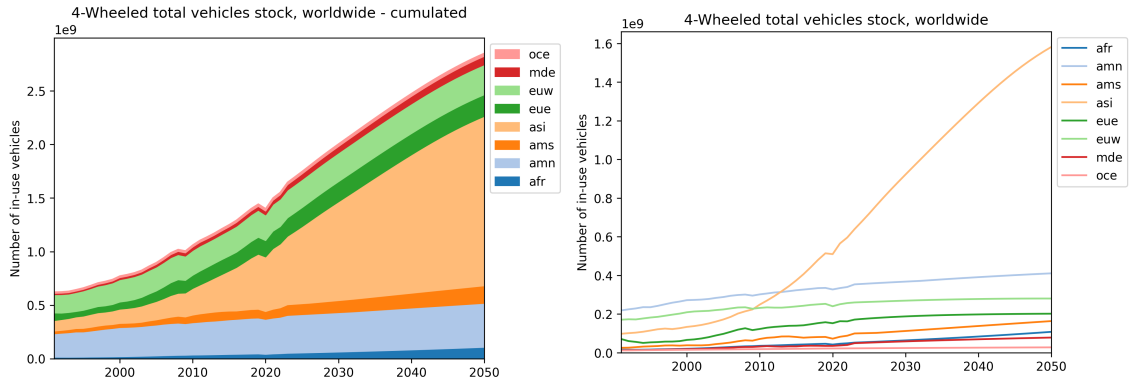


FIGURE D.1: Evolution of the stock of 4W at the global level.

Region	Modelled countries
Afr	DZA, EGY, LBY, MAR, NGA, ZAF
Amn	CAN, MEX, USA
Ams	ARG, BRA, CHL, COL, ECU, PER
Asi	CHN, IND, IDN, JPN, KAZ, KOR, MYS, PAK, PHL, THA, VNM
Eue	BLR, BGR, HRV, CZE, GRC, HUN, POL, ROU, RUS, SRB, SVK, TUR, UKR
Euw	AUT, BEL, FIN, FRA, DEU, DNK, IRL, ITA, NLD, NOR, PRT, ESP, SWE, CHE, GBR
Mde	IRN, IRQ, ISR, SAU, SYR, ARE
Oce	AUS, NZL

Region	Other countries
Afr	AGO, BEN, BWA, CMR, COD, COG, CIV, GNQ, ERI, SWZ, ETH, GAB, GHA, KEN, MDG, MUS, MOZ, NAM, NER, RWA, SEN, SSD, SDN, TZA, TGO, UGA, ZMB, ZWE
Amn	CUB, DOM, HTI, JAM, PAN
Ams	BOL, CRI, CUW, GTM, GUY, HND, NIC, PRY, SLV, SUR, TTO, TUN, URY, VEN
Asi	BGD, BRN, KHM, HKG, LAO, MMR, MNG, NPL, PRK, SGP, TAI, LKA
Eue	ARM, AZE, BIH, CYP, EST, GEO, KGZ, LVA, LTU, MDA, MNE, SVN, TJK, TKM, UZB, XKX
Euw	ALB, GIB, LUX, MLT, ISL
Mde	BHR, JOR, KWT, LBN, OMN, QAT, YEM
Oce	—

Table D.2: Disaggregation of regions into their modeled and other countries.
"Afr" designates Africa, "Amn" Nothern America, "Ams" Southern America, "Asi" Asia, "Eue" Eastern Europe, "Euw" Western Europe, "Mde" Middle East, "Oce" Oceania.
Countries are designated by their alpha-3 code, see section D.1.

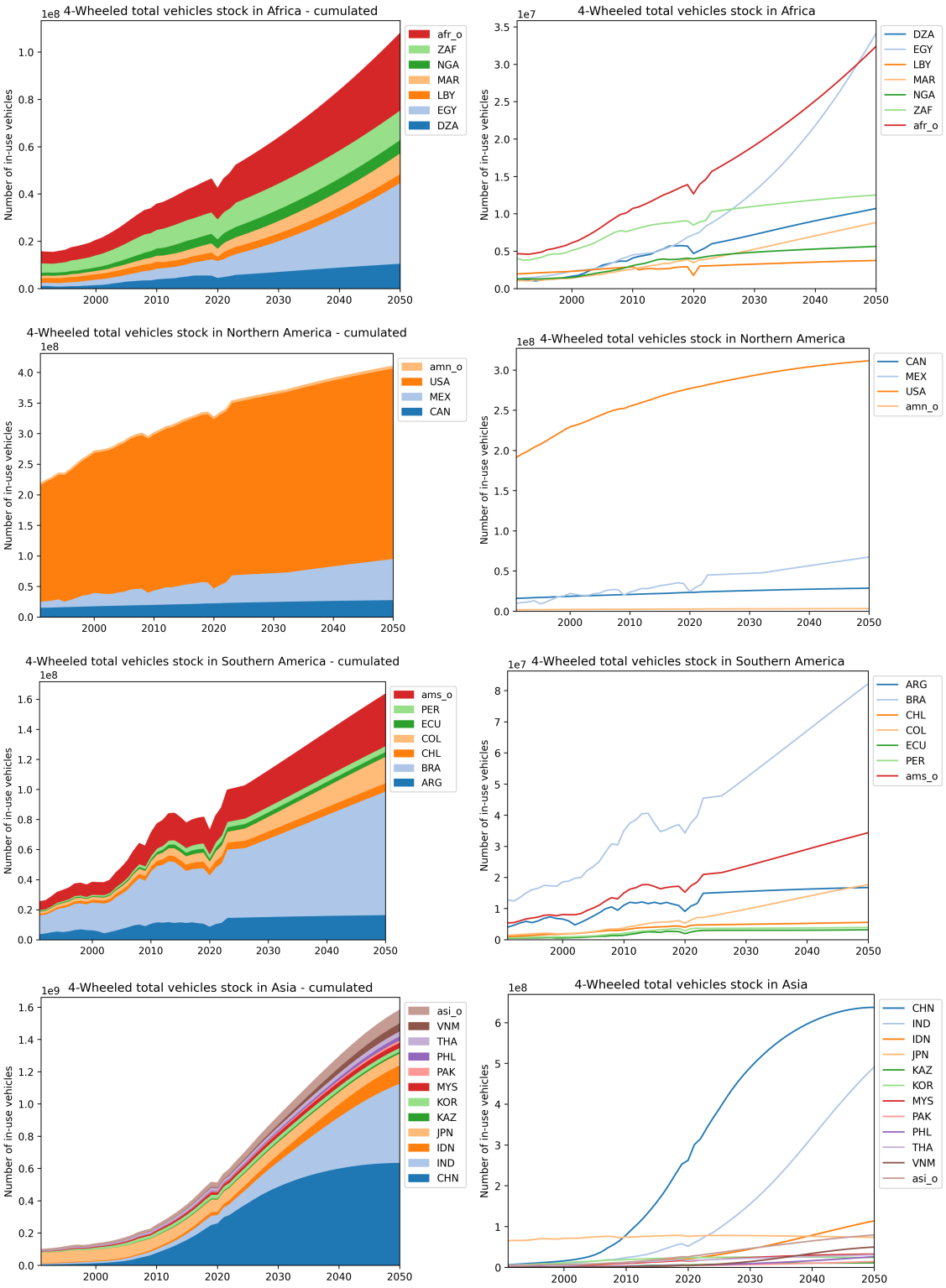


FIGURE D.2: Evolution of the stock of 4W in regions (first part)

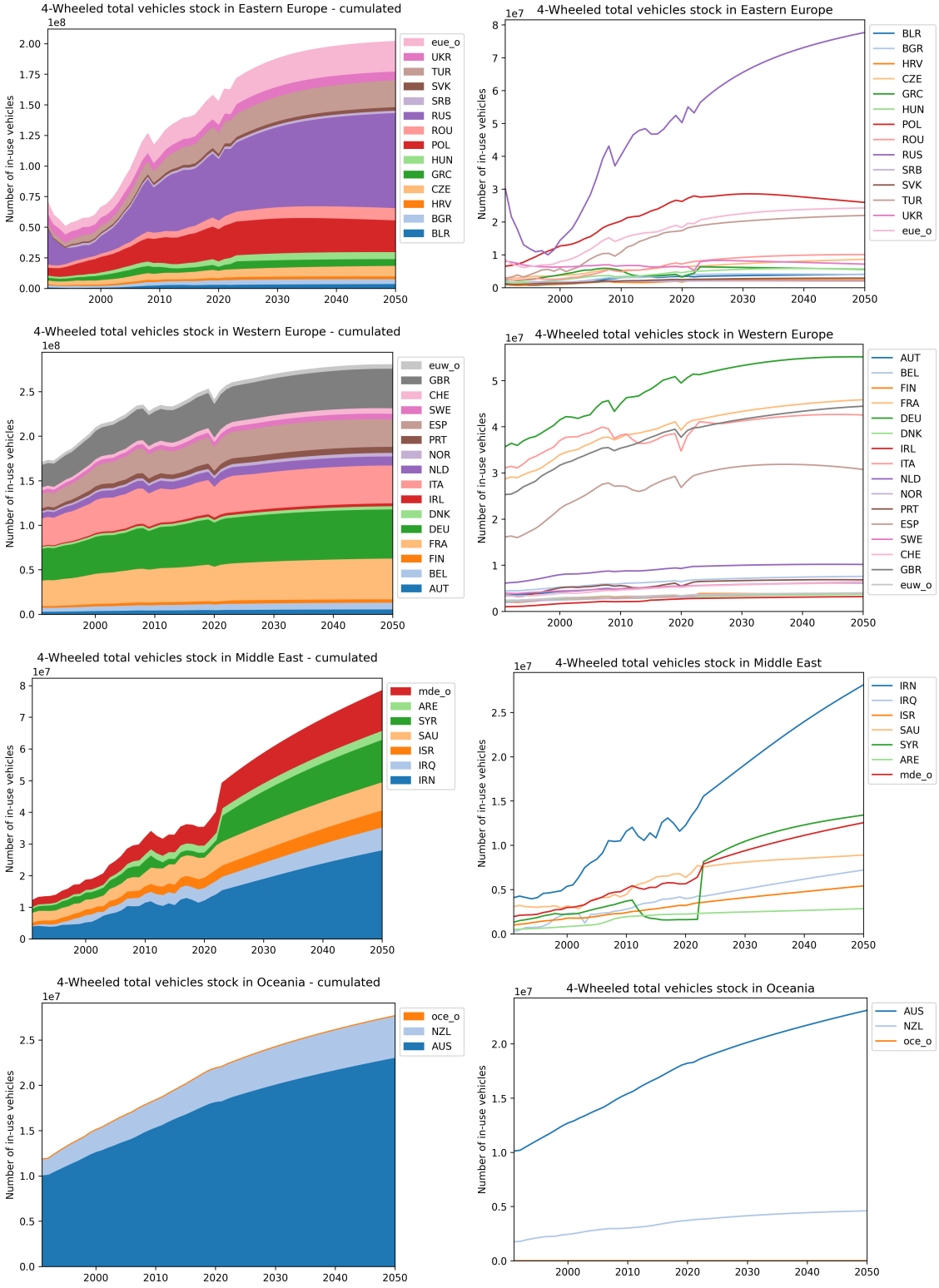


FIGURE D.3: Evolution of the stock of 4W in regions (second part)

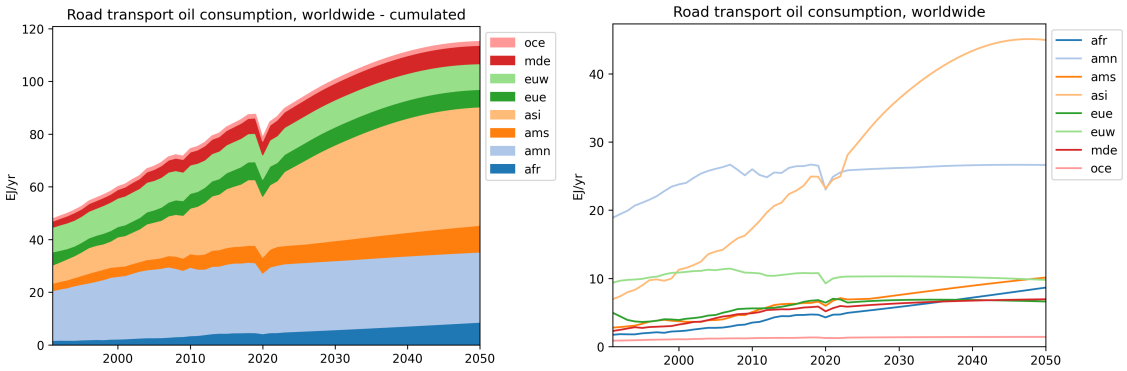


FIGURE D.4: Evolution the consumption in the road transport sector (PV + CV + 2W) at the global scale. These results are from the "0% EV" scenario which assumes no EV deployment.

D.3. ROAD TRANSPORT OIL CONSUMPTION RESULTS: ADDITIONAL FIGURES

The evolution of oil consumption in the road transport sector in shown in Figs. D.4, D.5 and D.6. We that the road transport sector is composed of private vehicles (PVs), commercial vehicles (CVs) and motorcycles (2W).

These results are obtained in the "0% EV" scenario, that assumes no EV deployment. These figures quantify the evolution of the regional demand of energy in the road transport sector. On the other hand, and in the absence of dedicated model and information, the deployment EVs is assumed to be the same in all regions. More precisely, the share of the EV stock over time is assumed to be the same in each country, and the evolution of this stock is defined by a logistic function fitted on their observed deployment rate and with its saturation defined by each scenario: 0%, 25%, 50% or 100% of the vehicle stock for PVs. See the dedicated sections of the main articles for more details.

D.4. GDP REGIONAL PROJECTIONS

The data and projections on the GDPs of countries and regions are shown on Figs. D.7, D.8 and D.9.

The GDP projections of other countries are assumed proportional to the GDP projections computed for the modeled countries of each region. This follows the same rationale as for the projections of the oil demand of these other countries. The coefficients used for GDP projections are derived from the share of GDP of these other countries in the region, in historical data.

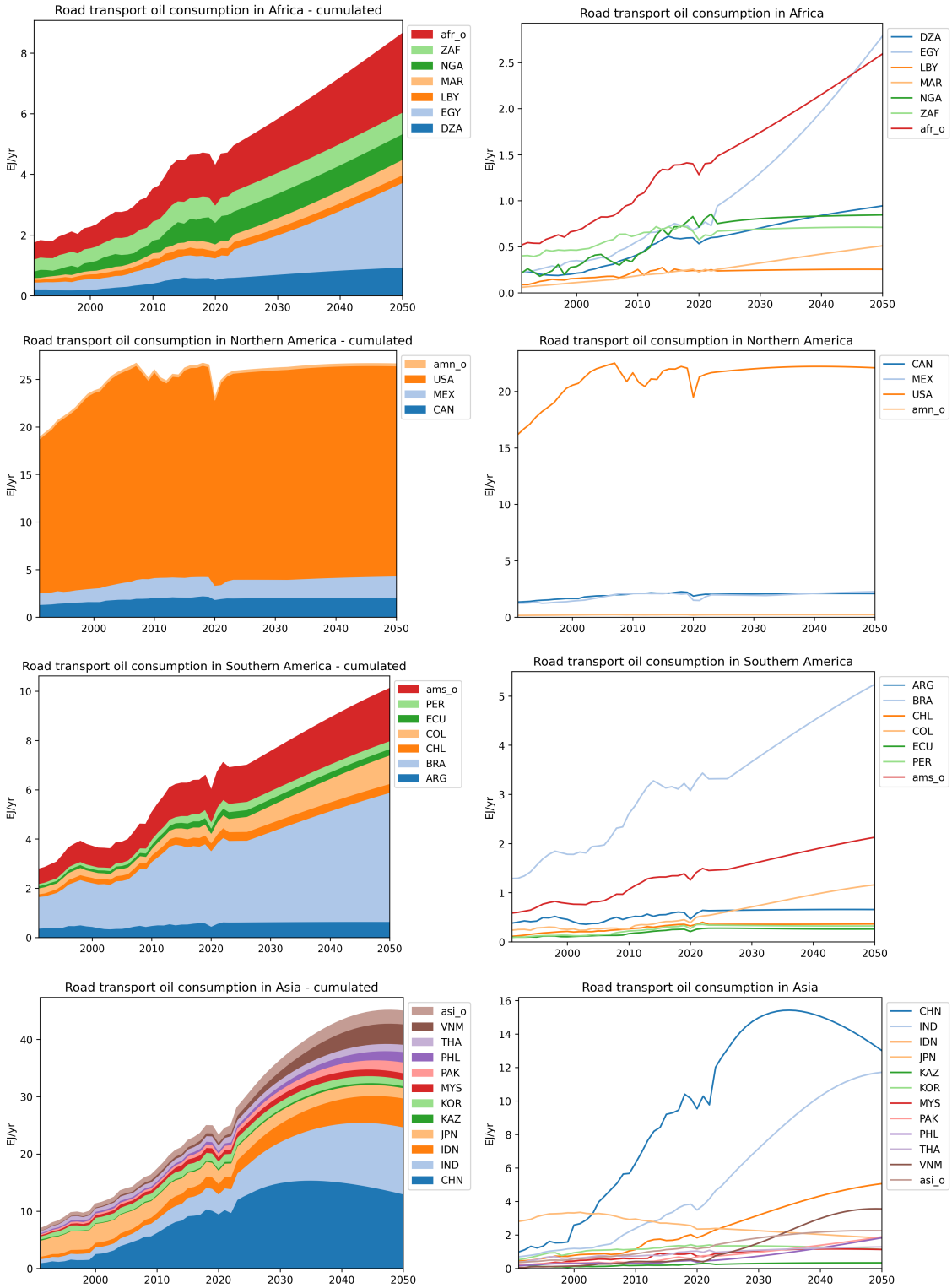


FIGURE D.5: Evolution the oil consumption in the road transport sector (PV + CV + 2W) in regions (first part). These results are from the "0% EV" scenario which assumes no EV deployment.

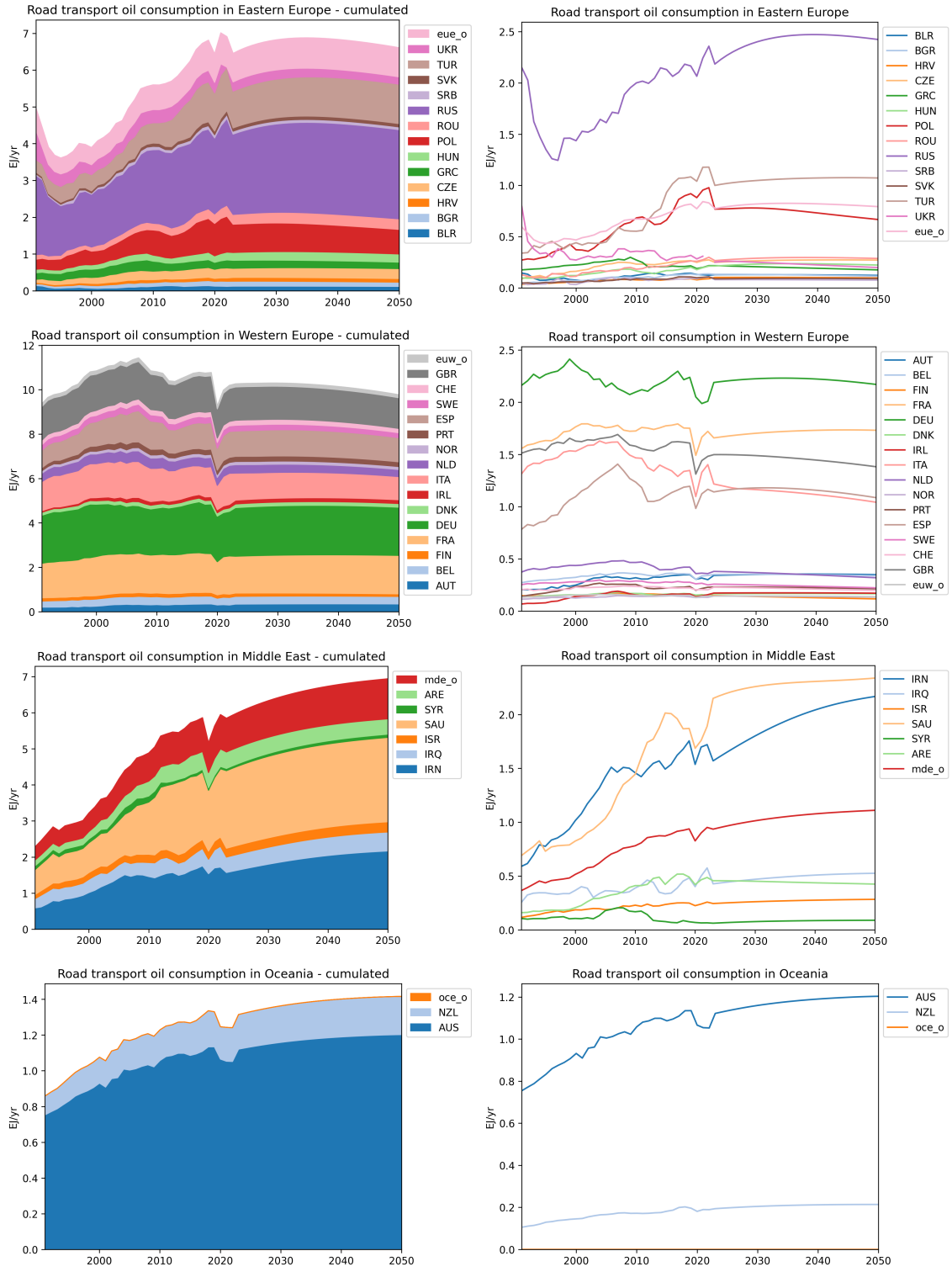


FIGURE D.6: Evolution oil consumption in the road transport sector (PV + CV + 2W) in regions (second part). These results are from the "0% EV" scenario which assumes no EV deployment.

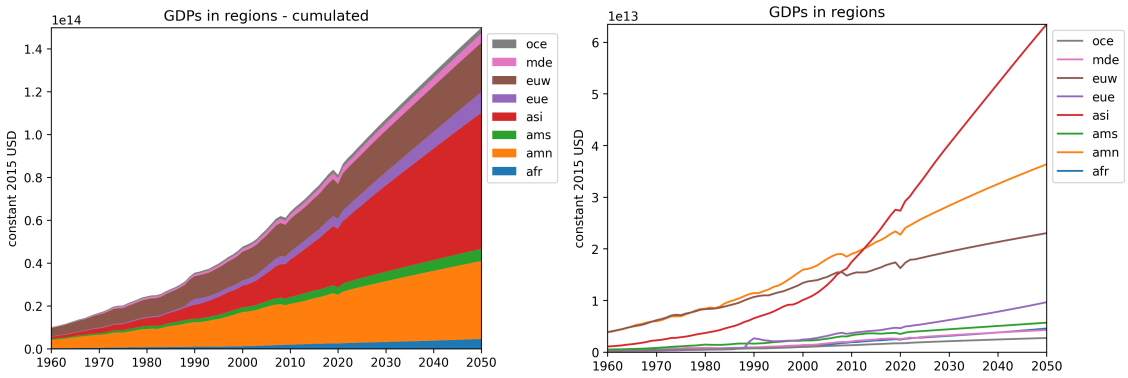


FIGURE D.7: GDP Data and projections, cumulated worldwide. Projections start in 2024.

D.5. GOMPERTZ FITS ON VEHICLE OWNERSHIP

The Gompertz fits of some major countries are shown on Fig. D.10. Figures for other countries are available on request.

D.6. ANNUAL OIL CONSUMPTION OF A VEHICLE

Data and projections for the annual oil consumption $C^c_{o,PV}$ of PVs are shown on Fig. D.11. Historical data the result from the solution the equations of the problem. We recall that $C^c_{o,PV} = E^c_{o,PV}/v^c_{o,PV}$. As the data on vehicle stocks may not be robust (see the dedicated section of the article), depending on the country, an additional quantity $C^c_{o,PV,gomp}$ is determined, based on the same calculation but with vehicles stocks inferred from the Gompertz function of vehicle ownership fitted on the ownership data rather than on the initial vehicle stock data themselves. In the analysis made for the projections of the annual oil consumption of PVs, $C^c_{o,PV,gomp}$ has sometimes been taken as more reliable than $C^c_{o,PV}$ and therefore used instead of historical data.

D.7. GDP GROWTH RATE PROJECTIONS: CHOICE OF THE CALIBRATION PERIOD

The choice of the regression time period used to establish our GDP growth rate projections depends on countries. For all countries, the time period was chosen with the objective of depicting current economic trends. We then fit an exponential decay of the growth rate on the chosen data and use it for future GDP projections.

We have excluded data points from 2020 to 2022 due to the global economic impacts of the COVID-19 pandemics, which are not characteristic of long term trends. Similarly, some data points between 2008-2010 have been excluded in the regression due to the global 2008 crisis. The rationale presiding to the exclusion of such data points is that we wish to make BAU projections, and therefore ignore past points influenced by economic crises and recessions,

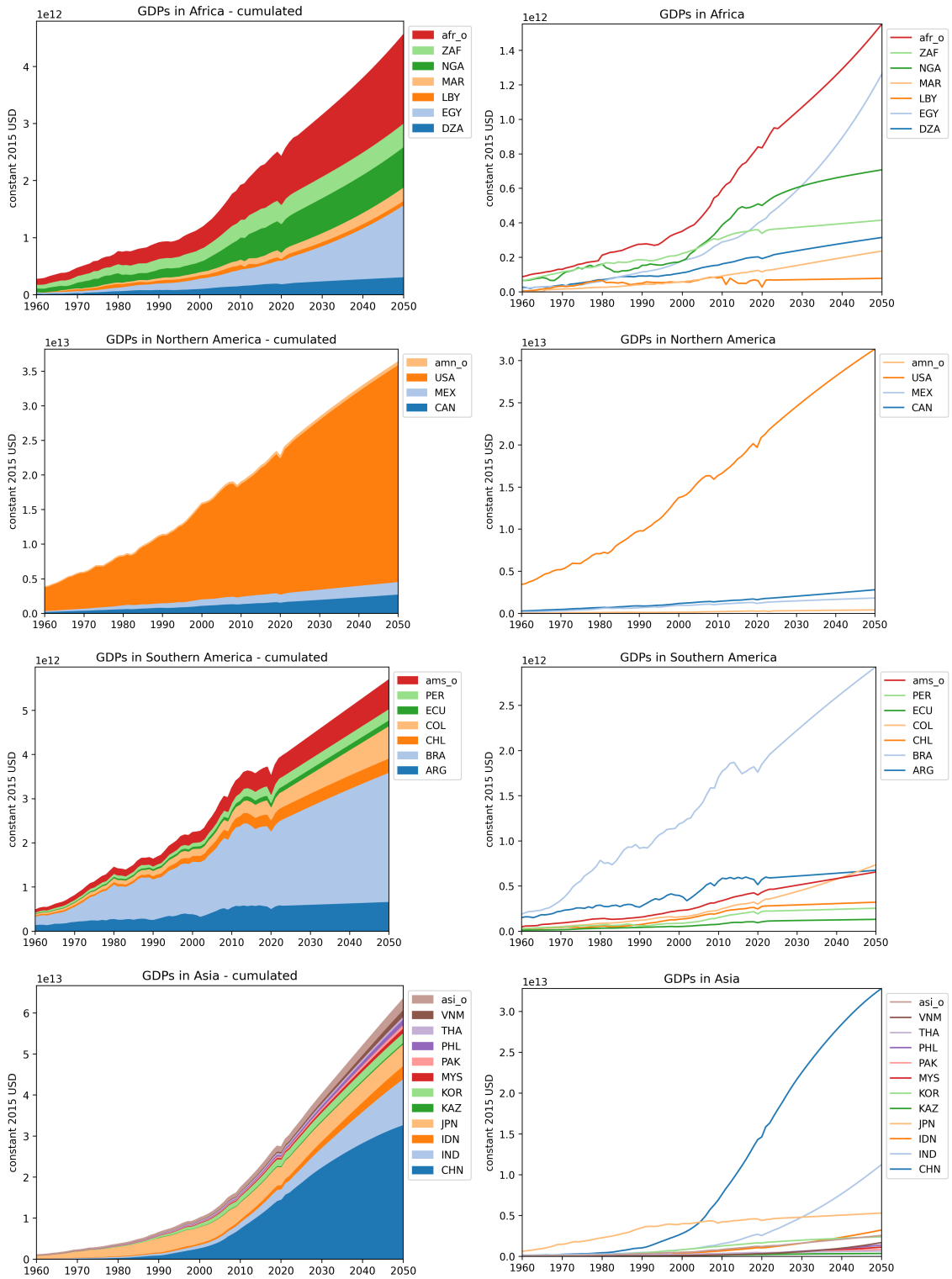


FIGURE D.8: Regional GDP data and projections. Projections start in 2024.

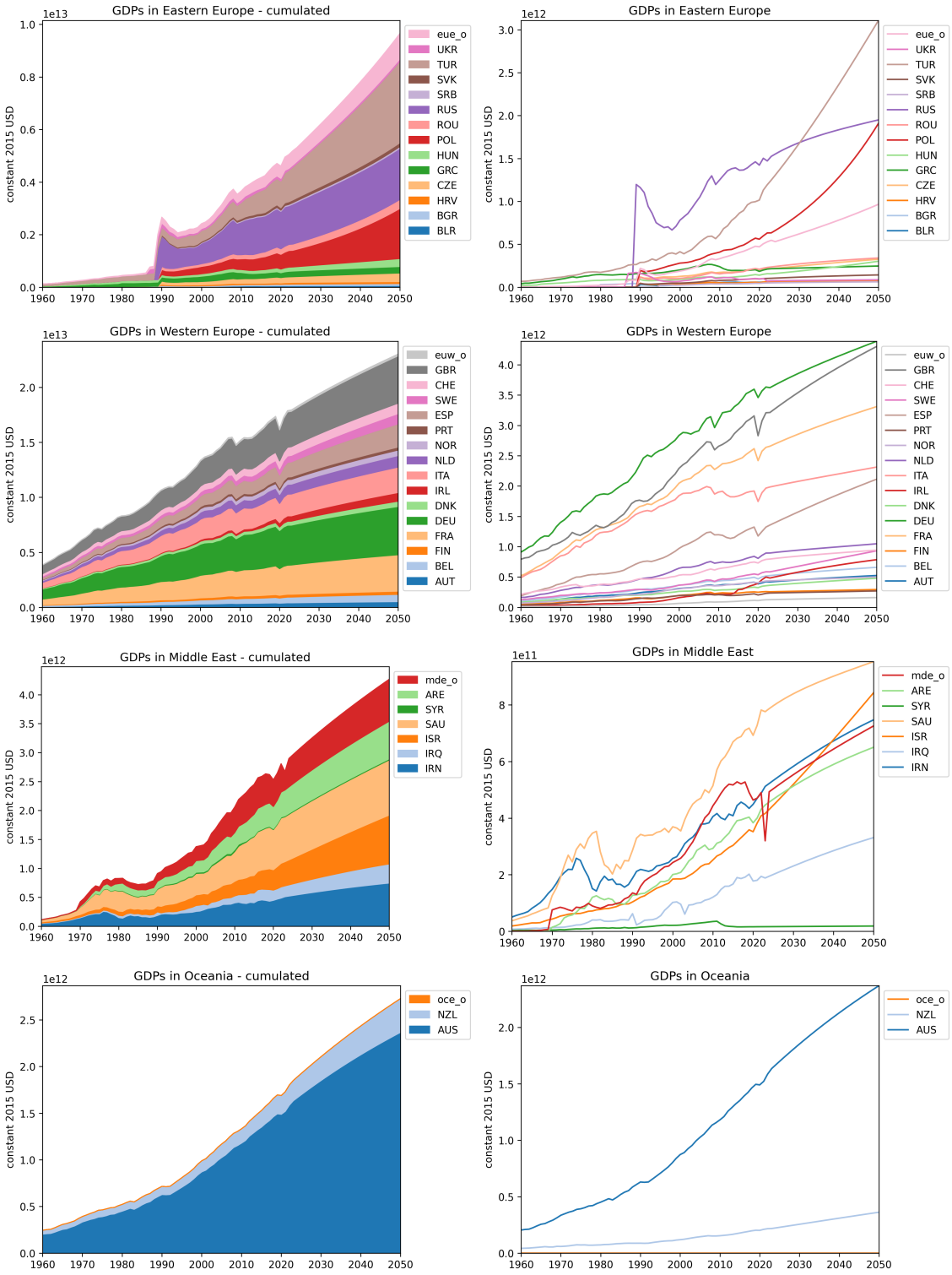


FIGURE D.9: Regional GDP data and projections. Projections start in 2024. The former Soviet Union is not modeled, which explains the discontinuity in the data in 1990 in Eastern Europe.

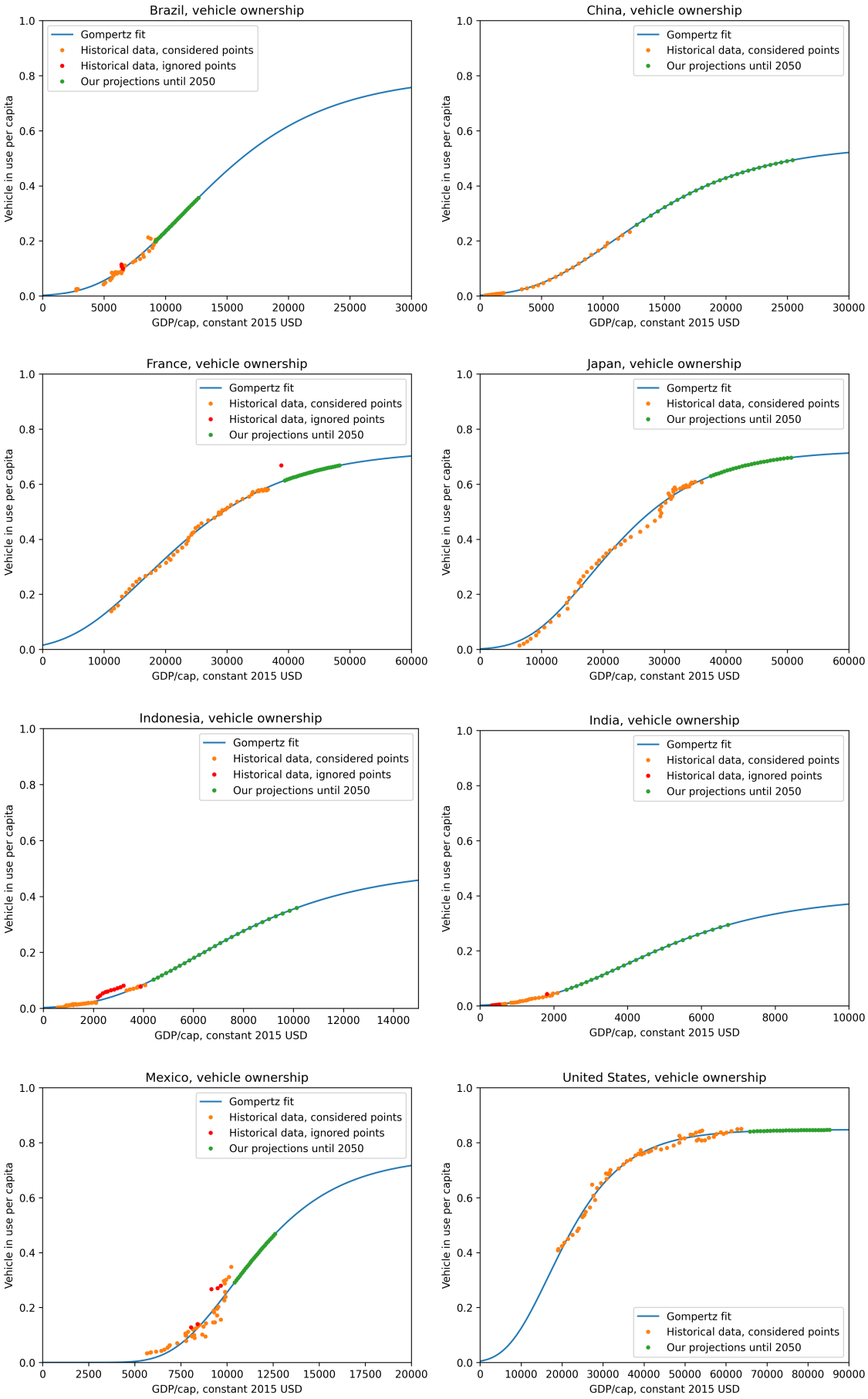


FIGURE D.10: Gompertz fits on vehicle ownership for some major countries

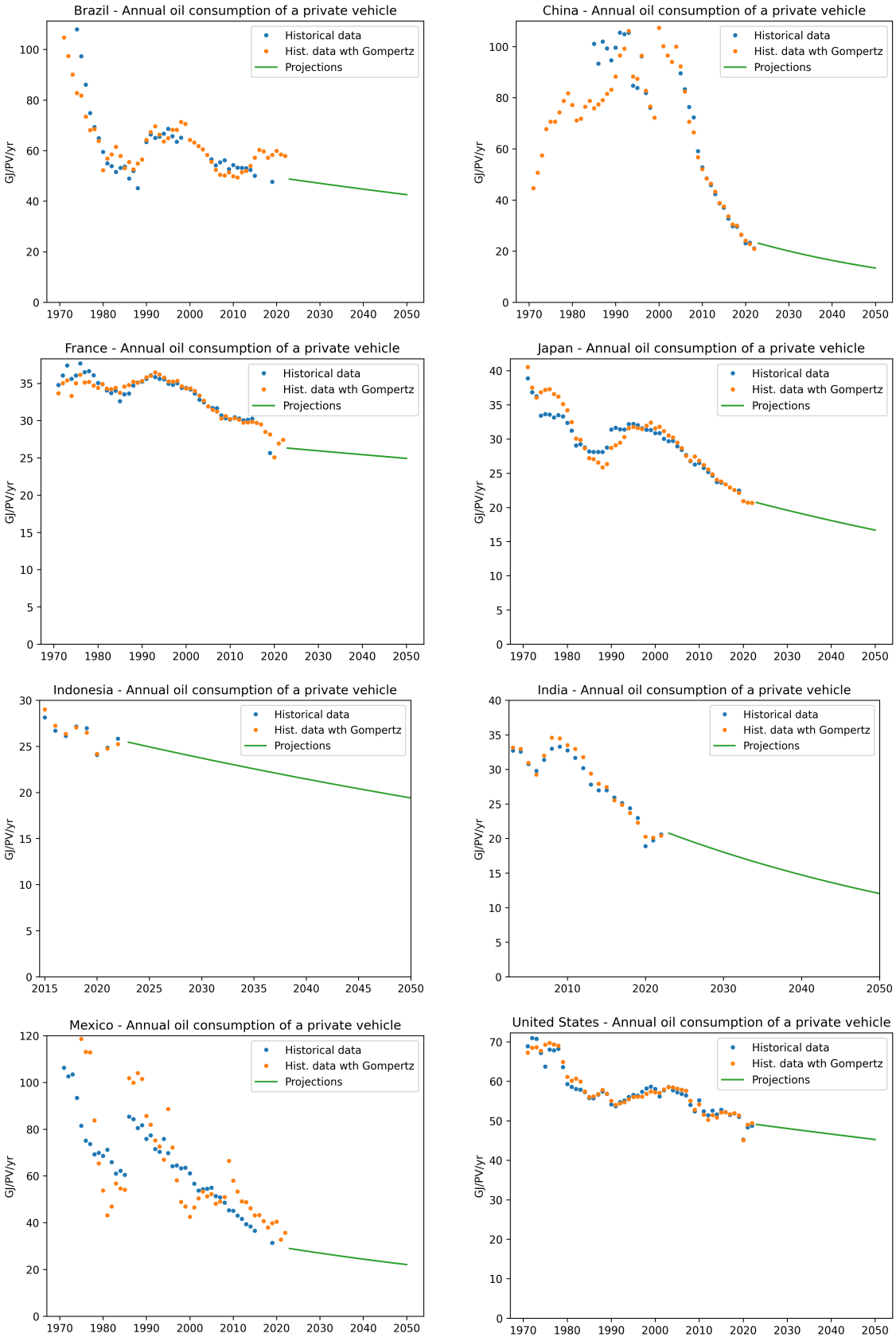


FIGURE D.11: Annual oil consumption per private vehicles (PVs) and associated projections. As the original data on vehicle stock may not be robust, "historical data with Gompertz" points are computed using the stock of vehicles derived from the Gompertz fit of vehicle ownership instead of the initial data. In countries where these initial data are observed to be highly variable, Gompertz's derived data may be used in the analysis for the purpose of inferring general past trends.

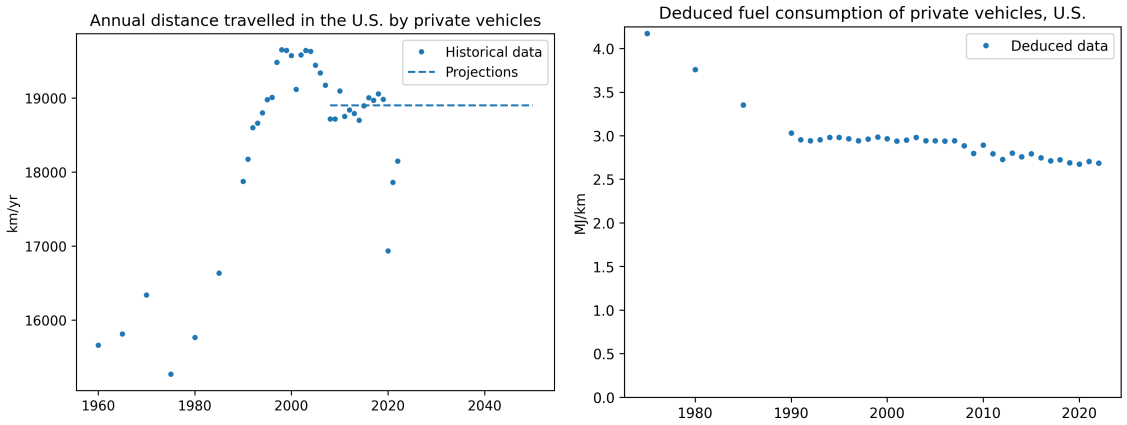


FIGURE D.12: Historical evolution of the annual mileage of PVs in the USA from the data of Bureau of Transportation Statistics (2024), and the fuel consumption of a PV deduced from that data combined with the data on the annual oil consumption of a PVs computed in the present study.

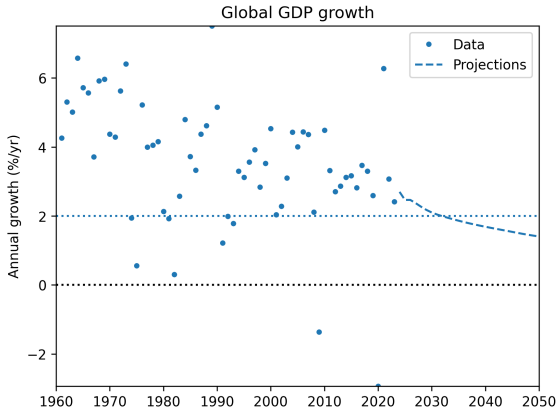


FIGURE D.13: Global GDP growth rate and projections. The BAU projections are designed to be slightly underestimated, consistently with the approach of the article.

which would bias a BAU projection. There is some small level of arbitrariness in such choices, but the reader can check by himself that our projections represent a fair extrapolation of past trends, especially when looking at GDP and not at growth rates, as the latter are usually very noisy (see later on below).

More precisely:

- The selected Brazilian time period begins in 1993 as the "plano real" stabilized the economy. The 2014-2016 points have been ignored due to an economic recession driven by commodity price shocks (while Brazilian economy was reliant on it) and political scandals leading to president Rousseff's impeachment.
- Due to the fast changing Chinese economy, the selected time period for China extends from 2012 to 2019, where the data are very stable. We note that the International Monetary Fund (IMF) October 2023 short-term projections are in line with our projections [1].
- 2003 is taken as the beginning of the selected time period for India. We however exclude 2019, affected by financial sector challenges such as the Non-Banking Financial Companies (NBFC) liquidity crisis.
- Similarly, the period selected in the case of Indonesia is from 2005 to 2019.
- The German data has been selected starting from 1971 as the data is very noisy and as there does not seem to be a marked break in trend over this whole period. The 1974-1975 data are ignored because of the impact of the global oil crisis. 1982 is ignored because of the consequences of the second global oil crisis. 1990, 1991, 1993 are ignored because of the economic impacts, both positive and negative, of German reunification. The year 2002 and 2003 were ignored as they indicate that the country has undergone a sharp recession.
- The regression time periods for France start in 1994 as this period appear to mark the onset of stable trends. 2000 is ignored as we observe a spike in a lot of countries possibly linked to economic enthusiasm at the start of a new millennium, investment in digital technology or anticipation of the adoption of Euro as a new currency.
- The selected time period for Japan begins in 2000. Japan is still in the throws of a long deflation crisis that started in the 1990s'. We have excluded the transition the previous large growth period in our regression.
- For Mexico, the start of the regression period is set to 1989, after the "Milagro Mexicano", a decade of sustained economic growth following the 1982 debt crisis and the 1986 oil prices drop. 1995 is ignored because of the "Tequila crisis", a period of financial turmoil. The following 1996-1998 years are ignored as they saw high growth rates, probably due to the NAFTA (North American Free Trade Agreement) economic effects, the Tequila Crisis recovery, and related policy measures. 2019 is also ignored due to a pronounced recession, probably due to President López Obrador election (considered as less liberal than his predecessor), by the uncertainties about USMCA (United States Mexico Canada Agreement) ratification, or by impacts on Mexico of United States-China trade tensions.
- The selected regression period begins in 2001 for Russia, where an economic stabilization can be seen in growth rate data after the collapse of Soviet Union. The 2013-2017 data

[1] see `https://www.imf.org/en/Publications/WEO/weo-database/2023/October`

points are ignored due to a succession of economic recessions, international sanctions following Crimea's annexation, the 2014 oil price crash, and a gradual recovery in 2017.

- Finally, 1992 was chosen as the United States' starting regression year. Despite a relatively stable trend since the 1970s, the 1990s were chosen to reflect more recent economic realities. 1999, 2001 and 2002 are ignored due to deviating growth rates that are probably due to the dot com bubble (characterized first by increasing investments and then by collapse) and/or to 9/11 terrorist attacks and their financial and economic consequences.

Figures D.13 and D.14 show the projections made from historical data for the world and some countries. The graphs may exclude a small number of growth rate points falling outside the displayed range.

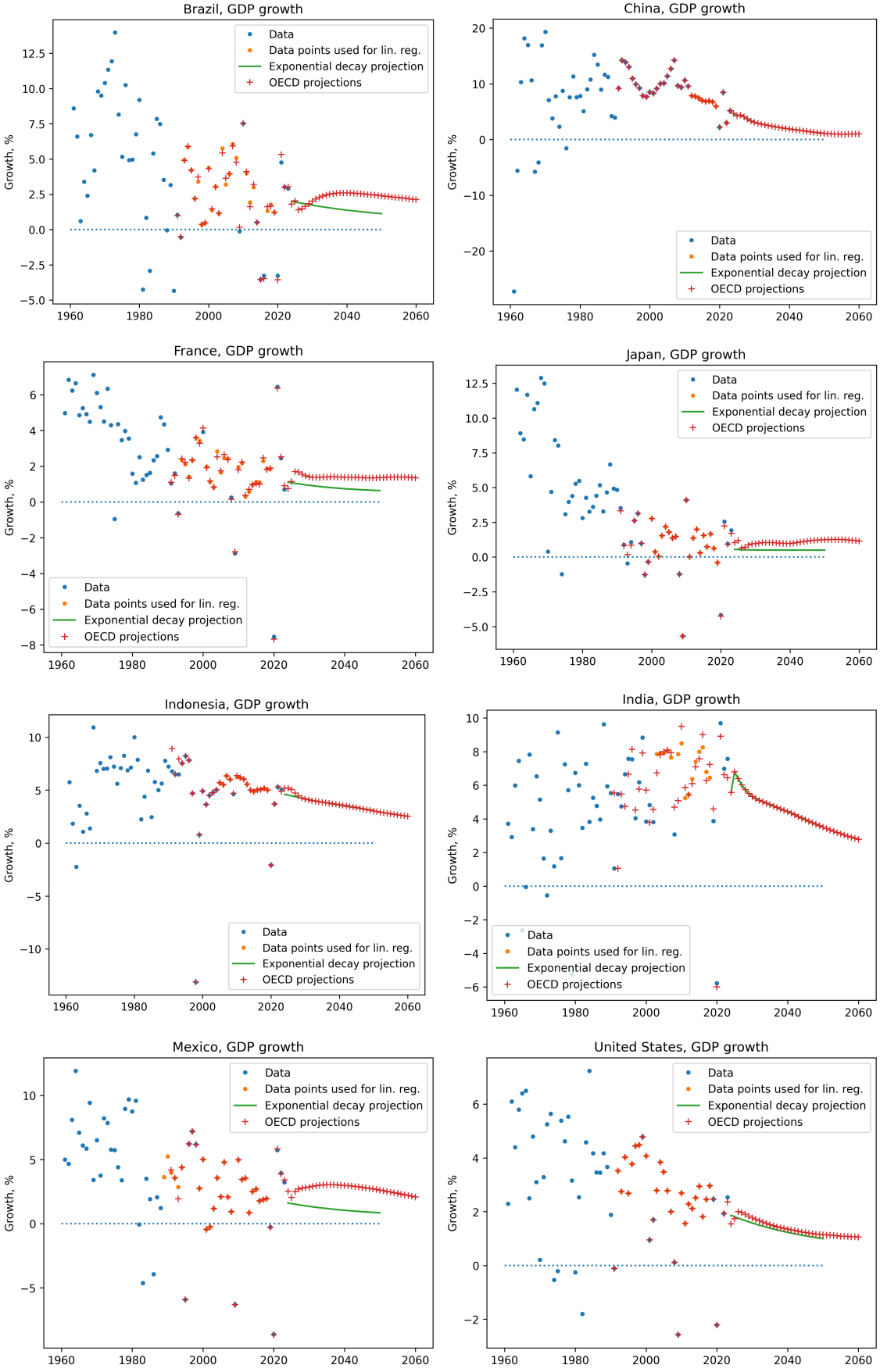


FIGURE D.14: GDP growth rate data and projections

APPENDIX E | SUPPLEMENTARY MATERIALS: MODELING PRIVATE VEHICLE OWNERSHIP AS A FUNCTION OF INCOME INSTEAD OF GDP PER CAPITA

E.1. GDP AND INCOME DISTRIBUTION CONVERSION METHODS

E.1.1. DEFINITIONS AND NOTATIONS

The GDP (or GDP per capita) of any given country can be expressed in a number of ways:

- The simplest one is to express GDP in local currency, at the current value (i.e., ignoring inflation), or in constant (inflation-corrected) value.
- GDP can also be expressed in local currency or in another country currency. This provides a first way to compare GDP between different countries. In general US dollars are used as a common currency.
- Such a comparison is however of limited relevance to compare standards of living, as a given product (or directly equivalent products such as local agricultural products) may have widely different prices in different countries, even after conversion into a common currency. As a consequence, GDP (either current or constant) is often converted in "purchasing power parity" (PPP), using a common basket of goods and services between different countries to define comparable price indices allowing the conversion to be made. The PPP conversion involves both a currency conversion and an international relative price comparison. Although PPP GDP are thus more directly comparable at the international level, one should be warned that the conversion involves a number of conventions making

the resulting PPP GDP less reliable than their non-PPP counterparts. Also, they do not quite represent a standard of living index (Deaton and Heston, 2010).

- Finally all flavors of GPDs can be converted to GDPs per capita with the help of the countries population time series.

The objective of this Appendix is to summarize how these different types of conversions may be operated in practice, without delving into the technical aspects of the choices leading to the definition of the various converting factors. In this work, we use the World Bank data series to perform these tasks.

The following notations are adopted:

- Y refers to GDP, a common convention in macroeconomics.
- The current year is denoted t. The reference year for deflated GDP is denoted t_0 (or t_1 if more than one reference year is used). These years appear as variables and not as indices in order to limit the number of indices and exponents used in this Appendix. When referring to the base year where non-PPP to PPP conversions are performed (which, as pointed out right above, implies a comparative deflation and an currency conversion), we use the term benchmark year.
- Different indices and exponents are used to distinguish different flavors of GDP. The exponent c refers to a country, while p, when present, designates PPP GDPs. The index "LCU" (local currency unit) or \$ (dollar) refers to the currency unit in which the considered GDP is expressed. As mentioned above, the US dollar is the common international currency of reference. Finally, the indices C and R refer to current and real (inflation-corrected) GDP[1].
- Finally, two flavors of deflators are used: GPD deflators, and consumer price indices (CPIs). These are dimensionless by definition. GDP deflators are denoted d and CPI ones, $\bar{d}$, with appropriate indices that will be introduced when needed. The two are related by a form of inverse relation. The World Bank uses different types of deflator indices (e.g., Laspeyres, Paasche or Fisher indices to quote the most frequently used).
- Simple (non-PPP) currency converters are denoted e; their unit is a ratio of currency (usually, local currency to dollar). The two World Bank programs using PPP conversions (ICP and PIP, discussed below) use combined deflators and currency converters; these are denoted k (for currency converters combined to GDP deflators) and $\bar{k}$ (for currency converters combined to consumer price indices).

E.1.2. Non-PPP GDP conversion methods

E.1.2.1. Single reference year

The World Bank provides data time series for these different forms of GDPs, for a very large number of countries[2].

Let us focus first on non-PPP quantities. Constant GDP is obtained from current GDP (the quantity commonly produced by national statistics and accounting institutes) with the help of a deflator while currency conversion is performed with a currency converter.

[1] The World Bank often uses the symbol K to refer to constant monetary quantities instead of R.

[2] Depending on the quality of the available data, the various countries data series are more or less reliable.

Let us define $e_{LCU}(t)$ (in LCU/$) the exchange rate between a local currency and the US dollar (for any year t), $d^c(t, t_0)$ the dimensionless deflator with respect to the reference year t_0, which relates the value in current local currency to the reference year one. For the present work, when needed, we use the $t_0 = 2015$ data series. By convention, $d^c(t_0, t_0) = 1$[3]. One has:

$$Y^c_{C,LCU}(t) = e_{LCU}(t) Y^c_{C,\$}(t), \tag{E.1}$$

$$Y^c_{R,LCU}(t, t_0) = e_{LCU}(t_0) Y^c_{R,\$}(t, t_0), \tag{E.2}$$

$$Y^c_{R,LCU}(t, t_0) = \frac{Y^c_{C,LCU}(t)}{d^c(t, t_0)}. \tag{E.3}$$

Eqs. (E.1) and (E.2) only express a change in currency unit, based on international currency exchange rates, while Eqn. (E.3) is a more complex indicator, making use of a deflator. The Paasche index is in general used to compute the above deflator coefficient in the World Bank data series[4]. Correlatively, the World bank characterizes inflation through a Laspeyres index[5], coherently with the inverse relation between the two indices.

The World Bank provides data series for $d^c(t, t_0)$[6], $e_{LCU}(t)$[7], and the various current or constant GDP data series, $Y^c_{C,LCU}(t)$[8] and $Y^c_{R,LCU}(t)$[9]. Constant GDP per capita series are also available, either in local currency[10] or in dollars[11], or can be deduced from the previous one with the help of population data series[12].

E.1.2.2. Multiple reference year

Most countries constant GDP are given for 2015 as reference year, but this is not the case for a number of countries. For example, among our 11 major countries, constant GDP series are reported with 2010 as reference year for Brazil, 2011 for India, 2016 for Russia et 2018 for Mexico.

It is useful to be able to use constant GDPs with a single common reference year for all countries (namely 2015 in the present work). In order to do so, one must find a way to convert constant GDPs given in arbitrary reference year t_1 into constant GDPs in $t_0 = 2015$. This can be achieved if the deflator d satisfies the so-called circularity condition:

$$d(t, t_0) d(t_0, t_1) = d(t, t_1), \tag{E.4}$$

from which the $d(t, t_0)$ deflator can be obtained with the time series of the $d(t, t_1)$ deflator. This is not the case for the Paasche index used by the World Bank for computing deflators.

[3] A deflator index normalized to 100 at the reference year can also be found in the literature or at the World Bank, but not in the present work.

[4] `https://databank.worldbank.org/metadataglossary/world-development-indicators/series/NY.GDP.DEFL.ZS`

[5] `https://databank.worldbank.org/metadataglossary/world-development-indicators/series/FP.CPI.TOTL.ZG`

[6] See footnote 4.

[7] `https://databank.worldbank.org/metadataglossary/world-development-indicators/series/PA.NUS.ATLS`

[8] `https://databank.worldbank.org/metadataglossary/world-development-indicators/series/NY.GDP.MKTP.CN`

[9] `https://databank.worldbank.org/metadataglossary/world-development-indicators/series/NY.GDP.MKTP.KD`

[10] `https://databank.worldbank.org/metadataglossary/world-development-indicators/series/NY.GDP.PCAP.KN`

[11] `https://databank.worldbank.org/metadataglossary/sustainable-development-goals-(sdgs)/series/NY.GDP.PCAP.KD`

[12] `https://databank.worldbank.org/source/population-estimates-and-projections`. Long time series are not available for all countries.

However, the involved error is small when t_0 and t_1 only differ by a few years. We therefore use this relation to make reference year conversions when needed.

E.1.3. Non-PPP and PPP GDP conversion methods

The World Bank ICP[13] (*International Comparison Program*) uses a related but somewhat different methodology to convert constant and current GDPs to their PPP counterparts. This makes use of different types of conversions:

- Local currency to PPP US dollars (both current and constant) for a series of benchmark years (2005, 2011 et 2017 for the last ones; in this work we use the 2017 data series). These are based on data directly collected for the various countries in the program for benchmark years.
- As the construction of the conversion indices is quite data intensive, other years are estimated through dedicated interpolation and extrapolation methods[14] (Inklaar and Rao, 2019, 2020). In fact, ICP provides two closely related PPP conversion factors, one for GDP[15] [denoted here $k^c_{ICP}(t, t_1)$], and the other for household expenditures[16] [denoted here $\bar{k}^c_{ICP}(t, t_1)$]; both are expressed in units of $LCU/\$$. Because these conversion factors basically compare inflation between a country c and the United States, they are necessarily equal to one (and dimensionless) for the US: $k^{US}_{ICP}(t, t_1) = \bar{k}^{US}_{ICP}(t, t_1) = 1$;

Thus in practice non-PPP to PPP GDP conversions are encapsulated in a single index $k^c_{ICP}(t, t_1)$ for any given country and given year[17]:

$$Y^{c,p}_{C,\$}(t, t_1) = \frac{Y^c_{C,LCU}(t)}{k^c(t, t_1)}, \tag{E.5}$$

$$Y^{c,p}_{R,\$}(t, t_1) = \frac{Y^c_{R,LCU}(t, t_1)}{k^c(t, t_1)}. \tag{E.6}$$

The household expenditure conversion factor will be used in the next subsection. For ICP, the present benchmark year is $t_1 = 2017$. For other, direct GDP deflators, the reference year is often country dependent, with $t_0 = 2015$ being commonly presently reported at the World Bank; also, other types of World Bank consumer price indices series often use different reference years (e.g., 2010). This can be quite confusing at first. In any case, the World Bank ICP gives access to data series for $Y^{c,p}_{R,\$}(t)$[18], $k^c_{ICP}(t, t_1)$ and $\bar{k}^c_{ICP}(t, t_1)$; the series for $Y^{c,p}_{C,\$}(t, t_1)$ are deduced from the series for $Y^c_{C,LCU}(t)$ (see previous subsection). Series for constant PPP GDP per capita are also available[19], but can be also be obtained from the previous ones with the help of population data series[20].

[13] https://www.worldbank.org/en/programs/icp

[14] https://datahelpdesk.worldbank.org/knowledgebase/articles/665452-how-do-you-extrapolate-the-ppp-conversion-factors and https://github.com/worldbank/WDI-Production/tree/master/Projects/ppp-extrapolations

[15] https://databank.worldbank.org/metadataglossary/world-development-indicators/series/PA.NUS.PPP.

[16] https://databank.worldbank.org/metadataglossary/world-development-indicators/series/PA.NUS.PRVT.PP

[17] For more details, see the methodological review of Deaton and Heston (2010) and the ICP methodological manual World Bank (2013).

[18] https://databank.worldbank.org/metadataglossary/world-development-indicators/series/NY.GDP.MKTP.PP.KD

[19] https://databank.worldbank.org/metadataglossary/world-development-indicators/series/NY.GDP.PCAP.PP.KD

[20] See footnote 12.

E.1.4. PPP AND NON-PPP INCOME DISTRIBUTION CONVERSION METHODS

The income distributions provided by the PIP program of the World Bank are given in constant PPP 2017 dollars per day per capita. The income distributions are available in deciles[21] and centiles[22].

As indicated in the main text, we need to convert these in constant 2015 dollars per year per capita. The day to year conversion is immediate, but the PPP dollars to constant non-PPP dollars is not.

This conversion can be achieved through the use of the two conversion factors provided by the PIP program: a consumption price index (CPI), $\bar{d}^c_{PIP}(t, t_1)$ expressing current year t prices in local currency units of the benchmark year t_1; and a PPP conversion factor, $\bar{k}^c_{PIP}(t_1) = \bar{k}^c_{ICP}(t_1, t_1)$. The CPI index comes from *International Monetary Fund* IMF data while the PPP one comes, as indicated by the notation, from ICP[23]. Note that these two conversion factors are not given in the centile data series, but in the associated decile ones.

Let us denote $I^c(t)$ a given income value for the current year; this quantity can be indexed as described for GDPs. One has:

$$I^c_{R,LCU}(t, t_1) = \frac{I^c_{C,LCU}(t)}{\bar{d}^c_{PIP}(t, t_1)}, \tag{E.7}$$

$$I^{c,p}_{R,\$}(t, t_1) = \frac{I^c_{R,LCU}(t, t_1)}{\bar{k}^c_{PIP}(t_1)}. \tag{E.8}$$

In practice, the PIP program gives data series for $I^{c,p}_{R,\$}(t, t_1)$ (in decile or centiles, for the benchmark year $t_1 = 2017$), $k^c_{PIP}(t_1)$ (PPP factor) and $\bar{d}^c_{PIP}(t, t_1)$ (CPI factor), from which $I^c_{C,LCU}(t)$ is obtained with the help of the two previous equations.

The last step is to convert $I^c_{C,LCU}(t)$ to $I^c_{R,\$}(t, t_0)$ with

$$I^c_{R,\$}(t, t_0) = \gamma \frac{I^c_{C,LCU}(t)}{d^c(t, t_0) e_{LCU}(t_0)}. \tag{E.9}$$

from Eqs. (E.1) to (E.3) and where $\gamma = 365$ stands for the number of days per year in order to obtain income per year instead of per day[24].

Finally, for three countries (China, India and Indonesia), the PIP database provides independent income distributions for the rural and urban populations. For these countries, two different deflators $\bar{d}$ and currency converters $\bar{k}$ are also provided, one of each for the each subpopulation. One must therefore distinguish them with an additional superscript, r (rural) and u (urban). The previous relations are accordingly recast for each. Noting this extra superscript

[21] `https://pip.worldbank.org/poverty-calculator`. These can also be extracted with the help of the PIP *R* package, `https://worldbank.github.io/pipr/`.

[22] `https://datacatalog.worldbank.org/search/dataset/0063646`

[23] `https://datanalytics.worldbank.org/PIP-Methodology/non-technical-summary.html#step-3-converting-welfare-aggregates`, `https://datanalytics.worldbank.org/PIP-Methodology/convert.html`

[24] Leap years are ignored, but the resulting eventual $1/365$ fractional error is completely negligible compared to other sources of errors in the data.

$x\,(\in \{r, u\})$:

$$I^{c,x}_{R,LCU}(t, t_1) = \frac{I^{c}_{C,LCU}(t)}{\bar{d}^{c,x}_{PIP}(t, t_1)}, \tag{E.10}$$

$$I^{c,x,p}_{R,\$}(t, t_1) = \frac{I^{c,x}_{R,LCU}(t, t_1)}{\bar{k}^{c,x}_{PIP}(t_1)}. \tag{E.11}$$

E.2. Grouped vs individual data

The PIP documentation indicates that for a number of countries (Algeria, China, Guyana, Suriname, Turkmenistan, Trinidad & Tobago, Venezuela, and the United Arab Emirates and more countries for earlier years), primary data are not available. Instead, these countries have provided "grouped data". These result from an aggregation of the original data into 5, 10, 20, 25 or even possibly 100 quantiles of income distribution, each quantile providing a mean average over the number of points in the quantile of the original income data. For these countries, what is given in the PIP database is not the grouped data themselves but a Lorenz curve fit to the grouped data, that is reprojected in centiles[25]. These pseudo-data series are consequently extremely regular (see, e.g., the log-normal fit figure for China).

This raises the question of the potential error introduced by fitting a log-normal distribution on a Lorenz curve fit of original data. However, we do not know how many quantiles the PIP program had at its disposal for countries providing grouped data, nor if these data were fitted with a general quadratic or Beta Lorentz curves — the only two possibilities in the PIP procedure (see section E.2.2 below for a definition of these functions). In order to estimate the error of this double fit procedure, we have taken an indirect approach. We decided to go through our own grouped data procedure for a country for which the centile data are available, and compare in the end the final log-normal fits of Lorenz fits with the one performed directly on the original data.

E.2.1. Lorenz curves in a nutshell

Lorenz curves were introduced by Lorenz (1905). A Lorenz curve represents the cumulative income share L as a function of the cumulative population share Π; this function $L(\Pi)$ is implicitly defined by the definition of $\Pi(I_k)$ and $L(I_k)$ in the "Income data and fit method" Appendix. It turns out that, in the econometric field specialized in the characterization of income inequalities, it is often more useful to start from the Lorenz curve itself instead of the income distribution. Because of this, there is by now a whole literature dealing with Lorenz curve models and their properties (see McDonald 1984 and references therein for the most frequent and useful Lorenz curve models).

Some understanding of the generic properties of Lorenz curves is necessary for the present purpose, in particular in order to retrieve the underlying income distribution $g(I)$ from $L(\Pi)$.

First, because L and Π represent, respectively, the cumulative income share and the cumu-

[25] `https://datanalytics.worldbank.org/PIP-Methodology/acquiring.html`, section 1.4.

lative population share to this income, one necessarily has

$$L(0) = 0, \tag{E.12}$$

$$L(1) = 1. \tag{E.13}$$

These are the first two necessary conditions for $L(\Pi)$ to be a Lorenz curve.

Furthermore, for any Lorenz curve, the definition of $\Pi(I_k)$ and $L(I_k)$ in the "Income distribution data and fit method" Appendix imply

$$\frac{dL}{dI} = \frac{Ig(I)}{\mu}, \tag{E.14}$$

$$\frac{dL}{dI} = \frac{dL}{d\Pi}\frac{d\Pi}{dI} = \frac{dL}{d\Pi}g(I), \tag{E.15}$$

which yields

$$I(\Pi) = \mu L'(\Pi), \tag{E.16}$$

where $L'(\Pi) = dL/d\Pi$ is the first derivative of L and μ the mean income. Differentiating again Eq (E.16) with respect to I leads to:

$$\mu L''(\Pi)\frac{d\Pi}{dI} = 1, \tag{E.17}$$

where $L''(\Pi) = dL^2/d\Pi^2$ is the second derivative of L.

As one usually considers only positive income ($I > 0$), this implies that

$$L'(\Pi) > 0, \tag{E.18}$$

$$L''(\Pi) > 0, \tag{E.19}$$

In fact, Eq. (E.18) is too restrictive and one can show that $L'(0) > 0$ is sufficient. More generally, one can show that $L(0) = 0$, $L(1) = 1$, $L'(0)$ and $L''(\Pi) > 0$ are necessary and sufficient conditions for a function L to be a Lorenz curve (Sarabia, 2008).

This short discussion was provided to give some idea of the origin of this last result, and — mostly — to derive ways to retrieve $g(I)$ from $L(\Pi)$. First, inverting Eq. (E.16) gives $\Pi(I)$ which yields g through $g(I) = d\Pi/dI$. A second way follows from Eq. (E.17), which gives

$$g(I) = \frac{1}{\mu L''(\Pi(I))}, \tag{E.20}$$

where the inversion of Eq. (E.16) is also required to obtain $g(I)$ explicitly.

Finally, let us point out that the four conditions Eqs. (E.12), (E.13), (E.18) and (E.19) imply that $0 < L < \Pi$ for $\Pi \in]0, 1[$. The first inequality is already obvious from the definition of $L(I_k)$.The second one follows because L is convex. This can be seen empirically from a graph, but can also be shown analytically, e.g., by reduction ad absurdum. This property is a well-known feature of Lorenz curves, and is used to define inequality measures such as the Gini index.

E.2.2. Lorenz curve fit and associated probability distribution function

The PIP documentation indicates that two different types of Lorenz fits may have been performed, depending on the country: general quadratic (GQ) Lorenz curve fits and Beta Lorenz curve fits.

E.2.2.1. General quadratic Lorenz curve

The Lorenz curve relates the cumulative income share L to the cumulative population share Π so that $L = L(\Pi)$ is now considered to be a function of Π (itself a monotonically growing function of I). The GQ Lorenz curve L_{GQ} is defined by:

$$\begin{aligned} L_{GQ}[1 - L_{GQ}] = a_{GQ}[\Pi^2 - L_{GQ}] \\ + b_{GQ} L_{GQ}(\Pi - 1) \\ + c_{GQ}(\Pi - L_{GQ}), \end{aligned} \tag{E.21}$$

where Π is the cumulative income distribution, and a_{GQ}, b_{GQ}, c_{GQ} are parameters. This relation defines L_{GQ} implicitly and is in fact a reorganization of a general second order polynomial in L_{GQ} and Π (Villaseñor and Arnold, 1989) which admits $L(\Pi = 0) = 0$ and $L(\Pi = 1) = 1$ as solutions (the form above makes this feature obvious).

The relevant analytic solutions $L_{GQ}(\Pi)$ of Eq. (E.21) reads[26]

$$L_{GQ} = \frac{1}{2}\left[(e_{GQ} - b_{GQ}\Pi) - D^{1/2}\right], \tag{E.22}$$

where

$$e_{GQ} \equiv 1 + a_{GQ} + b_{GQ} + c_{GQ}, \tag{E.23}$$

$$D \equiv (e_{GQ} - b_{GQ}\Pi)^2 - 4\Pi(c_{GQ} + a_{GQ}\Pi). \tag{E.24}$$

and D is the discriminant of the original second degree equation. With a little algebra, one finds that requiring $L_{GQ}(0) = 0$ implies that $e_{GQ} \geq 0$ and $L_{GQ}(1) = 1$, $a_{GQ} + c_{GQ} \geq 1$. Furthermore in the limit $0 < \Pi \ll 1$, to first order in Π, $L_{GQ}(\Pi) = c_{GQ}\Pi/e_{GQ}$; the finiteness of $L_{GQ}(\Pi)$ excludes $e_{GQ} = 0$ and $L' > 0$ implies then $c_{GQ} > 0$. Similarly at $0 < 1 - \Pi \ll 1$, one excludes $x = 1$ and requires $b_{GQ} + 2a_{GQ} + c_{GQ} > 0$. Finally, the analysis of the sign of $D(\Pi)$ with $\Pi \in [0, 1]$ shows that it is always positive if $b_{QG}^2 - 4a_{QG} < 0$ or $b_{QG}^2 - 4a_{QG} > (2c_{QG} + b_{QG}e_{QG})^2/e_{QG}^2 > 0$, otherwise there is some range of Π where $D < 0$ and L_{QG} is

[26] Villaseñor and Arnold (1989) have shown that the probability density associated with the other root of the second degree polynomial, Eq. (E.21), does not have the right properties.

undefined. The constraints obtained in this way are therefore summarized as:

$$e_{GQ} > 0, \tag{E.25}$$

$$a_{GQ} + c_{GQ} > 1, \tag{E.26}$$

$$c_{GQ} > 0, \tag{E.27}$$

$$b_{GQ} + 2a_{GQ} + c_{GQ} > 0, \tag{E.28}$$

$$\alpha_1 > 0 \text{ or } \alpha_1 < -\alpha_2^2/e_{QG}^2 \ (< 0), \tag{E.29}$$

$$\alpha_1 \equiv 4a_{QG} - b_{QG}^2, \tag{E.30}$$

$$\alpha_2 \equiv -(b_{QG}e_{QG} + 2c_{QG}). \tag{E.31}$$

These extend and correct similar constraints derived by Villaseñor and Arnold (1989).

Analyzing the remaining constraints — Eqs. (E.18) and (E.19) over the whole range of Π — further yields rather convoluted and not very useful inequalities on the parameters, but these need not be specified: indeed, if a reasonably good fit of L_{GQ} on the data is possible at all, then the parameters will make L_{QG} satisfy Eqs. (E.18) and (E.19) as well. The constraints unveiled so far are sufficient to ensure that L_{GQ} exists in the whole range of Π (a necessity for the fit to be performed), and provide enough guidelines to design an initial guess for a numerical fit, especially once one recognizes that all three parameters must be of order unity, due to the range of Π and L.

The parameters (a_{GQ}, b_{GQ}, c_{GQ}) are obtained from a fit on the data couples (Π_k, L_k)Defining

$$\mathcal{L}_k = L_k(1 - L_k), \tag{E.32}$$

$$\mathcal{R}_k = a_{GQ}[\Pi_k^2 - L_k] + b_{GQ}L_k(\Pi_k - 1) + c_{GQ}(\Pi_k - L_k), \tag{E.33}$$

the three parameters are found in the least square sense by minimizing[27] $\sum_k(\mathcal{L}_k - \mathcal{R}_k)^2$.

Once the parameters are found, Eq. (E.21) — or (E.22) — defines a series $L_{GQ}(\Pi'_k)$ for any monotonically increasing series Π'_k with $\Pi'_0 = 0$ and $\Pi'_{k_{max}} = 1$. The question now boils down to finding the associated $g_{GQ}(I)$. This can be accomplished in two ways: analytically and numerically. The discussion of this point is postponed to subsections E.2.2.3 and E.2.2.4, in order to examine first the definition and properties of the Beta Lorenz curve.

E.2.2.2. Beta Lorenz curve

The Beta Lorenz curve is directly obtained from the following relation:

$$L_\beta = \Pi - a_\beta \Pi^{b_\beta}(1 - \Pi)^{c_\beta}, \tag{E.34}$$

where $a_\beta, b_\beta, c_\beta$ are the curve parameters. The form of this relation ensures that it is defined for all $\Pi \in [0, 1]$ and all b_β and c_β in $\mathbb{R}$.

The analysis of the conditions Eqs. (E.12), (E.13), (E.18) and (E.19) is much simpler than for L_{GQ}. The constraint $L_\beta < \Pi$ imposes $a_\beta > 0$; $L_\beta(0) = 0$ implies $b_\beta > 0$ and $L_\beta(1) = 1$, $c_\beta > 0$; $L'(\Pi) > 0$ in the vicinity of $\Pi = 0$ requires $b_\beta \geq 1$, but $L'(0) < 1$ requires in turn $b_\beta = 1$ and $a_\beta < 1$; $L''_\beta(1) > 0$ requires $c_\beta < 1$ and this suffices to ensure that $L''_\beta > 0$ everywhere; finally, the constraints collected so far ensure that $L'_\beta > 0$ everywhere.

[27] We chose to fit Eq. (E.21) instead of Eq. (E.22) in order to avoid numerical problems that may arise if the root finding algorithm explores

	L	L'	L''
Beta Lorenz	$\Pi - a_\beta \Pi^{b_\beta}(1-\Pi)^{c_\beta}$	$1 - a_\beta b_\beta \Pi^{b_\beta - 1}(1-\Pi)^{c_\beta}$ $+a_\beta c_\beta \Pi^{b_\beta}(1-\Pi)^{c_\beta - 1}$	$-a_\beta b_\beta (b_\beta - 1)\Pi^{b_\beta - 2}(1-\Pi)^{c_\beta} - a_\beta c_\beta (c_\beta - 1)\Pi^{b_\beta}(1-\Pi)^{c_\beta - 2}$ $+2a_\beta b_\beta c_\beta \Pi^{b_\beta - 1}(1-\Pi)^{c_\beta - 1}$
GQ Lorenz	$\frac{1}{2}\left[e - b\Pi - D^{1/2}\right]$	$\frac{1}{2}\left[-b + X/D^{1/2}\right]$	$B/(2D^{3/2})$

TABLE E.1: First and second derivatives of the Beta Lorenz and GQ Lorenz curves (the notations of sections E.2.2.1 and E.2.2.2 are used). The additional auxiliary quantity X and B are defined in Eq. (E.35) and (E.36).

.

However, this set of constraints poses a conundrum in light of Eq. (E.20). Indeed, $b_\beta = 1$ makes L'' a strictly increasing function of Π, thus producing a strictly decreasing g from $I = 0$ to $I \to \infty$ (this is apparent on the expressions of L'_β and L''_β provided later on). This behavior would provide a poor fit for $g(I)$. The simplest way around is to relax $b_\beta = 1$. In fact, having $g(I) \to 0$ as $\Pi \to 0$ (a much better expectation) requires $b_\beta < 1$. This makes $L' < 0$ in the vicinity of $\Pi = 0$. This violation is however limited to a small range of Π in the vicinity of $\Pi = 0$ if $1 - b_\beta$ is small enough (the range of violation $\to 0$ as $1 - b_\beta \to 0$).

To summarize this discussion, the three parameters a_β, b_β and c_β are constrained to lie in the $[0, 1]$ range, with, however, $0 < 1 - b_\beta \ll 1$ (inasmuch as possible) for realism.

As we will see, L_{GQ} suffers from a somewhat related problem of behavior at low income. This most likely explains why neither the Beta Lorenz curve nor the GQ one are commonly used in the specialized literature on income inequalities[28]. They are however used by the World Bank PIP program due to their simplicity.

As for the GQ Lorenz curve, the three parameters a_β, b_β and c_β are obtained from the minimization of $\sum_k [L_k - L_\beta(\Pi_k)]^2$ (least square fit), and the problem then reduces to finding g_β from L_β. This question is addressed in the next two subsections.

E.2.2.3. ANALYTIC SOLUTION

An analytic solution follows from Eqs. (E.16) and (E.20). It is useful to have at hand the analytic expressions of the first and second derivatives of both types of Lorenz curves.

The first and second derivatives of the Beta Lorenz curve are straightforward from the definition.

For the general quadratic curve, the results are simpler to obtain by introducing auxiliary quantities. These include α_1 and α_2 already defined in Eqs. (E.30) and (E.31); the following quantities are also introduced:

$$X = \alpha_1 \Pi - \alpha_2, \tag{E.35}$$

$$B = \alpha_1 e^2 + \alpha_2^2. \tag{E.36}$$

With these definitions, the discriminant Eq. (E.24) of the second order polynomial in L_{GQ}, Eq. (E.21), reads

$$D = \frac{B - X^2}{\alpha_1}, \tag{E.37}$$

from which the first and second derivatives of the general quadratic Lorenz curve are more easily and compactly derived.

parameter values making the discriminant D negative, even if the solution avoids this issue.

[28] The Beta income *distribution* is commonly used, but this does not lead to a Beta Lorenz curve as defined here.

The results of these derivative computations for both types of Lorenz curves are given in Table E.1.

The potentially difficult step is the analytical inversion of $I(\Pi)$ into $\Pi(I)$ from Eq. (E.16). This can be achieved by simple analytical means only for L_{GQ}[29]. The analytic solution is therefore only useful for this Lorenz curve. Eq. (E.16) yields:

$$b_{GQ} + 2\frac{I}{\mu} = \frac{X}{D^{1/2}}, \tag{E.38}$$

We proceed in the case $\alpha_1 > 0$, consistently with Eq. (E.29). As we shall see in subsection E.2.4, this holds for the fits of L_{GQ} we have performed. Under this assumption, the previous relation can be inverted into

$$X^2 = \frac{B\left(b_{GQ} + 2I/\mu\right)^2}{\alpha_1 + \left(b_{GQ} + 2I/\mu\right)^2}. \tag{E.39}$$

Combining this result with Eqs. (E.20) and (E.37) finally gives:

$$g_{GQ}(I) = \frac{2B^{1/2}}{\mu}\left(\left[b_{GQ} + 2\frac{I}{\mu}\right]^2 + \alpha_1\right)^{-3/2}. \tag{E.40}$$

which corrects a misprint in Villaseñor and Arnold (1989). One can check that for α_1 and with the other constraints of Eqs. (E.25) — (E.29), that I increases with X. From Eqs. (E.35), (E.38) and (E.37) (for $\Pi = 0$) or (E.24) (for $\Pi = 1$), the domain of existence of g_{GQ} is

$$\mu\frac{c_{QG}}{e_{QG}} \leq I \leq \mu\frac{2a_{QG} + b_{QG} + c_{QG}}{a_{QG} + c_{QG} - 1}. \tag{E.41}$$

One can check on the numerical results of subsection E.2.4 that this range is well defined. Outside this range, this solution for g_{GQ} does not exist[30]; g_{GQ} can be assumed to vanish there, but this introduces discontinuities at the limits just specified.

E.2.2.4. Numerical solution

Even if g cannot be obtained explicitly by analytical means, Eq. (E.16) provides a series I'_k and Eq. (E.20) a series g'_k for any series Π'_k. This provides directly g in numerical form from the couples (I'_k, g'_k). If needed, $g^*_{GQ}(I'_k)$ and $g^*_\beta(I'_k)$ are obtained next from the definition of $\bar{J}_k$ and g^*_k where $\bar{I}_k$ and $\bar{J}_k$ are replaced by I'_k and J'_k.

E.2.3. Lorenz curve fit on other types of quantile data

The procedure of the previous section works as is both on PIP centile data and decile data.

For other types of quantiles[31] (e.g., 20 quantiles, or 25 quantiles), one may construct quantiles from centiles, as long as the number of quantiles q is an exact divisor of 100.

Starting from the centile data, ι_j and ϖ_j are grouped $r = 100/q$ by r to produce their

[29] For L_β, an analytic inversion is possible only for specific and not relevant values of the parameters, e.g., when $dL_\beta/d\Pi$ is a polynomial of degree ≤ 4 in Π.

[30] This is a consequence of Eq. (E.38) and of $\Pi \in [0, 1]$. Note however that for $I \to +\infty$, $g_{GQ} \propto I^{-3}$, so that this integral of this probability density would be bounded in this limit, in particular for $a_{QG} + c_{QG} - 1 \to 0$.

[31] But this can also provide an alternative way of producing decile data analysis.

quantile counterparts ι_k^q and ϖ_k^q (the superscript q refers to the number of quantiles):

$$\iota_k^q = \sum_{j=1}^{r} \iota_{r(k-1)+j} \text{ for } k \in [1, q], \tag{E.42}$$

$$\varpi_k^q = \sum_{j=1}^{r} \varpi_{r(k-1)+j} \text{ for } k \in [1, q]. \tag{E.43}$$

The rest of the procedure then follows as described in section E.2.2.

E.2.4. Results and error analysis

We have chosen to go through the procedure (grouping data, fitting Lorenz curves and then log-normal distributions on the resulting synthetic distributions obtained from Lorenz fits) in the case of India, as this country is comparable to China (the country for which we look for an estimate of the error of the method) in terms of overall population. This choice is also motivated by the following considerations: India is also a country where the rural and urban population have been fitted independently, and contrary to China, individual data are available, from which grouped data can be produced and the error of fitting grouped data instead of individual data can be estimated. This was done on the decile and centile data.

Table E.2 lists the results of the parameter fits for both types of Lorenz curves.

India	β-Lorenz (rural)	β-Lorenz (urban)	GQ-Lorenz (rural)	GQ-Lorenz (urban)
a	0.51	0.70	0.78	0.73
b	0.91	0.98	-1.39	-0.85
c	0.47	0.46	0.22	0.30

Table E.2: Results of the fits of the parameters of the two types of Lorenz curve, for the rural and urban subpopulations of India.

The results of Lorenz curve fits to the decile data of India are shown on Fig. E.1, and compared to centile data points on the one hand, and to the direct log-normal fit of the centile data points on the other hand. The results of Lorenz curve fits on centile data are not shown as they differ very little from the decile fits shown here.

These fits suggest a number of comments. First, the general Lorentz curve fit g^*_{GQ} deviates noticeably from the data at low income, contrarily to g^*_β. As the Chinese pseudo-data points (coming from a Lorenz curve fit) displays exactly the same feature, we are drawn to the conclusion that the Chinese data result from a general quadratic Lorenz curve fit and not a Beta Lorenz one. Although less pronounced, the Beta Lorenz fit results also display a small dissymetry between low and large income, for both rural and urban data. This is more visible on the urban fit, which exceeds the data nearly everywhere in the left wing of the distribution. This dissymetry of both the Beta and general quadratic fits explains why there is a systematic deviation of their maxima towards slightly lower income with respect to the log-normal fit. This effect is quite moderate, though. Finally, the Beta Lorenz curve fits seem to follow more closely the data at very low or very high income, for both rural and urban data, but we found the deviation of the log-normal fit at these income ranges has no noticeable impact on vehicle ownership. In fact, the three types of curves (log-normal and the two Lorenz distributions) all provide sufficiently precise fits of the data for our purposes.

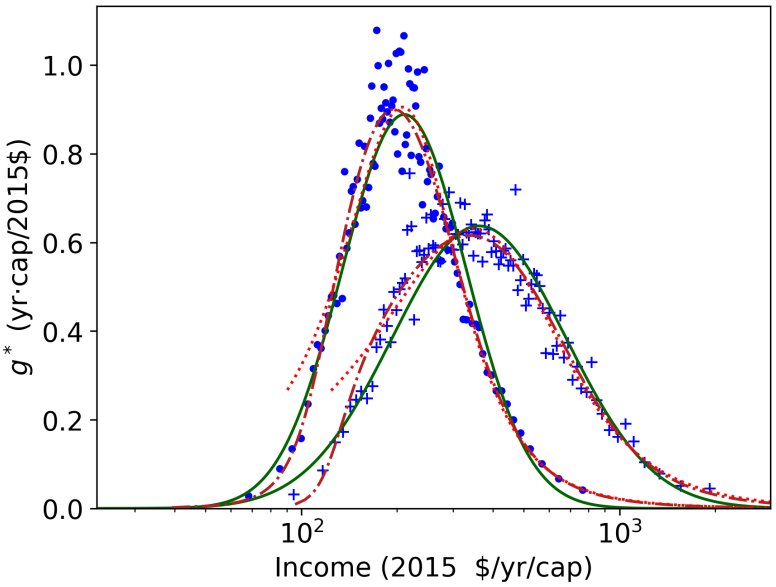


FIGURE E.1: Rural and urban Lorenz fits for India. The graph shows rural centile data (blue circles), urban centile data (blue crosses) for the logarithm of income distribution, along with the log-normal fit, g^* (continuous green curves). The distribution g^*_{GQ} coming from the general quadratic Lorenz curve fit on decile data is shown (red dots, both for rural and urban data) and compared to the centile data. Similarly, the fit g^*_β is shown (dot-dashed curves).

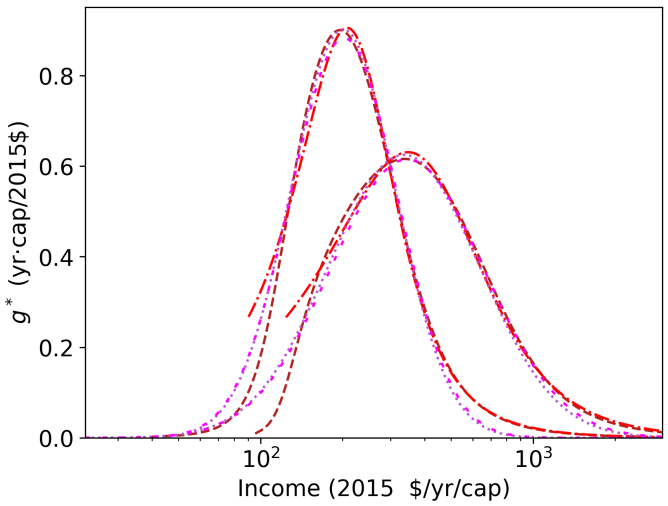


FIGURE E.2: Rural and urban Lorenz fits for India, and log-normal fits to these Lorenz fits; continuous green lines: log-normal fits to the original centile data; pink short-dashed lines: log-normal fits to g^*_{GQ}; violet dotted lines: log-normal fits to g^*_β.

The next step consists in fitting log-normal distributions to Lorenz curves. This is done in the least square sense. It is preferable to fit g^* instead of g. This follows because the Lorenz curve fits to the data is not very precise for low incomes, in particular for the general quadratic Lorenz curve where a substantial systematic excess is observed at low income; as $g = g^*/I$, $\sum_k (g(I_k) - g_{GL}(I_k))^2 = \sum_k (g^*(I_k) - g^*_{GL}(I_k))^2/I_k^2$: fitting g gives considerably more weight to low incomes than fitting g^*, and must therefore be avoided.

The results of log-normal fits on Lorenz curves fits to the income distribution are shown on Fig. E.2, while these log-normal fits to the Lorenz curve fits are compared to the direct log-normal fits on centile data on Fig E.3. The log-normal fits on Lorenz curve fits perform better than the general quadratic Lorenz curve fit at small income (both rural and urban) but ex-

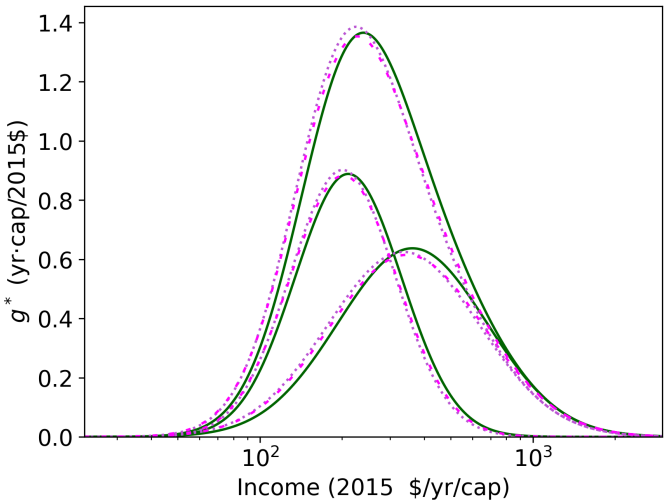


FIGURE E.3: Rural, urban and total log-normal fits for India; red dot-dashed lines: g^*_{LQ}; brown dashed lines: g^*_β ; pink short-dashed lines: log-normal fits to g^*_{GQ}; violet dotted lines: log-normal fits to g^*_β.

ceeds in a noticeable way the Beta Lorenz curve fits in this income range. Not surprisingly, they are slightly displaced towards lower income compared to the direct log-normal fit of the data. Again, the small excess of log-normal distributions on low incomes has no noticeable impact on vehicle ownership.

We also note that although we do not know what type of quantiles was used to produce these pseudo-data points for China, the lack of significant difference between decile and centile data fit results makes the exact choice unessential.

We conclude from this analysis that fitting log-normal distributions on the pseudo-data points of China does not lead to any significant or even noticeable error for the purposes of the present work.

E.3. μ^* AND σ^* FIT RESULTS

Our μ^* and σ^* fits on PIP data are available in the linked "fit_mu_sigma.csv" file for our 58 modelled countries.

"Country name" and "country_alpha3" represent the name of the country and its alpha-3 code. The available year are year where PIP gave data. "reporting level" tells if the data is given at "national" level or rather at "urban" or "rural" level. "mu_star" and "sigma_star" columns give data for μ^* and σ^*, which are dimensionless. μ, σ, "median" and "gini" are our values computed from our lognormal fit, see section "Income distribution data and fit method" of main article for their equations. "median_pip" and "gini_pip" designate the median income and the gini coefficient given by PIP in the decile data, see footnote 21.

E.4. Figures

The following sections provide multiple figures regarding key parameters of this modeling presented in the main text.

58 countries were modeled in this study. However, in order to avoid this supplementary file to be to big, the figures are shown only for 10 major countries representing 63% of the total 4W vehicles stock in 2020, and among which main contributors to the futur increase in that 4W fleet are included (China, India and Indonesia). The figures are then also shown for all countries that are modeled in this study.

Additional figures for individual countries would be available on request to the authors.

E.4.1. Income distributions: the log-normal fit figures

Figures E.4 and E.5 represent the log-normal fits for major countries in 2009 for India and 2008 for the others.

E.4.2. Median income share in GDP per capita projections

Median income share in GDP per capita projections are available in figures E.6 and E.7. The projections extend from 1960 to 2050.

E.4.3. Median income projections

The projections for the median income are shown in figures E.8 and E.9. It is reminded that it is directly linked to μ^* by $M(y) = U_I exp(\mu^*)(y)$.

E.4.4. σ^* projections

σ^* projections are shown as a function of GDP per capita in figures E.10 and E.11.

E.4.5. Fit of $V(y)$ by $V'^*(I'^*_\infty(y))$

The fit of the PV ownership at the country level $V(y)$ by the computed function $V'^*(I'^*_\infty(y))$ are shown for 10 major countries on the figures E.12 and E.13. The countries on which $V'^*(I'^*_\infty(y))$ does not fit as well as most countries are countries where $V'^*(I)$ depict a step function trend. Within major countries, this is particularly the case for Brazil, Mexico and Russia.

E.4.6. Private vehicles ownership as a function of income

The Gompertz function found describing the PV ownership as a function of income are shown in figures E.14 and E.15 for countries that depict a step-function behaviour.

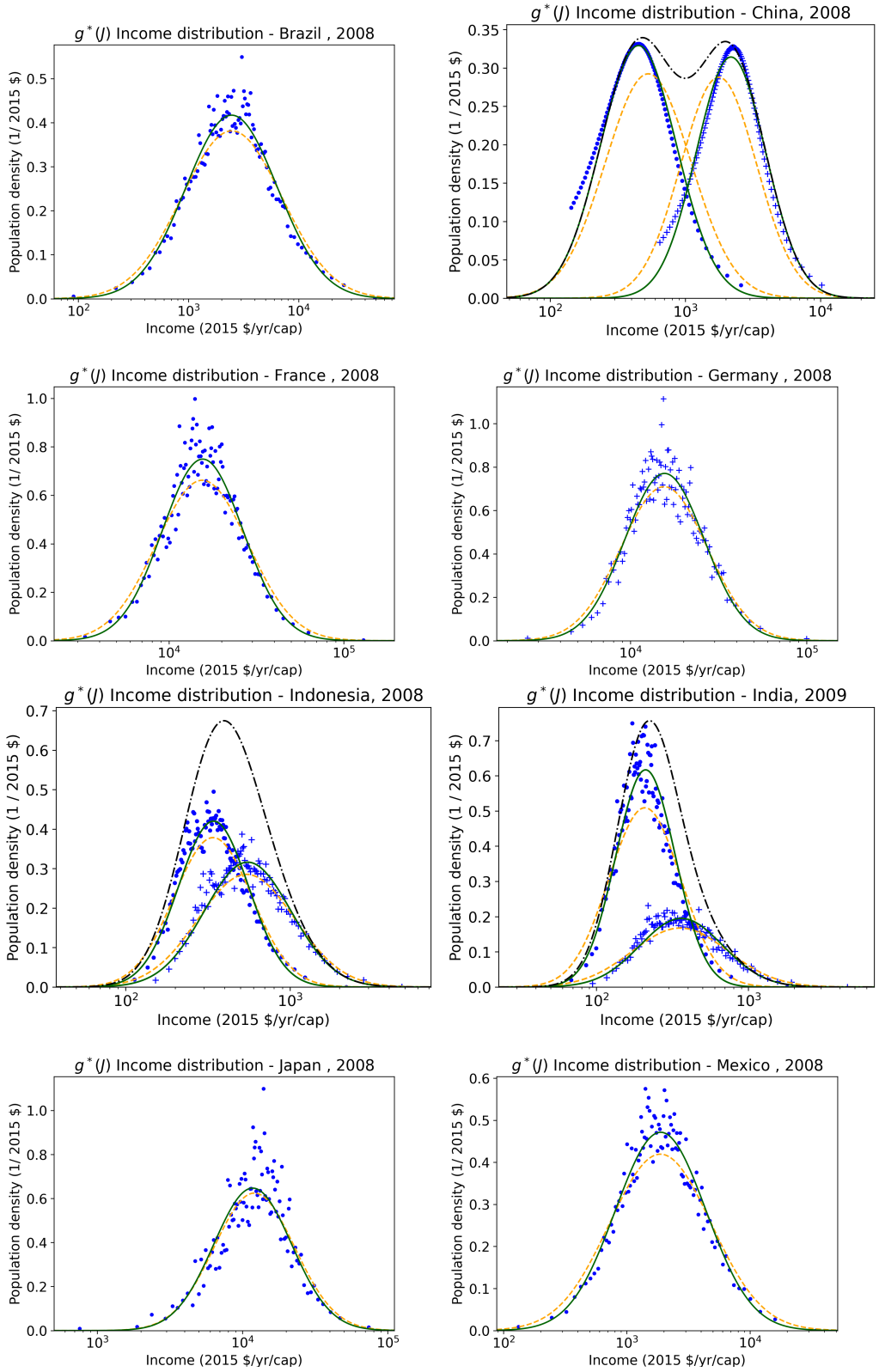


FIGURE E.4: PIP data (blue points), log-normal distribution fits $g^*(J)$ (dark green plain line), and log-normal distribution deduced from the PIP database estimates of the mean and deviation of the distribution of $g^*(J)$ (orange dashed line) for some major countries. For China and India, the income distribution of the rural population is shown in blue points and this of urban one in blue crosses, and the overall distribution (weighted sum of the rural and urban distributions) of our fits is shown (black dashed-dotted line).

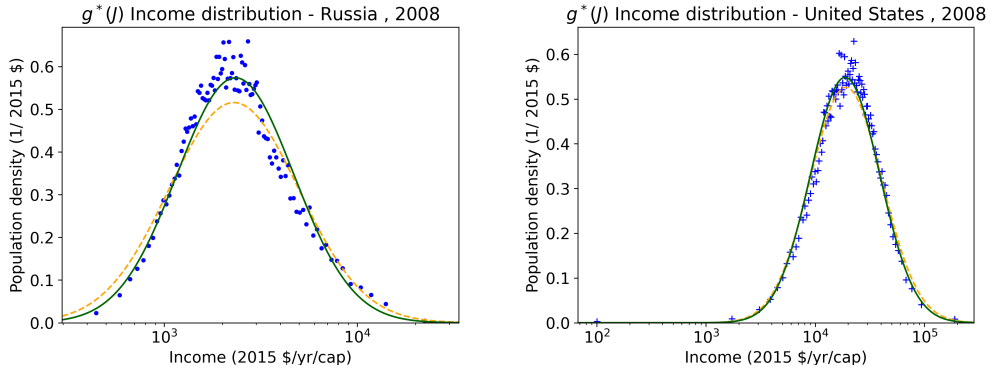


FIGURE E.5: PIP data (blue points), log-normal distribution fits $g^*(J)$ (dark green plain line), and log-normal distribution deduced from the PIP database estimates of the mean and deviation of the distribution of $g^*(J)$ (orange dashed line) for some major countries. For China and India, the income distribution of the rural population is shown in blue points and this of urban one in blue crosses, and the overall distribution (weighted sum of the rural and urban distributions) of our fits is shown (black dashed-dotted line).

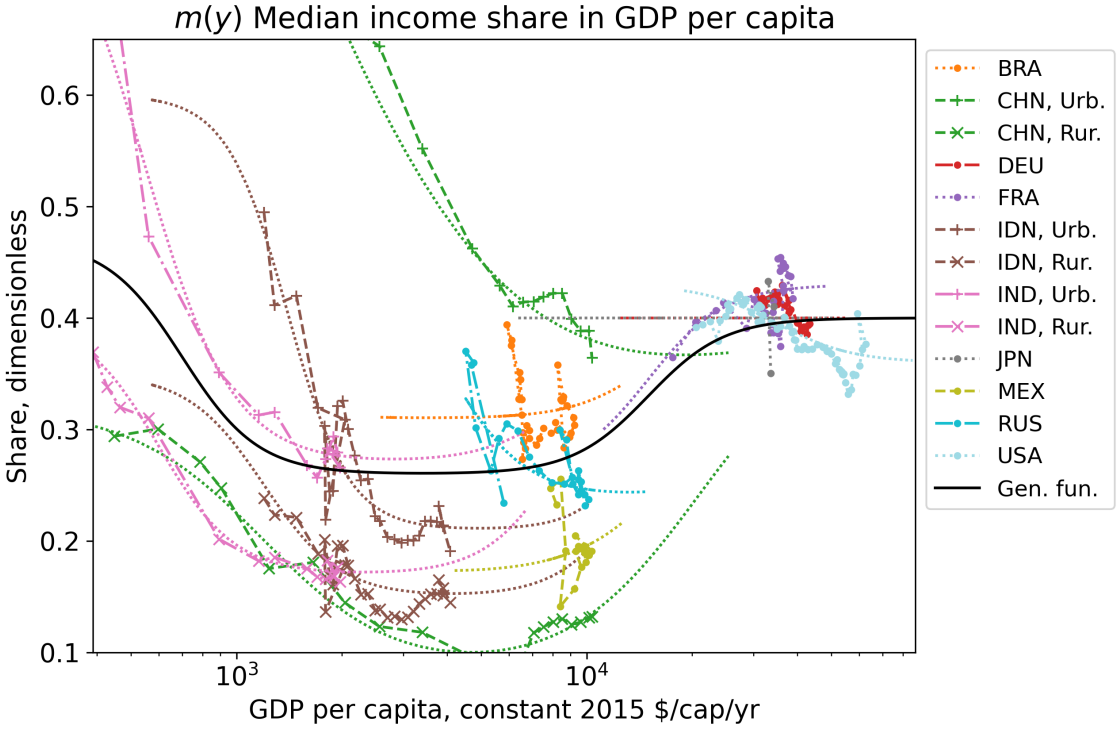


FIGURE E.6: Median income share in GDP per capita projections as a function of GDP per capita for 10 major countries

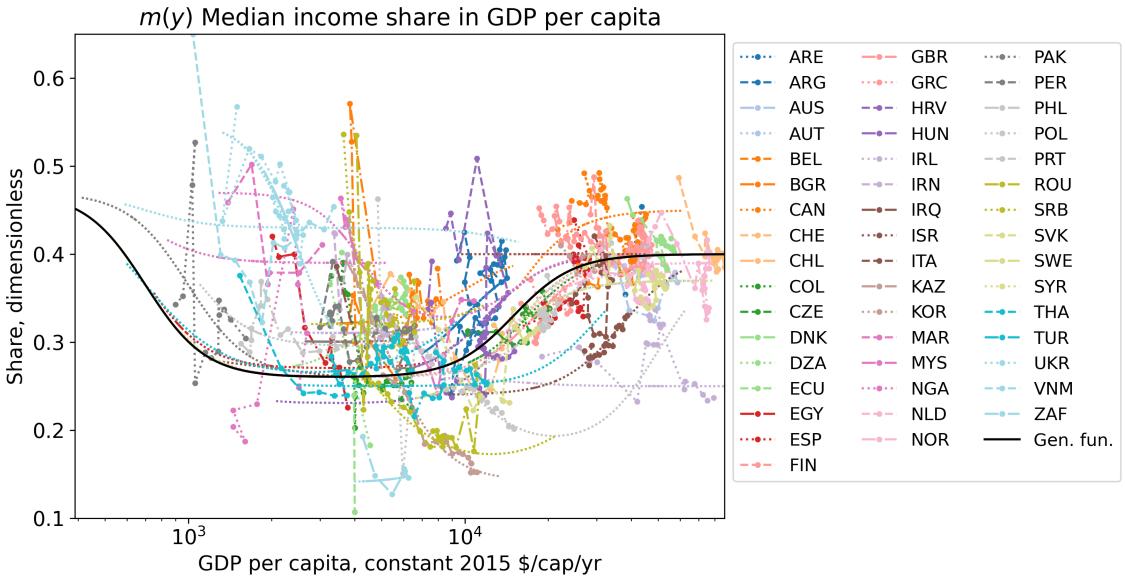


FIGURE E.7: Median income share in GDP per capita projections as a function of GDP per capita for the other countries.

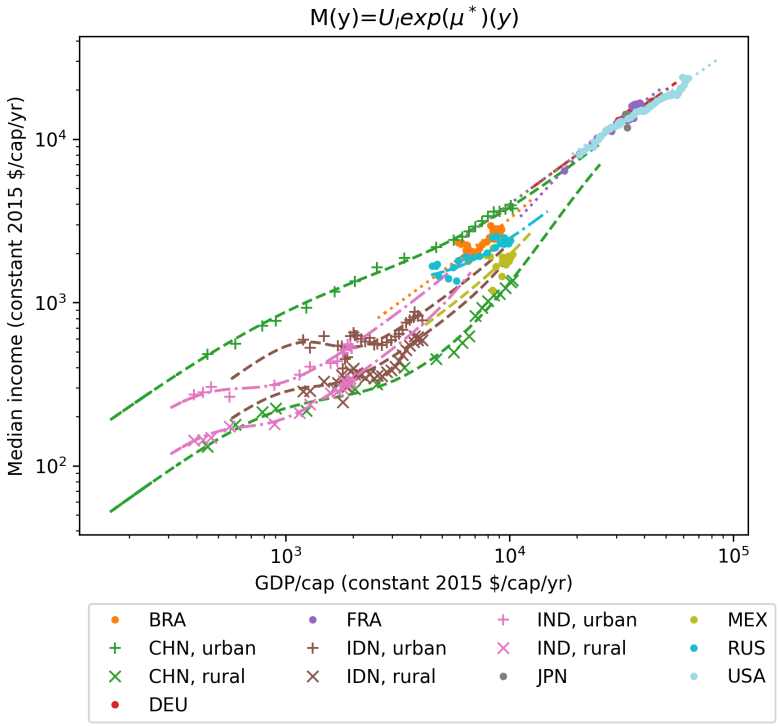


FIGURE E.8: Median income projections as a function of GDP per capita for 10 major countries

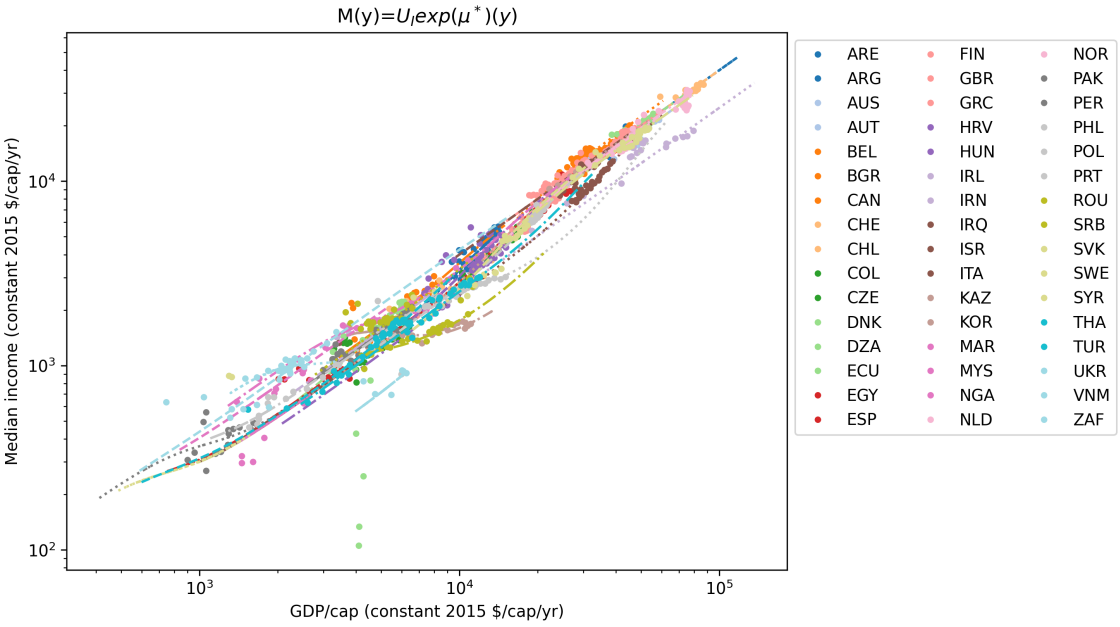


FIGURE E.9: Median income projections as a function of GDP per capita for the other countries

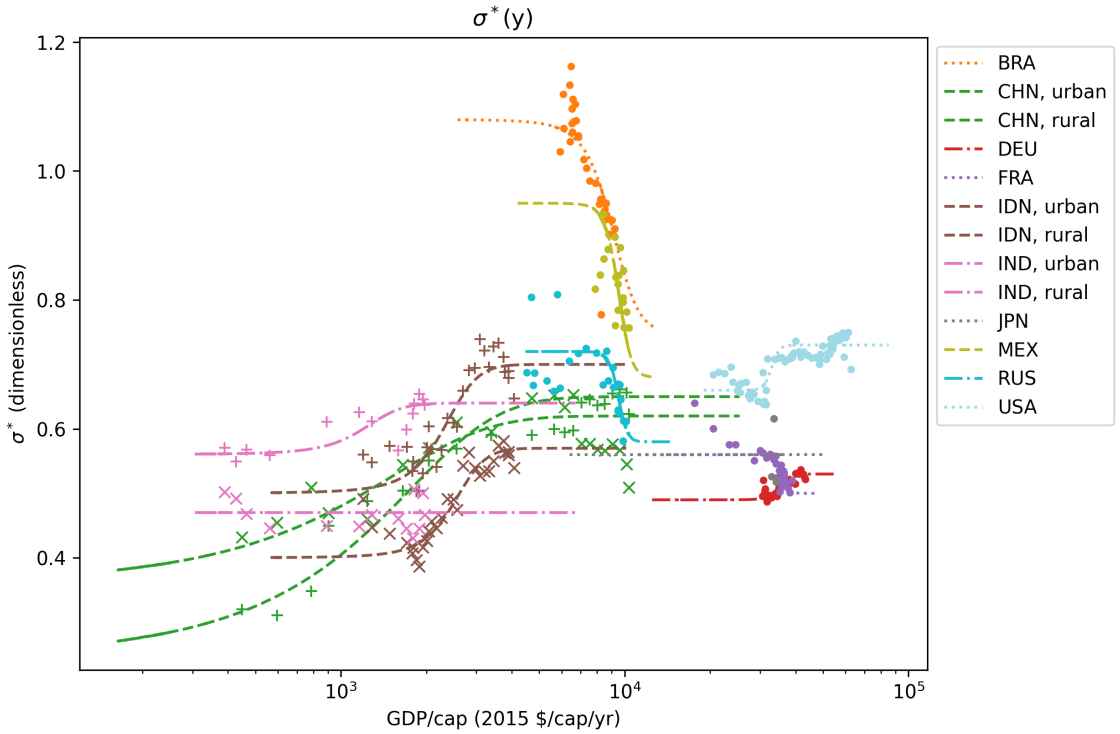


FIGURE E.10: σ^* projections as a function of GDP per capita for 10 major countries. If applicable, data for the urban population are represented with "+" and rural in "x".

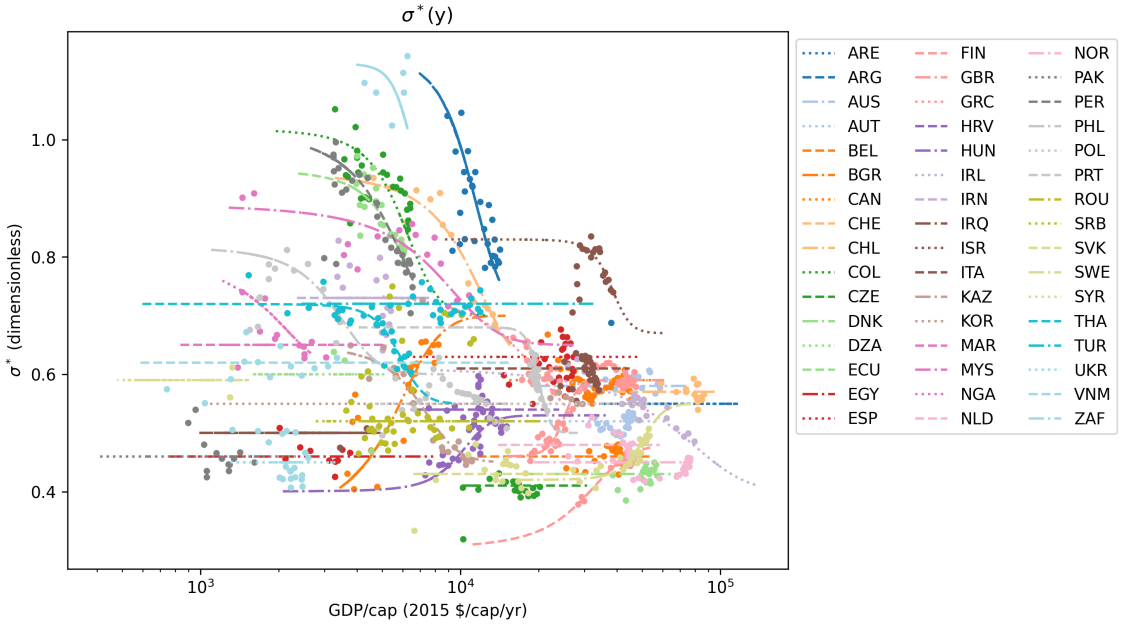


FIGURE E.11: σ^* projections as a function of GDP per capita for the other countries

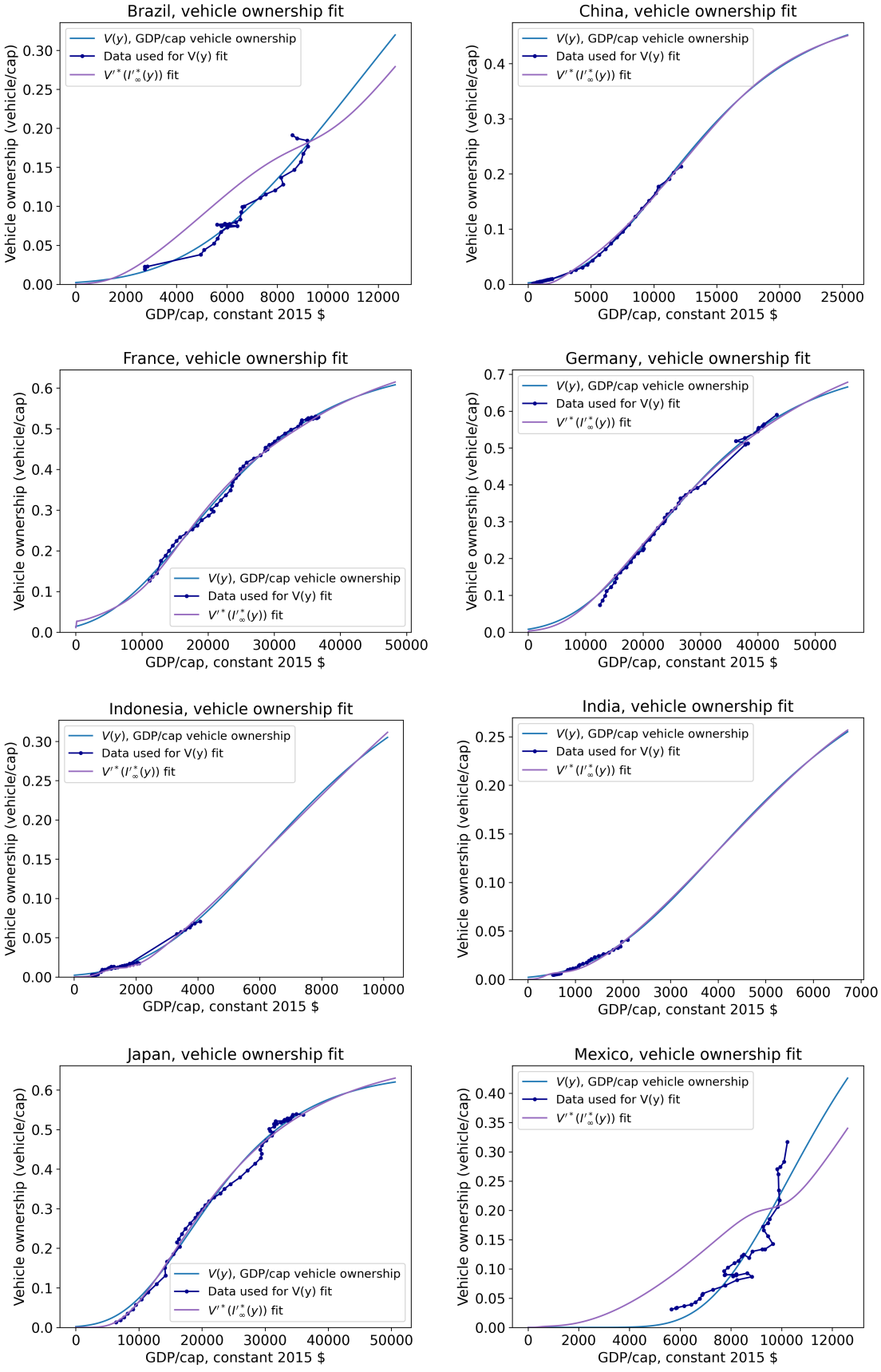


FIGURE E.12: Fit of $V(y)$ by $V'^*(I'^*_\infty(y))$ for major countries (1)

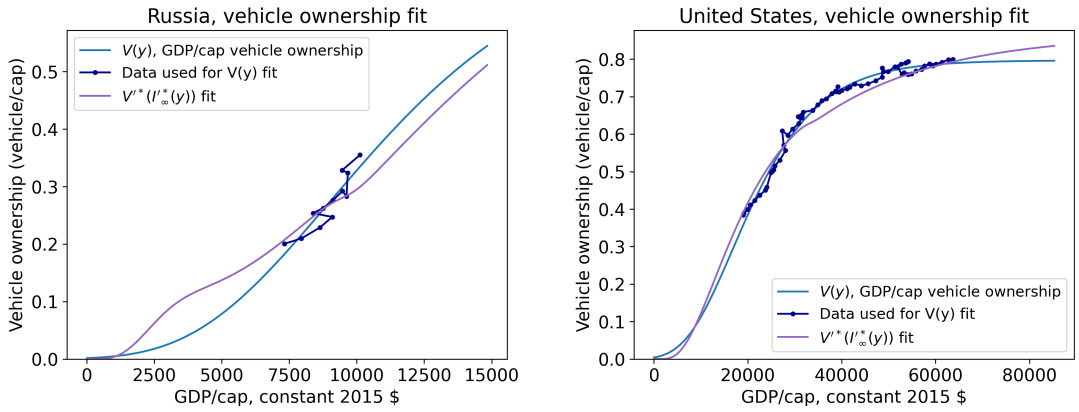


FIGURE E.13: Fit of $V(y)$ by $V'^{*}(I'^{*}_{\infty}(y))$ for major countries (2)

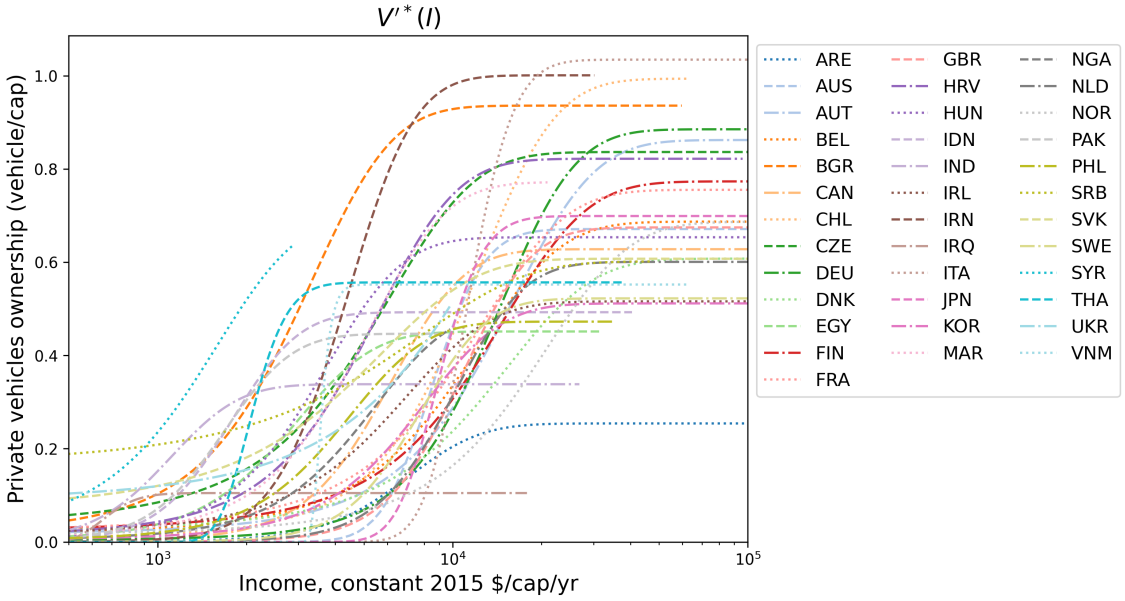


FIGURE E.14: PV ownership as a function of income in countries showing gradual evolution.

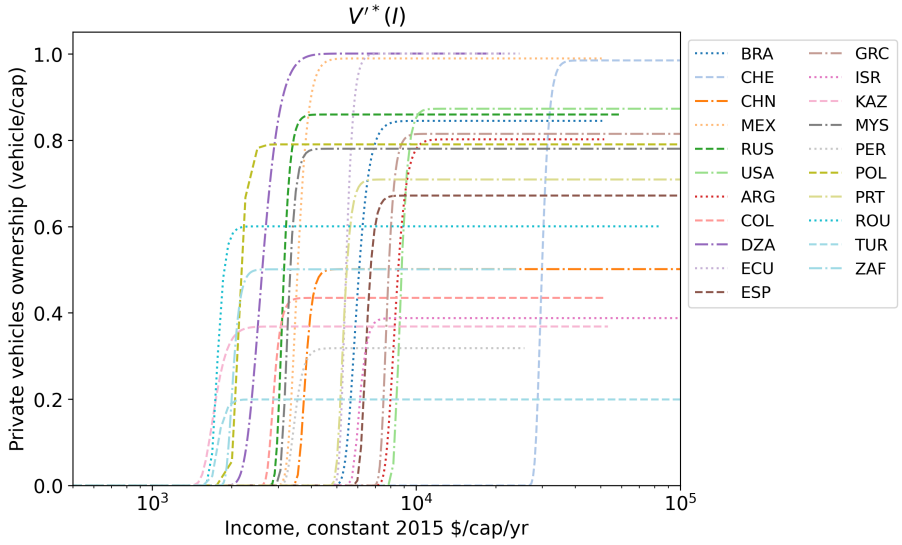


FIGURE E.15: PV ownership as a function of income in countries showing step-function behaviour.

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