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Commodity Price Uncertainty: Diffusion and Policy Drivers

Jacques Minlend

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Par

Jacques MINLEND

**Commodity Price Uncertainty: Diffusion and Policy
Drivers**

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Résumé

Les marchés des matières premières constituent une composante primordiale dans la dynamique de l'économie mondiale, et leurs fluctuations ont des répercussions majeures. Une meilleure compréhension des déterminants de l'offre et de la demande des matières premières permet de clarifier non seulement la nature des fluctuations de leurs prix, mais également les facteurs qui les régissent. Une telle analyse est essentielle pour élaborer des politiques visant à atteindre des objectifs économiques, sociaux et environnementaux tels que la croissance durable, la stabilité de l'inflation, la réduction de la pauvreté, la sécurité alimentaire et la lutte contre le réchauffement climatique.

L'historique des prix des matières premières a été marqué par certains événements majeurs. En 1973, la flambée des prix des matières premières est attribuée à l'embargo pétrolier décrété par l'Organisation des pays exportateurs de pétrole (OPEP) à l'encontre des États-Unis et des pays européens pendant la guerre du Kippour. Cette situation a entraîné des pénuries et une hausse des prix de l'énergie qui s'est répercutée, par effet domino, sur les prix des autres matières premières. En 1974, à la suite de la levée de l'embargo, les prix de l'énergie ont progressivement baissé et retrouvé leur niveau d'avant-crise. En 1979, la révolution iranienne a entraîné une rupture des exportations de pétrole au Moyen-Orient, ce qui a considérablement alimenté la spirale inflationniste sur le marché de l'énergie. Ces deux crises énergétiques des années 1970 sont principalement dues à des chocs négatifs d'offre.

Au début des années 2000, les prix des matières premières, qui étaient jusqu'alors relativement bas, ont progressivement commencé à augmenter. Cet épisode correspond à un choc positif induit par la demande. L'énergie, les céréales, les biocarburants et les autres matières premières non énergétiques ont atteint des niveaux record extraordinaires à la mi-2008. L'éclatement de la crise financière mondiale au second semestre 2008 a entraîné une récession sans précédent qui s'est accom-

pagnée d'un ralentissement de la demande de matières premières. Néanmoins, un rebond des prix a été observé en 2011 pour de nombreuses matières premières, dont les prix ont atteint, voire dépassé, les niveaux d'avant la crise. Cette observation trouve plusieurs explications: une reprise de la demande mondiale essentiellement tirée par les pays émergents, une politique monétaire expansionniste de la Réserve fédérale américaine, ainsi que des activités de spéculation et des stratégies d'aversion à l'inflation sur les valeurs refuges.

Deux autres phénomènes plus récents illustrent les effets d'un environnement incertain sur les prix des matières premières. Le premier concerne l'apparition de l'épidémie de Covid-19, qui a poussé les gouvernements à prendre des mesures protectionnistes telles que le confinement et la fermeture des frontières. Ces mesures ont créé des perturbations dans les chaînes d'approvisionnement de nombreux secteurs d'activité. L'épisode du Covid-19 s'est tout d'abord caractérisé par un choc de demande transitoire, avec une chute drastique du prix du pétrole en fin mars 2020, puis par un choc d'offre, se traduisant par des pénuries et des contraintes de capacité pour répondre à la reprise de la demande. En conséquence, une spirale inflationniste s'en est suivie dans divers secteurs d'activité. Le deuxième phénomène est le déclenchement du conflit russo-ukrainien en fin février 2022. Cet événement est d'autant plus marquant qu'il implique deux des plus grands exportateurs de céréales et d'énergies fossiles. En effet, la conjonction de l'embargo européen sur les importations d'énergies fossiles russes et du blocus militaire russe sur les exportations de céréales ukrainiennes a conduit à de nouvelles perturbations sur les marchés et à des schémas commerciaux plus coûteux. Ces perturbations ont également mis en évidence l'interdépendance des marchés des matières premières: les prix élevés de l'énergie ont fait augmenter les coûts de production d'autres matières premières (comme les engrais), entraînant une hausse généralisée des prix. Cette hausse des prix des matières premières intensifie la menace d'une inflation élevée et durable. Les économies européennes sont particulièrement exposées en raison de leur forte dépendance vis-à-vis du pétrole et du gaz naturel russes. Le débat sur la recherche de sources d'énergie alternatives est relancé.

Au-delà de ces facteurs fondamentaux de l'offre et de la demande qui régissent la dynamique des prix, un facteur beaucoup plus controversé dans la littérature émerge: la financiarisation. Elle traduit la prédominance des instruments financiers dans les échanges de matières premières depuis le début des années 2000. Le volume des transactions sur ces instruments financiers dépasse largement celui observé sur

le marché physique (Domanski et Heath, 2007; Redrado et al., 2009; Silvennoinen et Thorp, 2013).

Le changement climatique et la transition écologique ajoutent une nouvelle dimension aux incertitudes qui pèsent sur les marchés des matières premières. En effet, le changement climatique et les phénomènes météorologiques extrêmes plus fréquents sont susceptibles d'affecter la production de toutes les matières premières. En 2021, des conditions météorologiques extrêmes ont créé des perturbations dans la production de nombreuses matières premières: la sécheresse a réduit la production hydroélectrique dans plusieurs pays, dont le Brésil, la Chine et les États-Unis; le gel et les ouragans ont également perturbé la production de pétrole brut et de gaz naturel aux États-Unis; les inondations ont interrompu la production et le transport du charbon et de certains métaux en Australie; et la sécheresse au Brésil a réduit la production de café à des niveaux historiquement bas. Ce constat montre que les phénomènes climatiques ne se limitent pas qu'aux marchés agricoles.

Le contexte ci-dessus aborde les fluctuations des prix des matières premières comme un concept résultant principalement des chocs d'offre et de demande. Cependant, la nature de ces fluctuations peut être associée à des phénomènes de volatilité ou à des phénomènes d'incertitude intrinsèques aux marchés. En général, la littérature sur les fluctuations des prix fait davantage référence aux phénomènes de volatilité (Nazlioglu et al., 2013; Liu et al., 2013; Gozgor et al., 2016; Diebold et al., 2017). L'aspect de l'incertitude reste moins exploré en raison de la difficulté réelle à le définir et à le quantifier.

Cette thèse a pour objectif de mettre l'accent sur l'incertitude des prix des matières premières tout en mettant en lumière quelques facteurs qui influencent son évolution au travers de la diffusion de l'incertitude entre les marchés et de l'impact des politiques économiques, énergétiques et environnementales. Contrairement à la volatilité, l'incertitude mesure les variations non anticipées des prix des matières premières (Balli et al., 2019). Pour développer notre mesure de l'incertitude des prix des matières premières, nous nous référons aux travaux de Jurado et al. (2015), qui ont initié une méthodologie basée sur la prévision pour construire une mesure de l'incertitude macroéconomique expliquant avec précision les fluctuations observées de l'activité réelle. Cette nouvelle perspective d'analyse des fluctuations des prix ouvre la voie à des outils d'évaluation et de prise de décision pour les investisseurs et les autorités publiques.

Cette thèse propose trois études portant sur les facteurs qui influencent

la dynamique de l'incertitude des prix des matières premières. Sur le plan méthodologique, elle mobilise les outils de la macroéconomie des séries temporelles et de *Machine Learning*.

Le chapitre 1 est entièrement tiré des travaux de Cadoret et al. (2022).¹ Il vise deux objectifs principaux: premièrement, estimer avec précision une mesure de l'incertitude des prix au niveau agrégé pour quatre catégories de marchés de matières premières (énergie, agriculture, industrie et métaux précieux); deuxièmement, explorer a posteriori le mécanisme de transmission de l'incertitude des prix entre les marchés. La question de l'incertitude est revenue sur le devant de la scène à la suite de la crise financière mondiale de 2007-2009, qui a révélé divers mécanismes de diffusion entre les marchés des matières premières. Ce chapitre adopte une approche basée sur la prévision des prix pour construire une mesure de l'incertitude des prix sur les marchés des matières premières. Ainsi, nous apportons une contribution à la littérature sur les fluctuations des prix de deux manières à deux niveaux: premièrement, nous développons des mesures individuelles de l'incertitude des prix pour de nombreux marchés de matières premières, qui sont basées sur la volatilité de l'erreur de prévision des prix. Ces mesures sont utilisées pour calculer une mesure globale de l'incertitude des prix pour chaque secteur des matières premières. Contrairement à la volatilité, nos mesures d'incertitude se révèlent être des indicateurs avancés des crises économiques. Deuxièmement, nous examinons la transmission intersectorielle des chocs d'incertitude des prix et les mécanismes sous-jacents.

Les résultats de notre étude empirique indiquent une transmission bidirectionnelle de l'incertitude entre les marchés de l'énergie, de l'agriculture et de l'industrie. Parallèlement, le marché des métaux précieux est insensible aux chocs d'incertitude provenant des autres marchés, renforçant ainsi son caractère de valeur refuge lors d'événements économiques défavorables. De plus, nous constatons que la transmission de l'incertitude ne dépend pas seulement de liens spécifiques entre les marchés, mais également d'un facteur macroéconomique latent commun qui régit le mécanisme des mouvements conjoints excessifs (Pindyck et Rotemberg, 1990). Un autre résultat intéressant de ce chapitre révèle que l'incertitude industrielle apparaît comme le facteur commun de diffusion de l'incertitude entre les marchés de matières premières. Afin d'examiner cette conclusion de manière approfondie, une analyse comparative est réalisée entre notre indicateur d'incertitude industrielle

¹Cette contribution scientifique a été publiée dans *Applied Economics* (2022), pp. 1-25.

et l'incertitude macro-financière développée par Jurado et al. (2015). Il en résulte que l'incertitude industrielle peut être considérée comme un proxy de l'incertitude macro-financière, tant du point de vue de leur dynamique évolutive que de leurs contributions respectives aux chocs sur les marchés des matières premières.

Motivés par la conclusion du chapitre précédent sur l'importance du facteur macro-financier sur les marchés des matières premières, nous poursuivons notre analyse au niveau désagrégé des marchés du pétrole et du cuivre pour explorer un second facteur de l'incertitude des prix dans un cadre empirique très élaboré dans la littérature.

Le chapitre 2 vise à évaluer comment l'incertitude de la politique économique influence la dynamique d'incertitude des prix des matières premières.² Nous nous concentrons spécifiquement sur les marchés du pétrole et du cuivre, car le cadre empirique s'y prête mieux. De plus, comme indiqué dans le premier chapitre, le pétrole et le cuivre sont respectivement les matières premières les plus représentatives des secteurs de l'énergie et de l'industrie. Alors que la plupart des études de la littérature soutiennent que les fluctuations des prix des matières premières sont principalement dues aux chocs d'offre et de demande (Kilian, 2009; Pedersen, 2019; Cross et al., 2020), l'impact de l'incertitude de la politique économique a été moins exploré malgré l'intérêt croissant pour ce sujet au cours de la dernière décennie. En nous appuyant sur les travaux de Baker et al. (2016), qui ont développé un indice d'incertitude de la politique économique des États-Unis (EPU) basé sur le contenu informationnel de la presse, notre contribution consiste à analyser les implications de cet indicateur sur l'incertitude des prix du pétrole et du cuivre.³

Nos résultats montrent qu'un choc positif sur l'EPU contribue à une augmentation significative de l'incertitude sur les prix du pétrole et du cuivre, avec un impact plus élevé et plus persistant sur le marché du pétrole. De plus, notre modèle nous permet également de valider une hypothèse découlant du premier chapitre, selon laquelle l'incertitude sur le prix du cuivre se propage au marché du pétrole. De plus, les contributions relatives des chocs de l'EPU aux incertitudes du pétrole et

²Une version plus sommaire de ce chapitre a été publiée dans *Economics Bulletin* (2023).

³L'EPU de Baker et al. (2016) est un indice composite qui englobe des sous-indices catégoriels liés aux thématiques abordées dans les articles de journaux aux États-Unis, tels que: la politique monétaire, la politique fiscale, les dépenses publiques, les soins de santé, la sécurité nationale, les programmes de droits, la réglementation, la réglementation financière, la politique commerciale, la dette souveraine et les crises monétaires.

du cuivre sont respectivement de 11% et de 6% à court terme. En ce qui concerne les facteurs traditionnels, nous constatons qu'un choc négatif de l'offre de pétrole tend à augmenter l'incertitude du prix du pétrole, tandis qu'un choc positif de la demande réduit l'incertitude du prix du pétrole. De manière similaire, en analysant le marché du cuivre, nous observons que l'incertitude sur le prix du cuivre est principalement influencée par la demande globale, avec un effet à long terme.

Dans le chapitre suivant, nous nous intéressons plus particulièrement à l'aspect réglementaire de la politique énergétique et environnementale mise en œuvre dans l'Union européenne (UE). Étant donné que l'UE est l'un des plus grands importateurs mondiaux d'énergies fossiles, ce chapitre se concentre sur les effets potentiels d'une telle politique sur la dynamique de l'incertitude des prix des énergies fossiles (pétrole, gaz et charbon).

Le chapitre 3 pose la question de savoir si la politique énergétique et environnementale européenne influence la dynamique de l'incertitude des prix des énergies fossiles. Jusqu'à présent, cette idée n'a pas fait l'objet d'une étude empirique. Notre analyse s'articule autour de deux points principaux. Premièrement, nous nous appuyons sur des études qui développent des indicateurs de politique environnementale et climatique basés sur les articles de presse (Noailly et al., 2021, 2022; Gavriilidis, 2021). À cet effet, nous proposons: (i) un indicateur basé sur la presse européenne à deux volets: l'incertitude sur l'environnement global et la diffusion de la réglementation énergétique et environnementale dans la presse; (ii) un indicateur structurel basé sur les textes de lois, plus spécifique à la politique énergétique et environnementale européenne, qui met l'accent sur le cycle législatif. Deuxièmement, à la suite de nombreux travaux empiriques (Baker et al., 2016; Lemoine, 2017; Dorsey, 2019; Sen et von Schickfus, 2020), nous analysons les impacts des indicateurs construits sur la dynamique de l'incertitude des prix des énergies fossiles.

Nos principaux résultats suggèrent qu'un accroissement de l'indicateur basé sur la presse a un effet mixte significatif sur les incertitudes des prix du pétrole et du charbon. Nous observons notamment un effet positif résultant de l'incertitude sur l'environnement global, se traduisant par une légère augmentation à court terme des incertitudes sur les prix dans ces marchés. Cette légère hausse est suivie d'un effet négatif issu du volet réglementaire sur les incertitudes des prix. Ainsi, cet effet mixte reflète le fait que l'efficacité de la politique énergétique et environnementale sur la dynamique des prix n'est pas altérée en situation d'incertitude concernant le contexte global. Cependant, nous observons que le marché du gaz est davantage dominé par

le second effet, car la dynamique baissière de l'incertitude du prix est plus précoce et durable que sur les autres marchés. De manière similaire, une augmentation de l'indicateur basé sur les textes de lois entraîne une décroissance significative des incertitudes des prix du pétrole et du charbon. De plus, l'effet négatif s'opère à court terme sur le marché du pétrole, tandis qu'il est plus persistant sur le marché du charbon. Ce résultat souligne que l'indicateur composite basé sur les textes de lois joue un rôle stabilisateur significatif sur ces marchés, mais pas sur celui du gaz. Cependant, une analyse plus approfondie révèle que l'incertitude sur le prix du gaz ne se contracte de manière substantielle qu'à la suite de réglementations spécifiques à l'environnement. Une analyse complémentaire a été réalisée sur les effets de nos indicateurs sur le niveau des prix. Nous relevons que seul l'indicateur basé sur la presse contribue à réduire significativement les prix sur tous les marchés. Cela supposerait que les marchés anticipent la réglementation et s'ajustent à la baisse en conséquence. En conclusion, ce chapitre repose sur l'idée selon laquelle la politique européenne à faibles émissions carbone exerce des pressions différentes en termes de maturité sur les incertitudes des prix des énergies fossiles.

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General Introduction

”Uncertainty is an amorphous concept. It reflects uncertainty in the minds of consumers, managers, and policymakers about possible futures. It is also a broad concept, including uncertainty over the path of macro phenomena like GDP growth, micro phenomena like the growth rate of firms, and noneconomic events like war and climate change.”

Nicholas Bloom, *Fluctuations in Uncertainty*,
Journal of Economic Perspectives, 2014

This thesis deals with uncertainty as a particular aspect of price fluctuations in commodity markets, as well as their underlying drivers. In this introduction, we provide an overview of the historical evolution of commodity prices and developments in the sources and measures of uncertainty shocks, and finally we present the dissertation outline.

1 Context

The evolution of commodity prices on international markets is a key issue since it can affect most countries' economies in one way or another. Fluctuations in commodity prices are especially relevant for the global economy, which has periodically experienced episodes of commodity booms and busts characterized by broad and sharp co-movements of commodity prices. There have been a number of major events in the history of commodity price dynamics. In 1973, the spike in commodity prices was driven by the Organization of the Petroleum Exporting Countries' (OPEC) oil embargo on the United States (US) and European countries during the Yom Kippur War. This situation led to energy shortages and a subsequent rise in energy prices,

which spread to a few other commodity prices. In 1974, the embargo was lifted and energy prices started to decline progressively to reach their pre-embargo level. In 1979, the Iranian revolution triggered interruptions in Middle Eastern oil exports, causing a widespread panic which drove prices far higher than would be expected under normal circumstances. Both 1970s energy crisis events are attributed to negative supply-driven shock. Subsequently, commodity prices remained at a relatively low level, until prices witnessed a resumption of a significant upward trend in the early 2000s. This episode is known as a positive demand-driven shock, with energy, grains, biofuels and non-energy commodities all reaching extraordinarily high record levels in mid-2008. Unfortunately, with the eruption of the global financial crisis in the second half of 2008, which caused an unprecedented recession, the demise of the commodity boom was inevitable following the collapse of major commodity prices. Nevertheless, a rebound in prices was markedly observed by 2011, with many commodities matching and even exceeding their pre-crisis price peaks. There are several explanations for this last observation: a recovery in global demand mainly driven by emerging markets, an expansionary monetary policy by the US Federal Reserve (FED) and speculative activities and inflation-adverse strategies on safe haven assets.

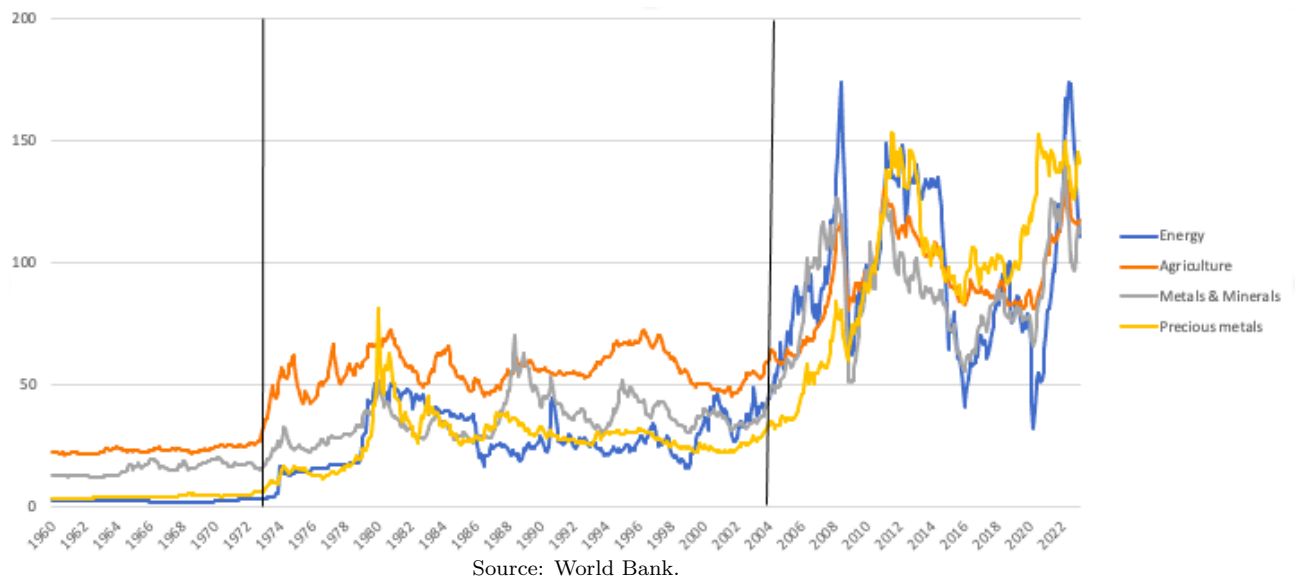
In the first quarter of 2020, the Covid-19 outbreak gave a clear illustration of price fluctuations in an unstable environment. Indeed, governments' responses, such as lockdowns and cross-border closures, strongly contributed to supply chain disruptions across all industries, including mining. Initially, the pandemic triggered a sharp fall in global demand for commodities, especially crude oil, however, commodity prices rapidly recovered with the rebound in demand, but supply was slow to respond due to capacity constraints and supply bottlenecks. This led to shortages of goods and services and higher prices for the items that were available. This situation fueled the jump in inflation to the point that predicting future inflation can be difficult since current readings only reflect where prices have been trending rather than where they are headed.

Far from being transitory, the spiral of price increases has been accentuated by the Russo-Ukrainian War that started in February 2022. The implementation of economic sanctions against Russia has mainly affected the post-Covid macroeconomic recovery. In particular, agriculture and energy markets have displayed an unprecedented spike in prices. Russia is one of the world's largest exporters of oil, natural gas, steel, nickel aluminum, and wheat. Likewise, Ukraine is the key pro-

ducer of corn, wheat, sunflower seeds, sugar beet, barley, soybeans and rapeseed. The war led to further disruptions in commodity markets and more costly patterns of trade, with a major diversion of trade in energy, as Ukraine could not export grain and some countries banned imports of Russian energy. The disruption also demonstrated how highly interrelated commodity markets are, with, for example, energy prices pushing up the production costs of other commodities (such as fertilizers), which fuelled a broad-based increase in commodity prices. The increase in prices had a major economic and humanitarian impact, especially for energy and food-importing economies. Higher commodity prices intensify the threat of long-lasting high inflation which increases the risk of stagflation and social unrest. Other sectors such as automotive, transport, and chemicals are likely more vulnerable. The exposure to imported inflation and trade disruptions varies across regions. For instance, European economies are more at risk due to their high dependence on Russian oil and natural gas. Hence, the war may have accelerated the energy transition as countries seek to reduce their reliance on fossil fuels.

Figure 1 provides an illustration of the above description on the historical price evolution of a panel of 4 groups of commodities.

Figure 1: **Evolution of commodity price indices on international markets.**



Note: This figure reports the historical evolution of commodity price indices (2010=100). Four groups are plotted: energy (including crude oil, natural gas, and coal), agriculture (including food, and beverages, and raw materials), metals and minerals (aluminum, steel, copper, iron ore, lead, nickel, tin and zinc), and precious metals (gold, silver, platinum).

Generally, the economic literature highlights three major explanations for long-lasting commodity price fluctuations.

First, the level of global growth is a prominent indicator of the demand for commodities. In the early 2000s, the advent of emerging countries (such as China and India) in world trade substantially boosted the global demand for commodities to meet their industrial and urbanization needs.

Second, the stance of the monetary policy – more specifically, a lax or accommodative monetary policy with low real interest rates (e.g. the case of the US Federal Reserve Bank in 2001-2004 and in 2008) – tends to reduce the cost of holding inventories because stockpiling commodities becomes cheaper. Such a policy therefore contributes to increasing the demand for commodities. Especially, Frankel (2008) underscores that, for a given expected price path, a decrease in interest rates reduces the carrying cost of speculative positions, making it easier to bet on assets such as commodities. Moreover, under certain conditions, this will put upward pressure on futures prices, and by arbitrage, also on spot prices. It should be noted that the 1970s commodity price boom was due to the relatively steady demand during the negative supply shock. In contrast, the 2000s commodity price boom was triggered by the lagging supply response to a persistent positive demand shock. As a result, supply-demand adjustments represent the fundamental determinants of commodity price fluctuations in the short run (during the 1970s) and in the long run (during the 2000s).

Third is the financialization of commodity markets. This last explanation does not find any consensus in the literature and is a subject of contention. Indeed, a strand of the literature underscores the preeminence of financial activity on commodity markets since the 2000s. One explanation is that the low interest-rate environment in the early 2000s led investment funds and non-commercial traders to explore other assets with higher returns. This new strategy of portfolio diversification increases exposures in the commodity futures market (Domanski and Heath, 2007, Redrado et al., 2009, Silvennoinen and Thorp, 2013, Christou et al., 2017, Ding et al., 2021). The volume of transactions on the commodity futures market rose subsequently from around US\$10 billion in 2000 to US\$450 billion by mid-2011 to the point of outperforming the physical market. In 2008, some argued that financialization was one of the main sources of the *subprime* crisis and pointed out that the speculative bubbles it generated in the context of financial liberalization started in 1980. This is the reason why, in 2010, the US dedicated part of the Dodd-Frank

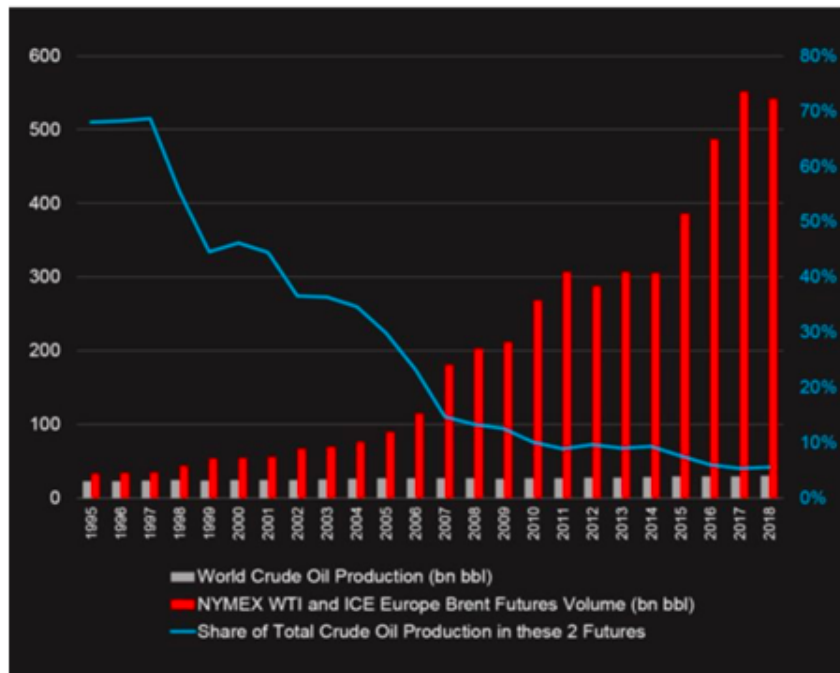
Act to regulate the financial derivatives market.⁴ The Commodity Futures Trading Commission (CFTC) was established to protect futures markets from excessive speculation that can cause unreasonable and unwarranted price fluctuations. In particular, the commission pays attention to cross-manipulation and excessive positions. The cross-manipulation reflects the ability of an investor to retrieve a profit by simultaneously taking a position on spot and derivatives markets to generate demand distortion by feeding scarcity (e.g. the Hunt brothers' attempt to corner the silver market in 1980). An excessive position limits the *weight-of-money effect*, allowing an investor to have an exclusive influence on the asset price by betting a large amount of money. Figure 2 gives an overview of the volume of transactions between oil futures and physical markets. We notice that the share of the total crude oil production in the cumulative volume of NYMEX WTI and ICE Brent futures contracts fell from 70% to less than 10% over the period 1995-2018. The remarkable gap between both markets is a sufficient proof that commodity futures indubitably play a role in commodity price fluctuations, and to some extent support the rise of commodity prices above fundamental values.

In addition to changes in these structural factors, markets are also exposed to climate change. Climate change and the transition to more climate-friendly sources of energy add another dimension to the uncertainties that roil commodity markets. The frequent extreme weather events are likely to affect the production of all commodities. For instance, agriculture commodity prices have become highly volatile since periods of drought or excess rains imply a potential drop in crop production. In what was perhaps a harbinger, extreme weather disrupted the production of many other commodities in 2021: droughts reduced hydroelectric generation in several countries including Brazil, China, and the United States; freezing weather and hurricanes disrupted crude oil and natural gas production in the United States; floods interrupted the production and transport of coal and some metals in Australia; and drought in Brazil reduced its coffee production to historic lows. Many of these climatic phenomena have been observed since the beginning of the 2000s and are tending to increase over time, as highlighted by the special report of the United Nations Intergovernmental Panel on Climate Change (IPCC, 2018).⁵

⁴See the Dodd-Frank Wall Street Reform and Consumer Protection Act.

⁵Special Report on Global Warming of 1.5°C, IPCC (2018).

Figure 2: Volume of transactions in oil futures and physical markets.



Source: Bloomberg

Previously, we presented the context that governs commodity price fluctuations through four structural factors: commodity demand, monetary policy, financialization, and climate change. However, price fluctuation also appears as a general concept. Both volatility and uncertainty are components of price fluctuations. The issue of volatility has already been widely addressed in the literature and in this thesis, we will focus on the uncertainty component. In the next section, we will review the sources and the measurement of uncertainty, which is crucial for establishing the distinction between volatility and uncertainty in commodity prices.

2 Uncertainty: sources and measurement

It is worth noting that this thesis deals with the notion of price uncertainty in commodity markets. In fact, commodity price uncertainty relies on a wide literature that does not reach a consensus on an objective methodology to measure uncertainty. Therefore, the bulk of uncertainty proxies has emerged according to newly developed methodologies. Ferrara et al. (2018) divide uncertainty measures into different categories: financial uncertainty, macroeconomic uncertainty, economic policy

uncertainty, and global uncertainty. In the following paragraphs, we propose to discuss these measures and approaches.

2.1 Financial uncertainty

To date, the common measure of financial market uncertainty has been based on volatility. For instance, Bloom (2009) considers the implied volatility index (VIX) as a reliable measure of financial uncertainty. Indeed, since the 1990s, the Chicago Board Options Exchange (CBOE) has developed the VIX index to measure 30-day option-implied volatility in the S&P 500 index. Based on high-frequency historical data, a high level of the VIX reflects high volatility in financial markets, which refers to periods of crisis. In general, authors highlight the VIX as a "fear index" representing agents' volatility expectations in the equity market (Whaley, 2000, 2009). A sudden upward trend of this index is interpreted as a signal of growing uncertainty. Thus, the dynamics of the VIX index have been corroborated by major events, including the 1998 Russian financial crisis, the 09/11 US terrorist attack, the Iraq War in 2003, the Lehman Brothers' collapse in 2008, and more recently the COVID-19 pandemic in 2020 and the Russo-Ukrainian War in 2022.

Other derivative measures have been developed to capture financial market uncertainty. One such case is the variance risk premium (Zhou, 2018) which represents the gap between an ex-ante risk-neutral expectation and an ex-post observation of the return variance, known as the realized variance. The risk-neutral expectation of the variance (or the implied variance) is measured by the VIX index since it proxies stock market expectations. According to Bollerslev et al. (2009), the realized variance describes the volatility of the S&P 500 index using high-frequency returns. A positive variance risk premium means that traders value the price of options more for market participants to hedge against a future riskier economic environment characterized by unexpected market volatility (Carr and Wu, 2009, Feunou et al., 2018). However, some authors (Rosenberg and Engle, 2002, Bekaert and Hoerova, 2016) argue that the variance risk premium only indicates risk aversion and not uncertainty (i.e. expected stock market volatility). Using machine learning techniques on Wall-Street journal articles, Manela and Moreira (2017) endeavor to construct a VIX index back to the 19th century. By doing so, the idea is to integrate business press information to get rid of timing constraints in the traditional VIX index.

Another point concerns measures of uncertainty at a micro-level based on the

standard deviation of companies' stock returns. While Bloom (2009) computes the cross-sectional standard deviation of US firm-level stock returns, Gilchrist et al. (2014) propose an idiosyncratic uncertainty index using daily stock return data from a large panel of non-financial firms. Corporate bond spreads are also identified as an indicator of financial market tensions (Bachmann et al., 2013). This measure states the difference between the yield of medium-grade corporate bonds (rated Baa) and the 30-year Treasury yield. An increase in the gap is assumed to reflect greater tension in financial markets as investors demand a higher yield because of uncertainty about the financial health of corporates.

2.2 Macroeconomic uncertainty

Several methodologies have been used to characterize macroeconomic uncertainty, such as confidence indices, forecast dispersion, yield spread, and forecast errors.

First, confidence indices are mostly survey-based and are considered proxies of uncertainty (Leduc and Liu, 2016). Relying on the Federal Reserve's Business Outlook Survey Bachmann et al. (2013), they elaborate a measure of forecast dispersion which provides qualitative information about firms' business conditions and their expectations. The Organization for Economic Cooperation and Development (OECD) has also developed a business confidence index that takes the pulse of the future economic state. This index indicates if producers are either optimistic or pessimistic about future economic conditions. Likewise, the OECD constructs a consumer confidence index whose level determines households' future behavior in terms of consumption and savings given their sentiment on the ongoing economic environment.

Second, forecast disagreement suggests that predicting macroeconomic variables is somehow tricky. Indeed, even if professional forecasters have access to the same dataset, there are discrepancies in interpretation and hence in forecasts. The lack of a minimum consensus among forecasters obscures the prediction of macroeconomic variables (Zarnowitz and Lambros, 1987). Thus, there is a long-run relationship between uncertainty and forecast disagreement (Bomberger, 1996, Giordani and Söderlind, 2003). Istrefi and Mouabbi (2018) use a Consensus Economics survey for some advanced economies to construct a subjective measure of interest rate uncertainty. Their measure is defined as the sum of the variance of disagreement

among professional forecasters and the conditional variance of mean forecast errors exploiting the difference between expected and observed interest rates.

Third, yield spread (i.e. the slope of the treasury yield curve) is the gap between long-term and short-term interest rates. It is a leading indicator of economic downturns when the spread is close to zero or negative (Estrella and Mishkin, 1998, Rudebusch and Williams, 2009, Bauer et al., 2018a,b).

Fourth, forecast errors have gained a lot of importance in quantifying macroeconomic uncertainty (Scotti, 2016). In this context, uncertainty deriving from a set of macroeconomic variables is calculated as the square root of the weighted average of the squared difference between the realization and the median expectation (Rossi and Sekhposyan, 2015, Jurado et al., 2015, Ismailov and Rossi, 2018). In addition, a time-varying volatility approach has been explored in modelling macroeconomic uncertainty. This methodology aims to rely on the volatility of forecast errors as a proxy of uncertainty (Fernández-Villaverde et al., 2011, Bali et al., 2014, Fernández-Villaverde et al., 2015, Chan, 2017).

2.3 Economic policy uncertainty

In order to highlight the wealth of words environment, researchers propose recent developments in textual analysis to elaborate new measures of uncertainty. In particular, Baker et al. (2016) paved the way by developing news-based Economic Policy Uncertainty (EPU) indices for many countries. The authors started their run-up investigation with the US to construct policy-related economic uncertainty using archives of 10 leading newspapers since 1985. More precisely, they selected articles that included terms related to the economy ("economy" or "economic"), policy ("white house", "congress", "regulation", "legislation", "federal reserve" or "deficit") and uncertainty ("uncertainty" or "uncertain"). To clearly identify articles describing the EPU, a meticulous manual process was engaged by research assistants across a pool of 12,000 articles. Finally, only articles pertaining to the following policy categories were labeled: fiscal policy, monetary policy, national security, regulation, healthcare, entitlement programs, sovereign debt, currency crisis and trade policy. Azqueta-Gavaldón (2017) replicated the US EPU of Baker et al. (2016) using an unsupervised machine learning approach, which proved to be less costly and more flexible. Following this thread, Larsen (2021) identified components of uncertainty by applying machine learning techniques to Norwegian newspapers.

In the same vein, other studies suggest a world EPU as the weighted average on national EPU indices (Davis, 2016, Ahir et al., 2022). Caldara and Iacoviello (2022) initiated a geopolitical risk index based on international newspapers discussing military conflicts, war and terrorism threats and acts.

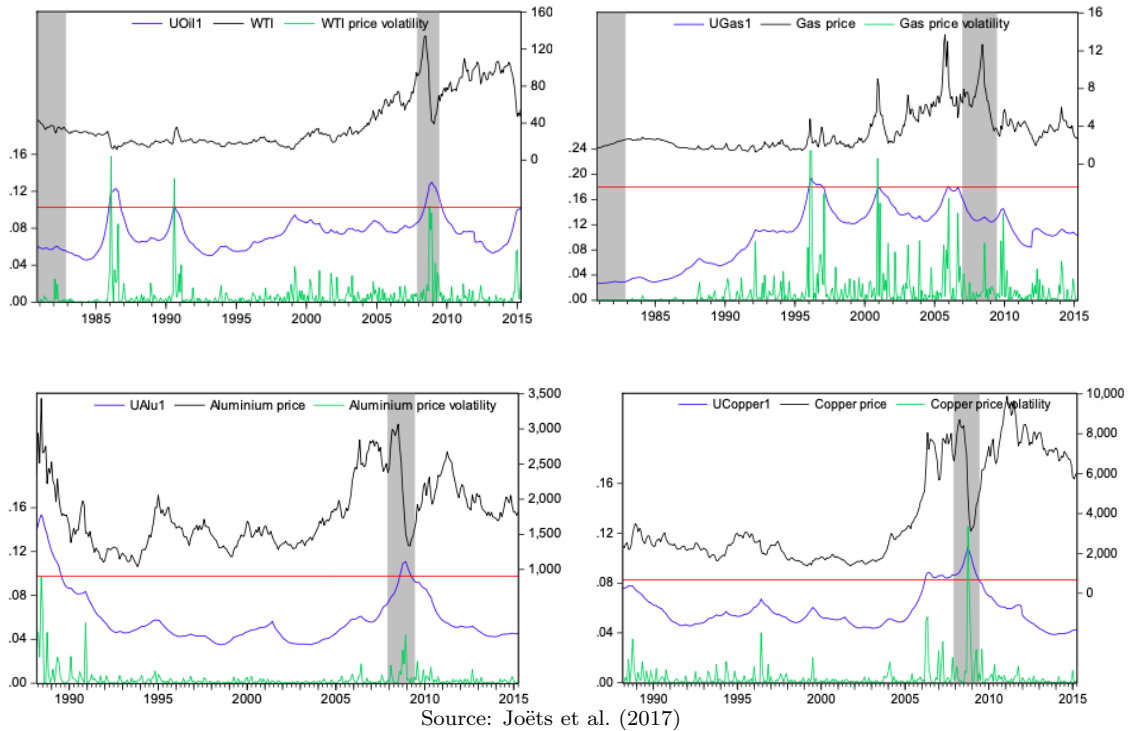
2.4 Global uncertainty

We can conclude from the analysis of the above measures of uncertainty that they are all unidimensional. Therefore, two possible methods could be used to combine various indices to yield a global uncertainty measure. First, a principal component analysis (PCA) that determines a common component to positively correlated individual measures of uncertainty. For instance, Haddow et al. (2013) and Larsen (2021) have respectively used this methodology to develop global uncertainty indices for the UK and Norway. Second, Himounet (2022) conducted the same analysis to identify a global measure of uncertainty for the US. He relied on a dynamic factor model (DFM) by Doz et al. (2012) that consists of disentangling two orthogonal components across variables: idiosyncratic and common (or latent) factors. Charles et al. (2018) used the DFM framework to construct a global uncertainty index for the US based on six individual uncertainty measures: the VIX, the economic policy uncertainty index developed by Baker et al. (2016), the macroeconomic uncertainty index proposed by Jurado et al. (2015), the measure of dispersion constructed by Bachmann et al. (2013), the corporate bond spreads, and the financial uncertainty index proposed by Ludvigson et al. (2021).

In summary, this section reviews different approaches to constructing an uncertainty measure according to its source. Thus, three major sources of uncertainty can be identified: financial, macroeconomic and economic policy. However, uncertainty in commodity markets remains less explored in the literature although major commodities are strongly related to the global business cycle. This research perspective requires a particularly in-depth analysis of commodity markets. Therefore, our dissertation builds on the idea developed in the renowned investigations of Joëts et al. (2017) and Joëts et al. (2018), emphasizing macroeconomic uncertainty, in addition to supply and demand shocks, as another key channel through which economic fundamentals impact commodity prices. By way of illustration, the figure 3 below is extracted from the work of Joëts et al. (2017) and it depicts the evolution of price uncertainty in energy (oil and gas) and industry (aluminum and copper) markets

at the 1-month horizon (blue line), along with the evolution of the corresponding prices (black line) and volatility (green line). The horizontal red line represents a 10% significance threshold for commodity-related uncertainty series. The authors point out that the coincidence between the vertical gray bands and commodity price uncertainty illustrates the transmission from macroeconomic uncertainty to commodity market uncertainty, as both events occur in the same period. Otherwise, each market reports some specific individual characteristics between periods of volatility and heightened uncertainty. Nonetheless, we note a common significant spike of price uncertainty (while volatility is below the horizontal red line) in oil, copper and aluminum markets during the global financial crisis in 2008. Over this period, the uncertainty and volatility nexus is more apparent in the oil and copper markets. Therefore, the macroeconomic uncertainty-induced commodity price uncertainty leads to the resurgence of volatility changes.

Figure 3: **Uncertainty versus Volatility in prices of oil, gas, copper and aluminum.**



Notes: This figure plots both uncertainty (blue line) and volatility (green line) scaled on the left axis along with prices (black line) scaled on the right axis for energy (oil and gas) and industrial metals (copper and aluminum). The horizontal bar indicates a 10% significance for price uncertainty. Grey bands represent recessionary episodes.

This thesis focuses on the insight of price uncertainty in commodity markets. In accordance with Joëts et al. (2017) and Joëts et al. (2018), we rely on the predictability-based approach of Jurado et al. (2015) as a suitable measurement of commodity price uncertainty. Then, we conduct empirical investigations on determinants of commodity price uncertainty. We summarize the main parts of this work in the following paragraphs.

3 Thesis outline

This thesis intends to contribute empirically to the ongoing discussion about price uncertainty in commodity markets and its drivers. In addition, it aims to provide further insightful policy recommendations. The thesis is structured in three chapters, each of which corresponds to a research question related to a specific driver of commodity price uncertainty. It should be noted that, although the chapters are self-contained and can be read individually, they are also related to each other. Specifically, while the first chapter discusses the macro-financial driver, the second chapter analyzes the economic policy driver of uncertainty among commodity markets. The third chapter pays particular attention to one aspect of the last factor, that of energy and environment policy and the implications for fossil energy markets.

3.1 Chapter 1: Uncertainty diffusion across commodity markets

This chapter is entirely drawn from Cadoret et al. (2022). It has two main objectives: first, to accurately estimate a measure of price uncertainty at the aggregate level for four categories of commodity markets (energy, agriculture, industry, and precious metals), and; second to explore the transmission mechanism of uncertainty between markets. Recently, much of the salient literature that has emerged analyzes commodity price fluctuations in terms of volatility and their comovements in terms of connectedness or spillover effects (Du et al., 2011, Arouri et al., 2011, Silvennoinen and Thorp, 2013, Mensi et al., 2013, Diebold et al., 2017, Barbaglia et al., 2020). In general, the major findings of these studies highlight volatility transmission between the energy, metals, agricultural commodities and stock market due to the reinforcement of financial integration since the early 2000s. Yet, more interesting are commodity price fluctuations that arise during periods of uncertainty in economic

and political events. This justifies the rationale behind the use of commodity price uncertainty instead of commodity price volatility, especially since uncertainty measures the unexpected variation in commodity price, while volatility is the expected variation of commodity price (Balli et al., 2019). The question of uncertainty has returned to the chessboard with the 2007-2009 global financial crisis that raised the question of whether economic and financial uncertainty may explain unpredictable components of commodity prices. Therefore, this chapter lays the groundwork for the predictability-based approach that we use to construct price uncertainty in commodity markets. In this chapter, we contribute to the literature on commodity price fluctuations in two ways: first, we develop individual measures of price uncertainty in numerous commodity markets based on the volatility of price forecasting error. Then, these are used to compute an aggregate measure of price uncertainty by sector of commodities. Our estimated commodity price uncertainties show evidence of being leading indicators of uncertainty rather than volatility in commodity markets; second, we look at the intersectoral diffusion of uncertainty shocks and the underlying mechanisms.

To achieve our goals, we consider a dataset of monthly commodity prices collected from the World Bank website. We classify commodities into four main groups: energy (oil, gas, coal), agriculture (cocoa, maize, lumber, coffee, cotton, soybeans, sugar, and wheat), industry (aluminum, lead, tin, copper, nickel, zinc, and iron), and precious metals (gold, silver, platinum). From these data, we construct a monthly price uncertainty measure at a given horizon for each market using a moving average stochastic volatility (MASV) model on price forecasting error over the period January 1995 to December 2018. We then construct an aggregate measure of price uncertainty per group of commodities. Finally, we perform an analysis of the uncertainty diffusion between groups of commodities based on generalized impulse response functions (GIRFs) of a vector autoregressive (VAR) model.

The results of our empirical investigation indicate a two-way uncertainty transmission between each pairwise market combination of energy, agriculture and industry. Meanwhile, the precious metals market is insensitive to other markets' uncertainty shocks, confirming its well-identified safe haven property, especially during unfavorable economic events. In addition, we notice that the uncertainty transfer does not only depend on specific links across markets but also on a common latent macroeconomic factor that drives the "excess comovement" mechanism as pointed out previously Pindyck and Rotemberg (1990). Another interesting finding

of this chapter is the identification of industry uncertainty as a common receiver factor of uncertainty, which ensures the uncertainty diffusion channel between heterogeneous commodity markets. To extensively examine this finding, a comparative analysis was conducted between our constructed industry uncertainty and the famous macro-financial uncertainty developed by Jurado et al. (2015). As a result, it appears that industry uncertainty is a proxy for macro-financial uncertainty with respect to the evolutionary dynamics and contributions to other commodity market shocks.

Highly motivated by the contribution of this chapter, which concludes on the macro-financial driver of uncertainty in commodity markets, we take our investigation to a disaggregated level of oil and copper markets to explore a second driver of commodity price uncertainty in an empirical framework widely developed in the literature.

3.2 Chapter 2: Uncertainty in oil and copper prices: Does the Economic Policy Uncertainty matter?

This chapter is an extended version of Minlend (2022) and aims to assess whether economic policy uncertainty could serve as a driver of commodity price uncertainty in a supply-demand identification model. We restricted our study to the oil and copper markets because the empirical framework suits them better. Moreover, as reported in the first chapter, oil and copper are the most representative commodities in the energy and industry sectors. The bulk of studies in the literature argue that demand and supply shocks, known as macroeconomic fundamentals, are responsible for great fluctuations in commodity prices (Kilian, 2009, Pedersen, 2019, Cross et al., 2020). However, the literature has not sufficiently examined the impact of economic policy uncertainty, which has attracted interest during the last decade. According to Baker et al. (2016), the EPU describes economic policy uncertainty as: *"uncertainty about who will make economic policy decisions, what economic policy actions will be undertaken and when, and the economic effects of policy actions (or inactions) – including uncertainties related to the economic ramifications of 'non-economic' policy matters, e.g. military actions."* Relying on this definition, authors have developed a news-based methodology to construct a monthly measure of EPU for the United States (US) from a list of newspaper articles discussing topics on Economy (E), Policy (P) and Uncertainty (U). The robustness of their analysis has been acknowl-

edged through the popular use of their measure in many research studies. As far as we are concerned, our specific contribution is to appraise the implications of the EPU on the oil and copper markets in an endogenous empirical framework.⁶

Our empirical strategy relies on a structural vector autoregressive (SVAR) model with recursive short-run restrictions for each commodity market. The model specification includes each market's specific variable (commodity supply) and common variables (aggregate demand, EPU, copper price uncertainty, and oil price uncertainty). Due to differences in data availability, the estimation covers the period from March 1985 to March 2020 for the oil market, and from January 1997 to August 2018 for the copper market.

Our results indicate that a positive EPU shock significantly increases price uncertainty in both the oil and copper markets. The effect is more marked and persistent in the oil market. Our model also implicitly validates a hypothesis stemming from the conclusion of the first chapter about the spillover effect of copper price uncertainty on the oil market. Furthermore, the highest share of EPU shocks to forecasting shocks in oil price uncertainty and copper price uncertainty is about 11% and 6% at a 3-month horizon, respectively. Regarding the effects of traditional factors, we note that a negative oil supply shock tends to increase oil price uncertainty, whereas a positive demand shock reduces oil price uncertainty. Likewise, when analyzing the copper market, we observe that copper price uncertainty is mainly driven by aggregate demand with a long-lasting effect.

In the next chapter, we are specifically interested in a particular aspect of economic policy, namely the energy and environment policy implemented in the European Union (EU). The EU is one of the world's largest importers of fossil energy, as reported by the Eurostat database on fossil energy import dependency in 2020: 96.96% for oil, 83.6% for gas, and 34.8% for coal. Based on this observation, this chapter endeavors to tackle the potential effects of such a policy on fossil energy price dynamics.

⁶The news-based EPU of Baker et al. (2016) is a composite indicator that encompasses categorical sub-indices related to topics discussed in newspapers, such as monetary policy, fiscal policy, taxation, government spending, healthcare, national security, entitlement programs, regulation, financial regulation, trade policy, sovereign debt and currency crises.

3.3 Chapter 3: Does the European Low-Carbon Policy impact price uncertainty in fossil energy markets?

This chapter questions whether European energy-related environmental policy influences price uncertainty in fossil energy markets. So far, this insightful idea has not been fully tested empirically. However, to the best of our knowledge, what might come close to our perspective are a few studies pointing out a significant correlation between the OECD’s environmental policy stringency indicator (as well as other proxies of environmental policies) and energy prices indices at the country or industry levels (Sato et al., 2015, Garsous and Kozluk, 2017). In the same vein, Dlugosch and Kozluk (2017) extend this analysis to business investment by linking part of the variation in energy prices to environmental policies. They find evidence that the negative effects of rising energy prices on investment can largely be attributed to tightening upstream environmental policies through their impact on energy prices. According to these studies, the underlying mechanism could be that a large share of the manufacturing sector’s CO_2 emissions is indirect, via energy consumption. Consequently, fluctuations in energy prices will reflect, inter alia, both market-based upstream policies (e.g. carbon tax) and control regulations (e.g. air pollution norms) relevant to energy, and the firm’s exposure to a tightening of climate mitigation policies will to a large extent be via the higher energy prices paid. As far as we are concerned, our analysis on the nexus between European energy-related environmental policy and price uncertainty in fossil energy markets revolves around two main points, each contributing to a particular strand of the literature. First, we build on studies that develop news-based indicators about US environmental policy (Noailly et al., 2021, 2022) and US climate policy (Gavriilidis, 2021). Next, we propose two composite indicators: (i) a news-based composite indicator with two underlying factors: uncertainty on the global environment and the regulations on energy and environment as reflected in the press, and (ii) a structural law-based composite indicator that is more specific to European energy and environmental policy, which emphasizes the legislative cycle. Second, following numerous empirical studies (Baker et al., 2016, Lemoine, 2017, Dorsey, 2019, Sen and von Schickfus, 2020), we investigate the impacts of our constructed indices on price uncertainty dynamics in fossil energy markets.

To construct our monthly indices, this chapter required a textual analysis methodology relying on an unsupervised machine learning algorithm called Latent

Dirichlet Allocation (LDA) developed by Blei et al. (2003). Applied separately to both news and law datasets, this method yields two indices, accordingly. A side-by-side analysis of the news-based and law-based indices shows periods of comovements during salient events in the history of EU energy and environmental policy. In addition, the cross-correlation function identifies a short-run significant unidirectional relation from the law-based index to the news-based index. We then estimate a 5-factor Bayesian vector autoregressive (BVAR) model to evaluate the effects on price uncertainty in fossil energy markets. In our modeling, we include five variables: law-based index, news-based index, oil price uncertainty, gas price uncertainty, and coal price uncertainty. The estimation spans the period from March 1997 to May 2021.

Our main results suggest that an increase in the news-based composite indicator has a significant mixed effect on oil and coal price uncertainty. In particular, there is a positive effect from the global environment uncertainty component, which translates into a slight short-term increase in price uncertainty in these markets. This increase is followed by a negative effect of the regulatory component on price uncertainty. In this sense, this mixed effect reflects the fact that the effectiveness of energy and environmental policy on price dynamics remains unchanged in a situation of uncertainty about the overall context. However, we observe that the gas market is dominated by the second effect because the downward dynamics of price uncertainty is more premature and lasting than in other markets. By analogy, an increase in the law-based composite indicator leads to a significant decrease in oil and gas price uncertainty. While the negative effect is more persistent in the coal market, it is shorter in the oil market. This result indicates that the law-based composite indicator plays a significant stabilizing role in these markets, but not in the gas market. However, a more comprehensive analysis shows that gas price uncertainty contracts substantially after environmental regulations. Moreover, following supplementary analysis at the price level, in contrast to the price uncertainty level, our overall finding shows that only the news-based index contributes to reducing prices across markets. This result supposes that markets anticipate regulations and consequently adjust the prices down. In conclusion, this chapter considers the idea that European low-carbon policy exerts different pressures in terms of maturity on price uncertainty in fossil energy markets.

This dissertation is structured as follows: for each chapter, the body of the chapter is first presented, followed by a dedicated appendix. Then, the dissertation

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proceeds to the next chapter until the general conclusion. Each chapter and each appendix contains a reference section with the related bibliography.

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Chapter 1

Uncertainty diffusion across commodity markets¹

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Summary

While numerous studies investigate volatility transmission across commodity markets, particularly oil and agricultural markets, uncertainty diffusion across commodity markets remains absent from the literature. This circumstance is primarily related to the lack of appropriate measures of commodity price uncertainty, which differs from volatility. This chapter focuses on measuring commodity price uncertainty and how it is transferred from one commodity market to another. Our contributions are twofold. (i) We construct an aggregate predictability-based measure of uncertainty for each group of commodity markets and different maturities, and (ii) we analyze uncertainty diffusion across different commodity markets using a vector autoregressive model. Our findings clearly demonstrate a bi-causal uncertainty transfer between agriculture, energy, and industrial markets, excluding precious metals markets. Additionally, the industrial commodity market is assumed to be the transmission channel of commodity uncertainty spread, given its close link with global economic activity. Notably, we validate the efficacy of using industrial uncertainty as a proxy for macroeconomic uncertainty. Finally, our confirmation of precious metals' insensitivity to other markets' shocks reinforces its nature as a safe haven.

Classification JEL: Q02, C32, E32.

Keywords: Commodity uncertainty, vector autoregressive model, macroeconomic uncertainty.

1 Introduction

The new landscape of commodity markets shaped by the financialization phenomenon is characterized by high price volatility.² Given the centrality of commodities in human activity, this ubiquitous volatility changes economic agents' behavior and has consequences on economic activity. Additionally, the pandemic, which affected the global economic context, led to the resurgence of an already uncertain environment on international markets; particularly in the commodity markets that are of interest to this chapter. Kyle and Xiong (2001) and the United Nations Conference on Trade and Development in 2009 detail the implications of the rising use of commodities assets amid higher volatility and the correlation between commodity prices. This suggests that countries' commodity-based financial indices are linked, and commodity price sensitivity is subject to international market conditions, exhibiting a contagious phenomenon. In a deeper way, the financialization of commodities since 2004 has led to more integrated markets, including the synergy of energy, industrial, agriculture, and precious metals commodities. According to Diebold et al. (2017), energy market has higher degree of financialization so that its shocks are transmitted to other commodity groups. The degree of integration has considerably increased between energy, metals and agriculture commodity markets (Tang and Xiong, 2012, Nazlioglu et al., 2013, Yang et al., 2021). However, the linkages including spillover effects and transmission mechanism among commodity prices are more complex and require further explorations.

This chapter considers uncertainty shocks as an important driving factor of the dynamic connectedness between commodity markets. Uncertainty shocks on commodity and stock markets are diverse and can arise from the economic uncertainty (Güngör and Taştan, 2021, Huang et al., 2021, Wen et al., 2022), health crisis (Jeris and Nath, 2021) or geopolitical events (Gong and Xu, 2022, Wang et al., 2022). In recent years, this last source of uncertainty shocks appears to be crucial in commodity interconnections since geopolitical threatens are more frequent and tend to occur in areas rich in energy and mineral resources. For instance, the war between Ukraine and Russia is a clear illustration. In fact, Russia being one of the world's largest producers of energy and food grains, the incident causes the prices of crude oil (as

²Commodity financialization is defined as the increase in the volume of transactions on financial instruments, such as "Futures" contracts on commodity markets. For more details about see Silvennoinen and Thorp (2013), Chari and Christiano (2017).

well as its by-products), natural gas, wheat and safe-havens assets (such as gold and silver) to rise sharply. Moreover, geopolitical tensions often imply adjustments and shifts in government policies, which generate broad implications for investors' sentiment on both commodity and financial markets (Asai et al., 2020). Thereby, assets pricing take into account investors' inflation expectations under time-frequency dynamics of volatility spillovers among commodity markets (Aybar et al., 2020). Therefore, extreme events resulting from geopolitical risk favor investor panic under uncertainty, that afterwards drive anomalous market volatility and ultimately affects the long-term stability of commodity markets (Tiwari et al., 2021). Commodity markets are inherently volatile because they are purely governed by expectations wherein agents are unable to determine the market equilibrium in advance. Given that economic activity is highly dependent on commodities, this context leads to reexamining the sufficiency of the common reliance on commodity price volatility when analyzing economic recessions.

Existing research investigates the concepts of volatility and uncertainty in an interchangeable manner, and volatility-based uncertainty measures have recently emerged (such as the Generalized Autoregressive Conditional Heteroscedasticity (GARCH) models, implied volatility index). Since Jurado et al. (2015) proposed a definition of uncertainty as the volatility of an unpredictable disturbance on some macroeconomic and financial factors, this subsequently created a major distinction in modeling volatility and uncertainty in various empirical works. Likewise, relying on this distinction when investigating the oil market, Joëts et al. (2018) conclude that volatility and uncertainty in prices are not alike. Diebold and Kilian (2001) proposed a predictability approach on economic variables that contributes more to uncovering agents' decision-making process than examining a simple dispersion degree on some interest variables. Since volatility and uncertainty are conceptually different, it might be erroneous to claim that volatility spillover is roughly equivalent to uncertainty diffusion. Commodity price volatility may or may not generate uncertainty, which could have macroeconomic implications. This assertion is not only related to the clarification regarding the distinction between volatility and uncertainty, but also confirmed by the empirical literature, which has widely investigated price volatility spillovers among commodity markets; oil and agriculture markets in particular (Busse et al., 2010, Zhang et al., 2010, Serra, 2011, Serra et al., 2011, Hassouneh et al., 2012, Kristoufek et al., 2012).

This chapter aims at exploring a new insight of commodity markets' instability.

We focus on the diffusion of unpredictable shocks (such as COVID-19 outbreak or Ukraine-Russia war), involving markets' disturbances. Therefore, this chapter goes beyond the empirical literature on volatility in two ways: First, we propose a practical measure of commodity price uncertainty based on predictability, as opposed to volatility. For that purpose, we develop a price uncertainty aggregate measure for 21 commodity markets using a moving average stochastic volatility model on price forecasting error.³ By employing this perspective, we note that unlike the volatility measure, which relies on a backward-looking approach, the uncertainty measure includes agents' anticipation through forecasting based on financial or economic events (Joëts et al., 2017). In this sense, measuring uncertainty looks forward at financial or economic disturbances. Second, we emphasize the transmission mechanism of uncertainty shocks across different commodity markets by examining impulse response functions through a multivariate time-series model. We also present macroeconomic perspectives of uncertainty transmission mechanisms across markets.

Our investigation uncovers two notable findings. (i) The predictability-based uncertainty indicator outperforms the volatility indicator when considering the 2007-2008 financial crisis, suggesting that reasoning in terms of uncertainty, rather than volatility, could present a tool for investors for gauging economic expectations. (ii) A bi-causal effect is evident between agriculture, energy, and industrial markets' uncertainties, with the exception of precious metals markets. Moreover, we show that industry uncertainty could serve as a proxy for macroeconomic uncertainty, as it functions similarly to global demand uncertainty that ensures uncertainty diffusion across heterogeneous markets. The latter aspect is more observable in the energy market during economic turmoil than in other markets. In the same vein, one might argue that industry uncertainty as a proxy for macroeconomic uncertainty, captures the geopolitical uncertainty. It is notable that these results can be considered original, as such an aggregate measure of uncertainty in commodity markets has not yet been explored, including the resultant cross-market uncertainty transmission. Our outcomes shed light on some implications for both investors and policymakers. On the one hand, this chapter provides investors an at-hand instrument to appraise price uncertainty in various commodity markets, which may give perspective for the development of hedging strategies to rule out, as much as possible, uncertainty

³The aggregate measure of uncertainty is computed using weights provided by World Bank data.

spillover effects across commodity markets. On the other hand, when formulating effective macroeconomic policies, policymakers should consider heterogeneous uncertainty transfer effects between markets. Notably, actions to promote energy and agriculture security in an economic cooperation framework could help reducing, at the country level, uncertainty spillover effects on markets with strong diffusion (energy, agriculture, and industry).

The remainder of the chapter is organized into five sections. Section 2 presents discussion of volatility versus uncertainty. Section 3 describes the construction of our aggregate uncertainty index for commodity markets. Section 4 presents the empirical strategy and results on commodity uncertainty shock transmission. Section 5 examines industry uncertainty as a potential proxy of macroeconomic uncertainty, presenting a vehicle through which the latter could spill over into other markets. Section 6 concludes the chapter.

2 Discussion on volatility versus uncertainty

This section presents some background on the concepts of volatility (or risk) and uncertainty in the economic literature for preliminary orientation.

2.1 Theoretical debate

From the microeconomic perspective, it is necessary to reference Knight (1921), the first author to highlight the distinction between risk (commonly volatility) and uncertainty, which then entered the lexicon of economics and decision theory. The difference between risk and uncertainty is generally interpreted as being related to whether agents can be assumed to function as if they possess well-defined probabilities for possible outcomes. If so, the situation is one of risk; if not, it is one of uncertainty. While the distinction between risk and uncertainty, so defined, is often encountered in the literature, until recently its role enables some economists (particularly those working in the neoclassical tradition) to rule out uncertainty (Hirshleifer, 1970). Indeed, the main reasons for doing so are found in the modern theory of choice wherein subjective probabilities are derived from agents' orderings over lotteries; therefore, most economists have more willingness to do this with the assumption of consistent choice.

In the neoclassical macroeconomics literature, the debate on risk-uncertainty

has resurfaced. In his famous critique, Lucas (1976) points out in a risk-uncertainty environment a discretionary regime of the monetary policy makes it difficult for private agents to understand the policymakers' incentives and form their expectations accordingly. In that sense, agents' behavior adapts to economic policies structural changes. Keynes also sets out exactly the distinction commonly assigned to Knight (1921). Whatever the merits of this contention, it has acquired considerable currency in recent years, leading to renewed interest in the risk-uncertainty distinction. LeRoy and Singell (1987) argue that the common interpretation of Knight's risk-uncertainty distinction concerning whether agents possess subjective probabilities constitutes a misreading of Knight. On the contrary, Knight clearly shared the modern view that agents can always be assumed to act as if they possess subjective probabilities, even in the case of uncertainty. Knight's theory refers to risk situations where insurance markets exist and uncertainty situations where they do not. In that sense, uncertainty means a situation in which insurance markets collapse because of moral hazard and adverse selection. This latter view of uncertainty suggests a striking anticipation of the modern treatment of market failure. The economic outlook we can cast on this distinction is relative to entrepreneurship, as highlighted by LeRoy and Singell (1987). According to these authors, Knight's risk, uncertainty, and profit are properly read as an analysis of the consequences of entrepreneurship being uninsurable for economic institutions and economic theory. The central assumption of Knight's risk, uncertainty, and profit is the presence or absence of insurance markets and not necessarily the applicability or inapplicability of probabilistic calculus, as clearly established.

The macroeconomic perspective presents a similar interpretation to the Knightian risk approach in the sense that volatility (risk) measures the extent to which a macroeconomic aggregate fluctuates around its expected long-term value. Hence, economic uncertainty can be defined as a circumstance wherein the economic future is unreadable, agents' behavior becomes unpredictable, and projects become unreliable. Based on this definition, uncertainty is related to a lack of reliable forecasting of interest variables. Therefore, following this reasoning, volatility cannot always be accompanied by uncertainty, as part of the volatility can be captured using modern forecasting models (Joëts et al., 2018).

2.2 Empirical debate

To the best of our knowledge, the literature predominantly focuses on volatility and uncertainty measurement.

Uncertainty has a crucial role in many studies in terms of sources, measurement, potential effect on agents' behavior (Dixit, 1989), and economic activity (Bloom et al., 2007, Bloom, 2009, Bachmann et al., 2013, Jurado et al., 2015).⁴ Among studies regarding the real implications of uncertainty, Bloom (2009) and Bloom et al. (2018) were the first to highlight uncertainty as the main driver of business cycle fluctuations and point out during the United States (US) recession that uncertainty goes up by almost 50% on average. Likewise, these uncertainty shocks lead to a significant temporary fall in output and productivity.

Uncertainty is tough to quantify since it is an intrinsically unobservable concept to be measured. The literature on uncertainty is primarily based on proxies due to the challenging nature of accurately measuring uncertainty. Therefore, two approaches of observable and unobservable (latent) uncertainty measures are used. Observable measures are primarily volatility-based and rely on proxies using time-series variations of observable economic and financial indicators. Among others, we note cross-sectional dispersion of firms, industry earnings, or productivity (Bloom, 2009, Bloom et al., 2018)), and the implied volatility index also known as VIX (Bloom, 2009).⁵ In the same vein, several measures have also been developed, including the variance risk premium (Zhou, 2018, Bali and Zhou, 2016), consumers' perceived uncertainty from survey data (Leduc and Liu, 2016), and the volatility of fiscal instruments estimated under time-varying volatility (Fernández-Villaverde et al., 2015).⁶ Additionally, there are previous newspapers-based uncertainty measures, such as economic policy uncertainty (Brogaard and Detzel, 2015, Baker et al.,

⁴Bloom (2014) and Baker et al. (2014) provide large reviews of literature regarding uncertainty shocks.

⁵The VIX is a stock market-based option-implied volatility that can be decomposed into two components, a proxy of the risk aversion and expected stock market volatility. VIX represents the option-implied expected volatility of the S&P500 index with a horizon of 30 calendar days (22 trading days). It is an implied or "risk-neutral" volatility, as opposed to actual or physical expected volatility. If we consider a discrete state economy, physical volatility will intuitively use actual state probabilities to arrive at the physical expected volatility, whereas risk-neutral volatility would make use of probabilities adjusted for the pricing of risk.

⁶Several Studies of uncertainty shocks use either VAR models or Dynamic Stochastic General Equilibrium (DSGE) models (Bloom et al., 2018, Leduc and Liu, 2016).

2016, Azqueta-Gavaldón, 2017) and the geopolitical risk (Caldara and Iacoviello, 2020).

Latent or unobservable measures rely on the approach proposed by Jurado et al. (2015) for which fluctuations in observable economic indicators may vary for several reasons that are not imputed to uncertainty; hence, they define uncertainty as the volatility of an unforecastable component of a large group of macroeconomic and financial indicators. This latter approach provides predictability-based uncertainty measures (Scotti, 2016, Jurado et al., 2015, Rossi and Sekhposyan, 2015, Ludvigson et al., 2015, Bachmann et al., 2013) that are forecast-dependent.

All the measures presented above consider at least three sources of uncertainty that include macroeconomics, financial markets, and economic policy. Among studies investigating the impact of each source of uncertainty on the economic activity, Jurado et al. (2015) find that macroeconomic uncertainty shock has a sustained and adverse effect on industrial production and employment, as opposed to implied volatility or economic policy-based uncertainty. Other studies investigate the possibility of an aggregate measure of uncertainty based on several proxies: Haddow et al. (2013) use principal component analysis to extract an uncertainty index based on four indicators (financial and survey data), and Charles et al. (2018) use a dynamic factor model (Doz et al., 2012) to construct an uncertainty composite index (UCI). The former study is implemented for the UK in the 1985-2013 period. The latter study, conducted for the US, includes economic policy uncertainty source along with six uncertainty proxies used in the literature, including two macroeconomic and financial uncertainty factors based on unpredictability proposed by Jurado et al. (2015) and Ludvigson et al. (2015), a measure of microeconomic uncertainty with the forecast disagreement index proposed by Bachmann et al. (2013), the "former" implied volatility index, corporate bond spreads, and an index of economic policy uncertainty proposed by Baker et al. (2016).⁷ Charles et al. (2018) compared the sensitivity of macroeconomic variables (S&P500 stock market index, inflation, nominal wage, manufacturing production, employment, hours worked, and federal fund rate) to the UCI and six other individual standard proxies of uncertainty from VAR models. Following their results, an increase in the UCI leads to a significant drop in all macroeconomic variables, and only uncertainty measures based on pre-

⁷Baker et al. (2016) construct an economic policy-related uncertainty measure based on newspaper analysis and its impact on financial and macroeconomic variables.

dictability and corporate bond spreads are important, but not dominant, sources of macroeconomic variables' volatility.

Finally, the previous literature presents different sources and measures of uncertainty. In this chapter, we are interested in the macroeconomic side of uncertainty in commodity markets. To this end, it is beneficial to use Jurado et al. (2015)'s idea of predictability and the appropriate methodology corresponding to commodity markets' characteristics. The following section presents the construction of the aggregate uncertainty index in commodity markets.

3 Commodity markets' aggregate uncertainty index

3.1 Data description

Our sample consists of 21 world commodity markets classified into four main groups of energy, industry, agriculture, and precious metals. Commodity price data for all markets are extracted on a monthly frequency from the World Bank website. The period ranges from January 1995 to December 2018 (see Table A.1 in Appendix A.1).⁸

Figure A.1 (in Appendix A.3) illustrates the evolution of agricultural commodity prices. An upward trend occurs in the early 2000s for most agricultural markets (cocoa, maize, lumber, coffee, soybeans, sugar, cotton, and wheat). Figure A.2 (in Appendix A.3) presents the price dynamic of industrial commodities (aluminum, lead, tin, copper, nickel, zinc, and iron). These markets also experienced a significant upward trend in the early 2000s. Historically, China's entry into the World Trade Organization could justify this price increase. During that period, driven by the industrial production above 10%, a world growth cycle led to economic growth of 4.5%. Conversely, during the 2008 economic crisis, most industrial commodities experienced a considerable drop in prices before a slight rebound after the crisis. Oil, gas, and coal represent our energy markets. At first glance, Figure A.3 (in Appendix A.3) presents a bullish trend from the 2000s before slight drops in 2008, in

⁸World Bank Commodity Markets: Commodity-prices-pinksheets. The data are seasonally adjusted using a deterministic log-additive decomposition method with values close to those obtained with seasonal-trend decomposition using LOESS.

late 2014, and early 2015 for oil and gas. The fall in coal price was more premature in 2011-2012. Finally, gold, platinum, and silver markets represent the precious metals markets. Figure A.4 (in Appendix A.3) shows gold and platinum series with a steady upward trend in the early 2000s. These prices slow down after 2011. Note that these markets have particular specificities related to their components that are safe havens. Due to the stationarity issue, we log-differentiate the seasonally adjusted series at the first order to obtain returns. These data are used to obtain the uncertainty index, as described in the following subsection.

3.2 Methodology

The predictability-based uncertainty of Jurado et al. (2015) is defined as the conditional volatility of an unpredictable disturbance. In the same vein, we construct our aggregate uncertainty measure in commodity markets using the data described and based on the concept of predictability. Following Joëts et al. (2017), we compute the uncertainty measure of each market in three steps as follows:

(i) A fixed rolling window estimation of a AR(1) process for each stationary series of commodity price returns. Formally, let's consider Com_t denoting the time series of the individual commodity price returns.

(ii) The previous step allows, for each rolling window estimation, to extract a one-step ahead out-of-sample forecast $E(Com_{t+1}|I_t)$ defined as the expectation of the commodity price returns with respect to the information available at time t . Also, the associated forecast error w_{t+1} is given by:

$$w_{t+1} = Com_{t+1} - E(Com_{t+1}|I_t) \quad (1.1)$$

(iii) Estimation of the stochastic conditional volatility of the forecast error.⁹ Unlike recent empirical studies using AR terms and exogenous predictors to construct oil price uncertainty (Nguyen et al., 2019, Cross et al., 2020), in this chapter, we choose a large number of markets and for homogeneity and methodological convenience, we specify the forecasting model for each commodity market with the AR(1)

⁹In this chapter, we use one-month horizon uncertainty. For interested readers, an uncertainty for each market and different forecast horizon h is available upon request.

process.¹⁰ Note that this final step, referencing Chan and Jeliazkov (2009) and Chan and Hsiao (2014), relies on a moving average stochastic volatility (MASV) model that accounts for the volatility specifications over time and clustering phenomena that remain a characteristic of commodity markets. More specifically, it assumes that the forecast error w_t can be defined by the following equation:

$$w_t = \mu + v_t \quad (1.2)$$

where μ is a constant and represents the mean of the forecast error. The variable v_t is assumed to be serially dependent and follows the MA (q) of the form:

$$v_t = \varepsilon_t + \psi_1 \varepsilon_{t-1} + \dots + \psi_q \varepsilon_{t-q} \quad (1.3)$$

$$h_t = \mu_h + \phi_h (h_{t-1} - \mu_h) + \varsigma_t \quad (1.4)$$

where $\varepsilon_t \sim N(0, e^{h_t})$ and $\varsigma_t \sim N(0, \sigma_h^2)$ are independent of each other.¹¹ The variable h_t is the log-volatility of ε_t and is assumed to follow an AR (1) process, μ_h is the level of the log-variance and $|\phi_h| < 1$ represents the persistence of the log-variance. Note that this variance is not allowed to vary unrestrictedly with time. The feature of this model fundamentally differs from GARCH-type models where the time-varying volatility is assumed to follow a deterministic, rather than stochastic, evolution. The stochastic volatility model is thus conveniently expressed in hierarchical form and is center-parameterized. According to Chan and Hsiao (2014), under the assumption of moving average extension, the conditional variance of the series w_t is given by:

$$V(w_t | \mu, \psi, h) = e^{h_t} + \psi_1^2 e^{h_{t-1}} + \dots + \psi_q^2 e^{h_{t-q}} \quad (1.5)$$

The estimates of this stochastic volatility make it possible to capture both moving average and log-volatility effects, as shown in equations (1.3) and (1.4), respec-

¹⁰The forecasting model could also be improved for each individual market as proposed later in the chapter 2.

¹¹ $\varepsilon_0 = \varepsilon_1 = \dots = \varepsilon_{-q+1} = 0$. The roots of the characteristic polynomial associated with the coefficients of the MA process, $\psi = (\psi_1, \dots, \psi_q)'$ are outside the unit circle, which ensures the stability of the model.

tively.¹² From equation (1.5), an aggregate index of uncertainty for each group of commodity markets (agriculture, industry, energy, and precious metals) is obtained by computing a simple weighted average of individual price uncertainties noted as $V(w_t|\mu, \psi, h_t) = U_{i,h}$. Formally, we note $U_{m,h}$ our aggregate uncertainty index defined as follows:

$$U_{m,h} = \sum_{i=1}^n \alpha_i U_{i,h} \quad (1.6)$$

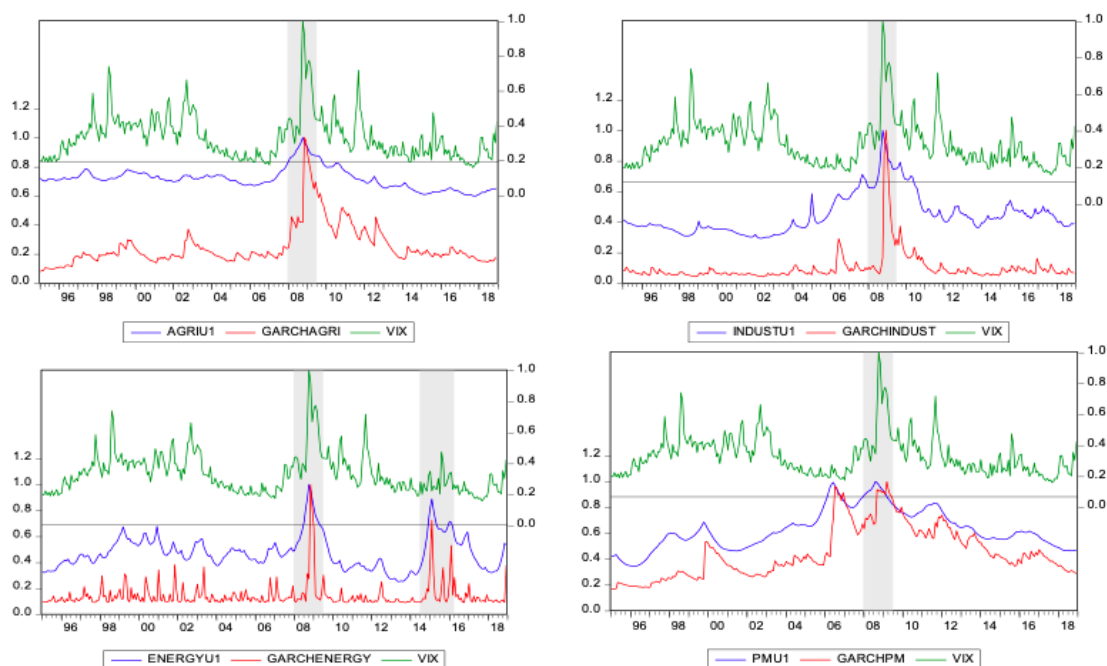
where m indicates a given group of commodity markets, i an individual commodity market that belongs to group m , and h the horizon. Notice that α_i represents the weight of the individual market i .¹³

For each group of commodity markets, Figure 1.1 presents the one-month commodity price uncertainty (blue line) we computed above in comparison to GARCH (1,1) volatility measure (red line), and VIX (green line). Simultaneous presentation of these measures allows us to emphasize the relevance of our predictability-based measure of uncertainty with respect to other indicators based on volatility. Table A.2 (in Appendix A.1) gives an overview of variables' labels and description.¹⁴

¹²See Chan and Jeliaskov (2009) and Chan and Hsiao (2013) The MATLAB code used to estimate the MASV model is freely available from Joshua Chan's website. For each variable, we obtain 20000 loops or draws from the posterior distribution using the Gibbs sampler after a burn-in period of 1000.

¹³Markets weights are available on the World Bank Commodity Markets website: Commodity-pricespink sheets.

¹⁴GARCH stands for Generalized Autoregressive Conditional Heteroskedasticity model. For each group of commodity markets, we compute a GARCH (1,1) volatility measure of commodity price returns. In turn, the VIX represents implied volatility.

Figure 1.1: **Uncertainty versus Volatility.**

Note: These figures depict one-month uncertainty, labeled AGRIU1, INDUSTU1, ENERGYU1, and PMU1 for agriculture, industry, energy, and precious metals markets (blue line scaled on the left axis), respectively (Table 2, in Appendix A). The volatility is based on the estimation of a GARCH(1,1) on market groups (red line scaled on the left axis) labeled GARCHAGRI, GARCHINDUST, GARCHENERGY, and GARCHPM. The VIX is the green line scaled on the right axis.

The vertical gray bands correspond to heightened uncertainty episodes that are generally associated with economic turmoil, such as the great recession of 2008. We consider a given period to correspond to an episode of heightened uncertainty for a commodity market when the measure of uncertainty exceeds the horizontal bar that represents 1.65 standard deviation above the unconditional mean of the commodity price uncertainty. During these periods of heightened uncertainty, different measures of uncertainty and volatility have reached a peak; however, the upward slope before the peak began earlier for our measure of uncertainty compared to other measures. This indicates that the predictability-based measure of uncertainty captures the slope a few months earlier economic turmoil episodes, whereas volatility-based measures, such as VIX and GARCH, react a few months later. For instance, analyzing the recent financial crisis, which lasted 19 months (December 2007-June 2009, represented by the gray band) according to the NBER recession dates disclosure, market price volatility (red line) is accompanied by uncertainty (blue line). Agriculture, in-

dustry, and to a lesser extent, energy markets' uncertainties start an upward trend around June 2007 (three months before the crisis), before VIX and GARCH volatility indices (July and August 2008, respectively), reaching their peak in October 2008 at almost the same time as VIX, but two months prior to GARCH. Furthermore, the timing gap is also observable in the precious metals market where the uncertainty upward dynamic begins earlier, reaching a peak in July 2008, along with implied volatility in October 2008, and GARCH in March 2009. Therefore, compared with volatility, predictability-based uncertainty can be considered a leading indicator that reflects investors' expectations and a forthcoming economic turmoil signal at a significant level. This early warning signal of global economic recession indicates the potential negative effects of uncertainty in agricultural, energy, and metals markets on economic activity for a given forecasting horizon, as highlighted by Jurado et al. (2015), Joëts et al. (2017), and Triantafyllou et al. (2019). Moreover, for reasons already discussed in section 1 and emphasized in section 2, it is less surprising that volatility measures seem more unstable before 2008; thereby, it permits the exposure of a clear distinction between patterns of episodes of volatility and uncertainty. While periods of significant uncertainty amplify volatility, periods of high volatility are not necessarily accompanied by heightened uncertainty. Having constructed uncertainty indices, the next consideration is whether interactions between markets' uncertainties exist.¹⁵

4 Uncertainty diffusion within commodity markets

4.1 Empirical strategy

Thus far, the commodity markets analysis has captured the diffusion of volatility, but not uncertainty. Some studies have highlighted volatility diffusion within commodities using either conditional variance or implied volatility measures. For instance, Nazlioglu et al. (2013) conduct an empirical analysis to examine the volatility transmission of oil to common agricultural commodity prices (wheat, corn, soybeans, and sugar). They specified a GARCH model for each market and performed a variance

¹⁵Table A.4 (in appendix A.1) displays the descriptive statistics of uncertainty variables.

causality test analysis for the 2005 pre-crisis and post-crisis period, demonstrating the spillover effects of oil market volatility on the agricultural markets during the 2005 post-crisis period except for sugar. Gozgor et al. (2016) replicate this analysis on the same commodity markets using a GJR-GARCH approach, finding a higher correlation of oil market volatility with the four agricultural markets. Liu et al. (2013) analyze short and long run volatility transmission between crude oil implied volatility and other important volatility indices, including stock market volatility (VIX), the euro/dollar exchange rate volatility index, and the gold price volatility index. They argued that only short run relationships exist among these indices, and oil market volatility is influenced by the other indices in terms of volatility expectations in the oil market becoming sensitive to other markets' volatility shocks when global economic activity is extremely unstable.

This chapter endeavors to fill the literature gap on the issue of uncertainty diffusion between commodity markets. For this purpose, we propose to assess the transmission of one-month (very short term) aggregate uncertainty across markets. Table A.3 (in Appendix A.1) presents the markets' uncertainties correlation matrix and the level of significance. Positive relationships notably arise from the interconnections among markets. For instance, industry and precious metals record the highest correlation coefficient of 72%. To conduct our analysis, we rely on a vector autoregressive (VAR) modeling, which allows us to capture each variable's response to any change in another variable. This property is suitable to capture uncertainty diffusion across commodity markets once a measure of uncertainty is available. The reduced form of the VAR model is defined as follows:

$$U_t = C + \Phi_1 U_{t-1} + \dots + \Phi_p U_{t-p} + D_m + V_t \quad (1.7)$$

where U_t corresponds to a vector of four endogenous variables of uncertainty for each commodity markets' group; namely, the one-month uncertainty in agriculture, energy, industry, and precious metals markets. However, the way we manage the variables' classification order will be presented later. C is a vector of constants, and Φ_p is the matrix of autoregressive coefficients corresponding to a lag p of the system.¹⁶ V_t is the vector of orthogonal error terms. D_m represents time dummies

¹⁶The lag length criteria retained is two, following standard information criteria. We use different lag specifications to test the robustness of our results. The qualitative results of our study are not affected by the choice of the lag specification.

specific to each group of markets and structural breaks that are identified by the Zivot-Andrews unit root test (see Table A.5, in Appendix A.1).¹⁷

To assess the uncertainty diffusion across commodity markets, we use Generalized Impulse Response Functions (GIRFs) to avoid ordering uncertainty variables. Indeed, it seems to be difficult to intuitively determine which uncertainty variable is more exogenous than others to establish the ordering in the Cholesky factorization; therefore, we reference Koop et al. (1996)'s GIRFs using the following equation:

$$GIRF_u(h, I_{t-1}, V_t) = E[U_{t+h}|I_{t-1}, V_t] - E[U_{t+h}|I_{t-1}] \quad (1.8)$$

where I_{t-1} is the information set at time $t - 1$ and V_t is a realization of exogenous shocks (that comes from the vector of the orthogonal error terms). The response of each variable in U_t at the horizon h is computed by simulating the evolution of the model conditionally to the initial condition I_{t-1} and to a given realization V_t . Having described the estimation strategy and the way we capture uncertainty diffusion among markets, we will present the results in the next section.

4.2 Results discussion

In the following GIRFs, a given uncertainty shock in one commodity market is helpful for evaluating how this uncertainty can be transferred to other markets. The explanation of the aggregate uncertainty diffusion mechanism between markets relies on prior identification of main components in each commodity group. We consider the main factors or drivers of aggregate uncertainty in each commodity group as those that register the highest weight. For instance, the crude oil market accounts for 84% of the total share of the aggregate energy market uncertainty and is considered as its leading component.

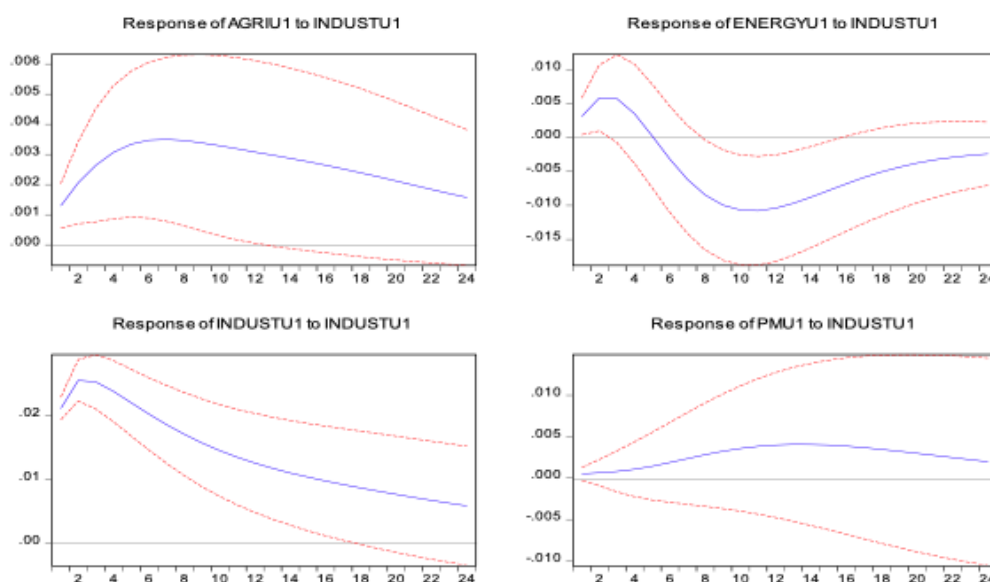
Figure 1.2 presents the transmission of industry uncertainty shock to other markets. The industrial market is strongly represented by copper (38% of the total share), which is one of the most important nonferrous metals in the modern industry.¹⁸ Uncertainty in the industrial market is transmitted to energy and agriculture

¹⁷The test reveals that our uncertainty variables are all stationary at a 5% significance level. Moreover, structural break dates identified by the test are 08/2012 for agriculture, 05/2010 for industry, 06/2009 and 08/2014 for energy, 09/2011 for precious metals.

¹⁸Although aluminum and iron have considerable weights, we insist on copper and its prominent role in the industry sector.

markets for two and six months, respectively. Concerning industrial and energy markets, it is necessary to highlight the close link between industrial commodities and global demand to understand the diffusion of the industry uncertainty to the energy market. Copper is the most used for industrial purposes, for infrastructure renewal, construction projects, and telecommunications. Thus, copper is considered a leading indicator of global economic health. More than any other base metal, copper is closely tied to manufacturing, electrical engineering, industrial production, information technology, construction, and the medical sector. In general, rising copper prices indicate strong demand and a global economic strength, whereas lower copper prices indicate a weaker economy; therefore, the diffusion of uncertainty from industry to the energy market is primarily conveyed through the demand channel. For instance, it appears that the 2008 economic crisis generated overall uncertainty in the industrial market, and in the copper market in particular, which was also reflected in the energy market. Copper is one of the main components of renewable energy systems, which uses more metal than traditional energy sources. Concerning industrial and agricultural markets, diffusion of uncertainty between these markets is also linked with global demand. Joëts et al. (2017) argue that beyond traditional supply and demand shocks, the macroeconomic uncertainty constitutes another key channel through which economic fundamentals may impact commodity prices.

Figure 1.2: **Responses to one-month industry uncertainty shock.**



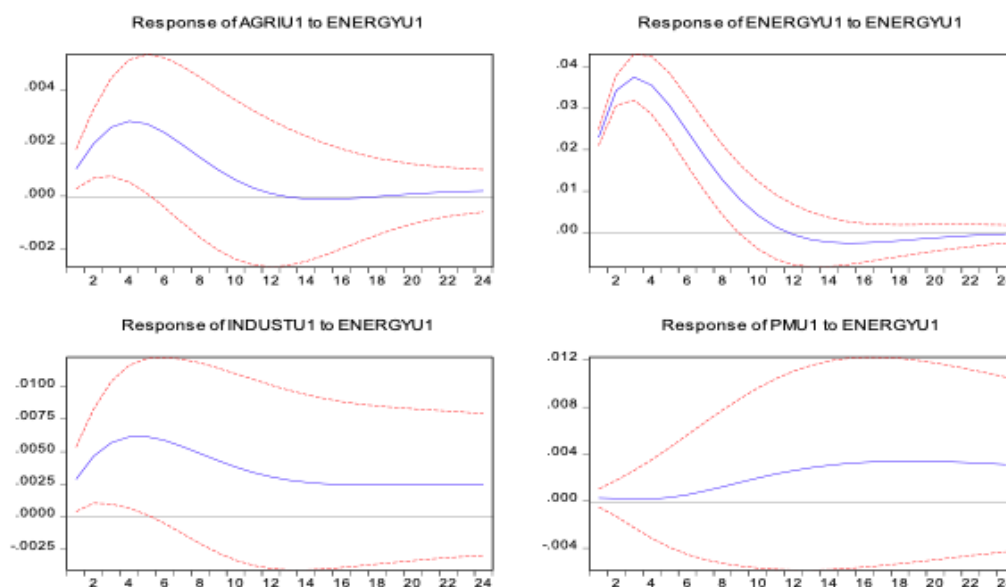
Note: AGRIU1 (one-month agriculture market uncertainty), INDUSTU1 (one-month industry market uncertainty), ENERGYU1 (one-month energy market uncertainty), and PMU1 (one-month precious metals market uncertainty).

Figure 1.3 illustrates the uncertainty transmission from the energy market to agriculture, industry, and precious metals markets. A positive and significant impact of energy uncertainty on agriculture and industry occurs for four and five months, respectively. It is sufficient to say that the spread of uncertainty occurs in the short-run from energy to both agricultural and industrial markets. Knowing that the oil market accounts for 84% of the energy market, thus has the same proportion in energy market uncertainty construction, oil market uncertainty is considered to be the main driver of this sector.

The energy market was strongly influenced by the discovery of coal in the 18th century (1797), which became a primary energy source until the advent of oil in the 19th century (1859). With oil exploration and the establishment of the oil industry that has developed making derivatives, oil has become the dominant component of the global energy market. Among many other natural resources, oil remains an object of covetousness among states to the point of generating geopolitical and strategic interests. This circumstance was compounded by the wars in Kuwait (1990), Afghanistan (2001), and Iraq (2002-2003). Due to the wars, a sharp increase in oil prices was followed by uncertainty that was linked to a rise in the precautionary demand with the establishment of reserves. During the recession of 2008-2009, there was a downward trend of prices, as in most sectors of the economy. Historically, there have been oil shortages with price spikes and high volatility in 1996, 2001, and 2005, but these have not led to much uncertainty (Kilian, 2010). Nazlioglu et al. (2013) investigate the transmission of volatility from oil to agricultural markets (corn, soybeans, and wheat) revealing a dynamic transfer of volatility after the food crisis in 2005. Following the food price crisis, a risk transmission dimension of the dynamic interrelationships between energy and agricultural markets emerged, as the latter are increasingly used as inputs in the former for biofuel production. Indeed, several studies analyze the link between oil and agricultural prices in terms of biofuels; for instance, Busse et al. (2010), Zhang et al. (2010), Serra (2011), Serra et al. (2011), Hassouneh et al. (2012), and Kristoufek et al. (2012). The common conclusion of these empirical investigations is that there is at least a direct short-run volatility transmission between oil and some agricultural commodities. Notably, according to our global uncertainty diffusion analysis, we also found a similar relationship, wherein uncertainty on the energy market spills over to the agriculture market and vice-versa, since oil derivatives are obtained from several crops' agri-

cultural commodities.¹⁹ Uncertainty in the energy market is transmitted onto the industrial market for up to five months. It is notable that energy costs are high for copper extraction, smelting, and refining processes. Copper and oil demonstrate a positive correlation at 84% since 2002. Ji and Fan (2012) find that there is significant volatility spillover effect from oil to nonenergy commodities of industrial metals (copper, aluminum, and nickel). According to this study, the dynamic correlation strengthened after the 2008 crisis, indicating that the consistency of market price trends was affected by the economic recession; therefore, if oil price fluctuates in the long run, so too does copper price. Likewise, both commodities are the main sources of uncertainty in the energy and industry markets and are strongly correlated to the same fundamental economic factors.

Figure 1.3: **Responses to one-month energy uncertainty shock.**



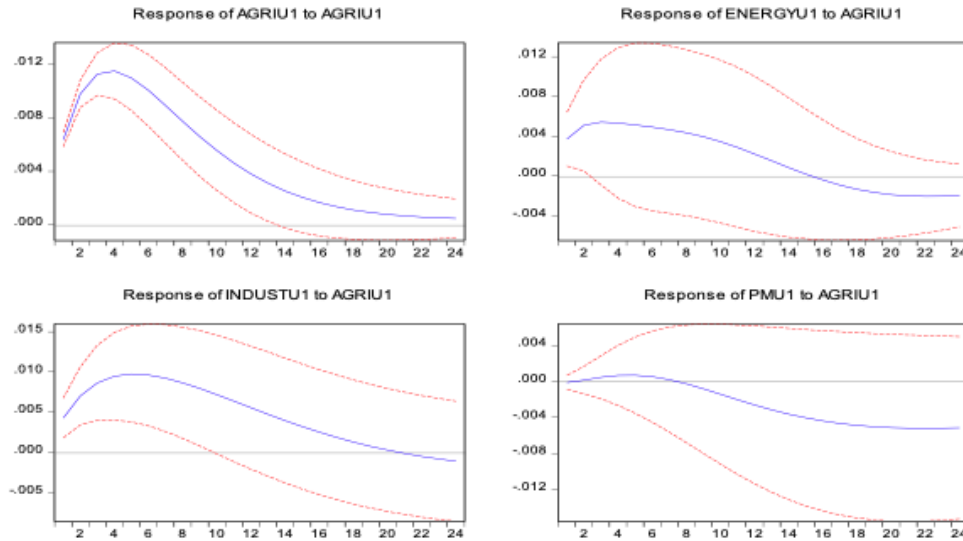
Note: AGRIU1 (one-month agriculture market uncertainty), INDUSTU1 (one-month industry market uncertainty), ENERGYU1 (one-month energy market uncertainty), PMU1 (one-month precious metals market uncertainty), and MACROU1 (one-month macroeconomic uncertainty).

Figure 1.4 presents the responses of various markets' uncertainties to agriculture uncertainty shocks. The impact is significant for industrial and energy markets. This finding indicates that an increase in agriculture uncertainty leads to an increase of

¹⁹The reverse causality of uncertainty diffusion from agricultural to energy markets is confirmed in Figure 1.4.

uncertainty in the energy and industry markets, which reach a peak after two and five months, respectively. Regarding the agricultural and energy markets, unlike studies based on volatility, which only demonstrate the one-way effect of volatility spillover from oil to some agricultural markets, our findings determine a two-way uncertainty diffusion between the two markets, particularly during crisis periods.

Figure 1.4: Responses to one-month agriculture uncertainty shock.



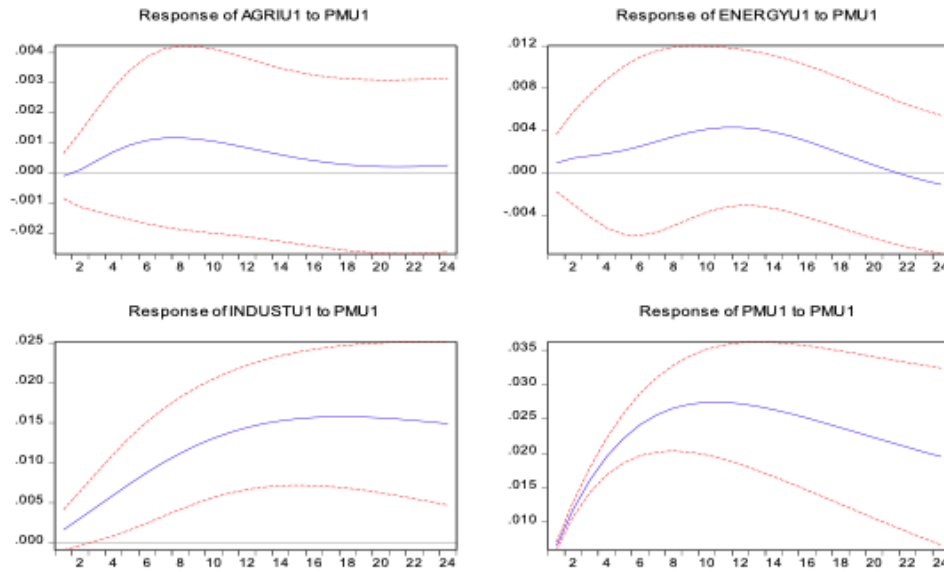
Note: AGRIU1 (one-month agriculture market uncertainty), INDUSTU1 (one-month industry market uncertainty), ENERGYU1 (one-month energy market uncertainty), and PMU1 (one-month precious metals market uncertainty).

Figure 1.5 depicts the precious metals uncertainty effect on other commodity markets. According to this graph, precious metals do not affect any other commodity market except the industrial commodity market, where the effect is persistent, vanishing within 36 months after the initial shock. This is not surprising since the correlation between both sectors' uncertainties is high and significant. Regarding the industry-precious metals relationship, the price of copper has historically been highly correlated with the price of gold, Chinese economy, world trade, and more commonly, with oil price. Also, the close connection between industrial and precious metals volatility may be related to the increasing importance of different metals in financial markets and their competitive role as hedging tools during market turmoil, such as gold and silver in traditional precious metals, and copper in industrial metals (Sakemoto, 2018, Baur and Smales, 2020, Sikiru and Salisu, 2021). Note that from Figure 1.2 to 1.4, precious metals remain insensitive to all other market shocks. This is less surprising, as long as they are considered safe havens used by investors

with high-risk aversion as hedging strategies. This market is strongly dominated by gold (78% of the total share) and has a countercyclical pattern.

Biatkowski et al. (2015), use a Markovian regime-change model with an Augmented Dickey-Fuller (ADF) test to calculate the fundamental value of gold and capture the explosive trajectories of the price of gold, finding the most significant historical boom to be in the early 1980s. The explanation is related to the fact that there is an increase in inflation caused by the oil crisis between 1979 and 1982, coupled with US accommodative monetary policy and expansive budget. This spiral has led financial market participants to turn to precious metals. It is also notable that commodity prices increased, and the influx of funds into gold-listed indices likely contributed to this price dynamic. Uncertainty in the precious metals market in the 1980s also coincides with the 1981-1982 recession. The fight against inflation by a contraction of the money supply initiated by Volker, the then president of the Fed, in response to Reagan's decision to oppose a return to the gold-standard monetary system, led to the crisis from 1981 to 1982. The uncertainty on the silver (19% of the total share) is more related to the different political crises between the United States, Iran, and Afghanistan. The price of silver rose sharply following the Hunt Brothers' affair, which made a fortune in the oil and silver financial markets between 1970 and 1990 (Bredin et al., 2022); however, the crisis of 2008 did not extend to the precious metals markets. While gold and silver prices rose slightly, platinum (3% of the total share) more easily accommodated to the industrial metals cycle. This suggests that agents' anticipation of this price increase as uncertainty in these markets has remained very low. In contrast to the recent financial crisis of 2008, the spillover mechanism of the 1981-1982 crisis is linked to the precious metals markets through Federal inflation targeting and interest rate policy.

Figure 1.5: Responses to one-month precious metals uncertainty shock.



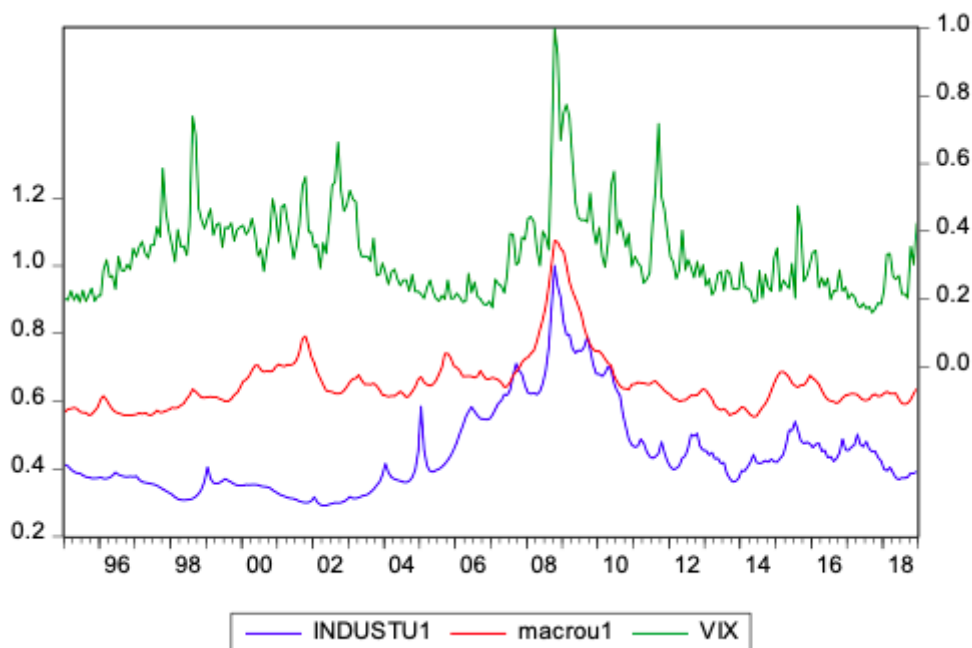
Note: AGRIU1 (one-month agriculture market uncertainty), INDUSTU1 (one-month industry market uncertainty), ENERGYU1 (one-month energy market uncertainty), and PMU1 (one-month precious metals market uncertainty).

The results demonstrate a reciprocal effect in uncertainty diffusion between commodity markets other than the precious metals market; however, the industrial market is the only one that reacts in a persistent way to precious metals uncertainty shocks. Therefore, industrial uncertainty has links with all other commodity markets that must be addressed, particularly in terms of interactions between heterogeneous markets.²⁰

5 Analysis of industry and macroeconomic uncertainties

Our findings present the uncertainty in commodity markets and the role of demand in the interaction between different markets. Figure 1.6 presents the comovement between industry market uncertainty, macroeconomic uncertainty, and the VIX, revealing that the evolution of industrial and macroeconomic uncertainties have been strongly linked since 2005, due to the intensification of international trade and commodity financialization.

²⁰Table A.6 in Appendix A.1 reports the variance decomposition of industry uncertainty shocks.

Figure 1.6: **Macroeconomic uncertainty, VIX, and industry uncertainty.**

Note: On the left axis, this figure depicts both macroeconomic (red line) and industry (blue line) uncertainty, labeled MACROU1 and INDUSTU1, respectively. The VIX (green line) represents the implied volatility index scaled on the right axis.

This section is geared toward interpreting industry uncertainty diffusion. First, we present the impact of macroeconomic uncertainty and stock market volatility on commodity markets to compare with industrial uncertainty. Second, we examine industry and macroeconomic uncertainty contributions in agriculture and energy markets during the financial crisis of 2008. This helps to determine whether industry uncertainty could be considered a proxy for the macroeconomic uncertainty.

5.1 Comparative impact of the predictability and volatility-based uncertainty measure on commodity markets

This section presents the comparative impact of the predictability-based uncertainty measure and the volatility-based measure on commodity markets. This is accomplished by removing industry uncertainty and adding the volatility (VIX) or macroeconomic uncertainty variables into the previously estimated VAR model to analyze their effects on commodity market uncertainty. The macroeconomic uncertainty constructed by Jurado et al. (2015) relies on 132 macroeconomic variables and 147

financial variables extracted from the FRED-MD monthly database.²¹ Both macroeconomic and financial indicators are unbalanced to avoid the over-representation of financial variables and prioritize macroeconomic variables.²² Jurado et al. (2015) emphasize that macroeconomic uncertainty proxy fluctuates countercyclically with global economic activity and business cycles.²³

Figures A.5 and A.6 (in Appendix A.3) show the effect of one-month VIX and one-month macroeconomic uncertainty on commodity markets, respectively. The response of energy and agriculture uncertainties following a VIX index shock is very low compared to that obtained with macroeconomic uncertainty. The magnitude is larger when the shock comes from the one-month macroeconomic uncertainty than from the implied volatility index. While the effect of macroeconomic uncertainty on energy uncertainty is more protracted (seven months), the response of energy market uncertainty after the VIX shock is more transient (two months). This confirms that the effect of the predictability-based uncertainty measure, whether related to overall economic activity (macroeconomic uncertainty) or individual sectors (commodity markets), is more persistent than the common implied volatility index. While agriculture uncertainty is slightly more sensitive to macroeconomic uncertainty shock (five months), the effect of the volatility shock in the agriculture market is not significant. This is especially true as financial markets, with dynamics that are replicated by the implied volatility, have a closer link with energy than with agriculture. To stick with the previous results, we recall that the effect of the industry uncertainty on the agriculture market reaches a peak within five months, whereas the effect on the energy market occurs within two months after the initial shock (Figure 1.2). We also observe that the timing effect of the industry uncertainty on commodity markets follows the pattern of the macroeconomic uncertainty on the agriculture market. Consequently, given that industry uncertainty affects both agriculture and energy markets, as does macroeconomic uncertainty, there appears to be a correlation that we will further investigate through the historical decomposition.

²¹This includes: real output and income, employment and hours, real retail, manufacturing and trade sales, consumer spending, housing starts, inventory sales ratios, orders and unfilled orders, compensation and labor costs, capacity utilization indices, price indices, bond and stock market indices, and foreign exchange rate measures.

²²A brief overview of the technical construction of macroeconomic uncertainty is presented in Appendix A.2.

²³The implied volatility measure (VIX) is available on Bloomberg or Yahoo Finance website. Macroeconomic uncertainty is free to access on Ludvigson homepage: [macroeconomic-uncertainty](http://macroeconomic-uncertainty.com).

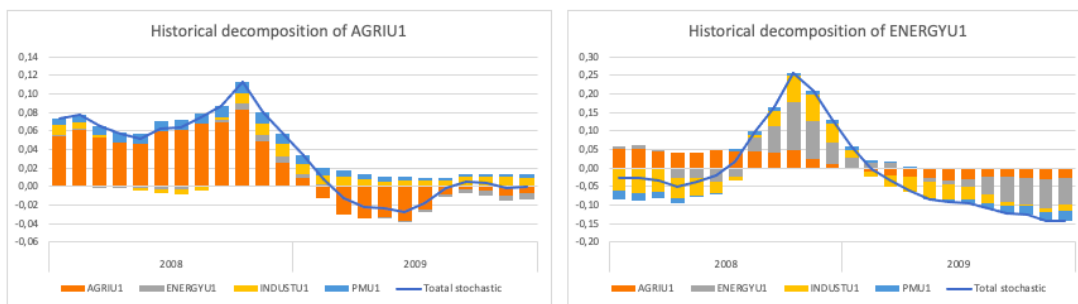
5.2 Historical decomposition of agriculture and energy markets shocks in terms of industry and macroeconomic uncertainty

We strongly established throughout this study that industry uncertainty is a special vehicle of global demand uncertainty to commodity markets. Central to this insight, the role of industrial metals in the global economic activity fluctuations must be explored. For centuries, and more particularly over the past two decades, demand has gradually connected with the industrial sector. From then on, the increase in sensitivity of industry uncertainty to other markets' shocks also clearly reflects global demand uncertainty to the same shocks. Based on economic intuition, this reasoning helps to overcome the issue of explaining the diffusion of uncertainty across heterogeneous markets. The historical decomposition analysis is an alternative method of variance decomposition that considers the different contributions of structural shocks to system components in the historical variation of a variable (Burbidge and Harrison, 1985). The purpose here is to compare the magnitude of the relative shares of macroeconomic and industrial uncertainties in agricultural and energy markets. This allows a better understanding of our proxy thesis.

We rely on Figure 1.6, presenting higher comovements between industry and macroeconomic uncertainty from January 2005 to December 2009, to scrutinize the historical decomposition from January 2008 to December 2009 with a focus on the 2008 financial crisis period. Figures 7 and 8 illustrate the relative contributions of uncertainty shocks in various markets to the decomposition of the agriculture and energy sectors. Agriculture contribution accounts for a large portion of its historical decomposition for the given period. This is primarily due to specific agriculture factors that have an indirect relationship with the economy. In fact, agricultural commodities often face weather conditions (seasonality) and producers often hold harvest stocks to smooth the supply chain until the following season. Moreover, crops' quality depends on how much they are protected from health disasters, such as plagues and insects that damage plants. Beyond those factors, due to permanent storage activity, the agricultural market is more resilient to economic shock; therefore, the contributions of other markets' uncertainty are limited in agriculture due to its low sensitivity. This insight holds for both industry and macroeconomic uncertainty shares in the agriculture market. The historical decomposition of energy, industry, and macroeconomic uncertainties' shares become more observable

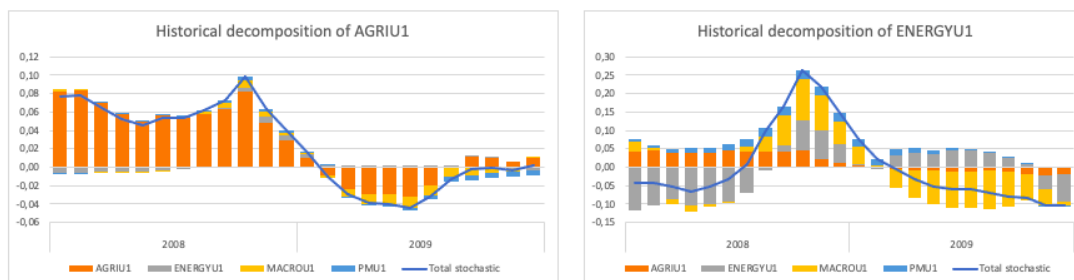
in relatively equivalent proportions for the second part of the 2008 financial crisis. In addition, with regard to energy, the contributions of both macroeconomic and industry uncertainties are, on average, more or less equal over the given period and follow the same trend, particularly in the second half of the crisis (from September 2008 to June 2009). This is less surprising, as unlike the agricultural market, which has an indirect link with economic activity and is less affected by exogenous shock, the energy market remains very sensitive. Likewise, due to the low-income elasticity of demand for agricultural commodities, these markets are less sensitive to global economic recession. Since it is established that the energy sector is sensitive to economic activity shock, using industry uncertainty as a proxy of the global demand uncertainty presents a viable method of shock replication.

Figure 1.7: **Historical decomposition of the energy and agriculture markets with respect to industry uncertainty.**



Note: Total stochastic (the demeaned one-month agriculture and energy uncertainty), AGRIU1 (one-month agriculture uncertainty contribution), ENERGYU1 (one-month energy uncertainty contribution), INDUSTU1 (one-month industry uncertainty contribution), and PMU1 (one-month precious metals uncertainty contribution).

Figure 1.8: **Historical decomposition of the energy and agriculture markets with respect to macroeconomic uncertainty.**



Note: Total stochastic (the demeaned one-month agriculture and energy uncertainty), AGRIU1 (one-month agriculture uncertainty contribution), ENERGYU1 (one-month energy uncertainty contribution), MACROU1 (one-month macroeconomic uncertainty contribution), and PMU1 (one-month precious metals uncertainty contribution).

In summary, our analysis demonstrates that industry uncertainty is a valid proxy for macroeconomic uncertainty. For practical purposes, we can argue, in addition to being an indicator of the macroeconomic uncertainty, our measure of industry uncertainty has the advantage of being easier to compute, as it uses only prices and not several factors as in Jurado et al. (2015).

6 Conclusion

This chapter endeavored to analyze uncertainty transmission between various commodity markets. To conduct our analysis, we construct an aggregate uncertainty measure for each commodity market category (agriculture, industry, energy, and precious metals). To assess the extent to which market uncertainty diffusion is possible, we estimate a standard VAR model that considers market-specific characteristics linked to structural breaks by incorporating dummy variables and GIRFs. Our results demonstrate a bi-causal relationship among agriculture, energy, and industry markets; however, the precious metals market does not react to any market uncertainty exogenous shock, due to their well-identified safe haven role during economic turmoil. Moreover, the industrial market is simultaneously sensitive to agriculture, energy, and precious metals market shocks; thus, we assert that industrial commodity uncertainty is an indicator of macroeconomic uncertainty, and has a predominant role in uncertainty diffusion across commodity markets. Additionally, we compared

the contributions of industry and the macroeconomic uncertainty shocks in agriculture and energy markets. Unlike the agriculture market, we particularly observe during the 2008 crisis that the contribution of the industry uncertainty is almost the same as that of the macroeconomic uncertainty in the energy market. It is also noteworthy that we clearly differ from studies on commodity volatility not only on the assessment of prices disturbances but also the diffusion mechanisms through the resulting findings.

Regarding the context of the COVID-induced economic uncertainty, our analysis may also shed light. In fact, beyond endogenous uncertainty diffusion across markets, the COVID-19 outbreak as an exogenous shock, has affected global economic activity by crippling many interconnected business sectors. For instance, oil price fell by two-thirds in January 2020, combined with a 24% decrease after the OPEC+ agreement failure (in March 2020). Agricultural price decline has been on the order of 9% since January 2020. The industrial red metal (copper) slowdown reached \$4,684 a ton in mid-March 2020, its annual lowest value. This context creates a global uncertainty environment that lowers economic activity and reinforces uncertainty diffusion across markets. Thereby, uncertainty over several agricultural commodities that are experiencing a fall in prices has large negative repercussions on oil and oil derivatives prices and vice-versa. Furthermore, copper uncertainty is tied to its price plunge, reflecting a slowdown in economic activity. The contagion effect that arises from this crisis could generate uncertainty within markets; thus, the consolidation of the uncertainty diffusion analysis across markets. Once more, the illustration of the health crisis' effects on specific markets indicates that the global demand channel driven by industry is the means through which uncertainty diffuses to agriculture and energy markets. Therefore, an exogenous shock such as the health crisis does not alter the mechanism. On the contrary, it passes through an induced-macroeconomic shock. In the same vein, the Russia-Ukraine conflict as a geopolitical event involving high macroeconomic uncertainty, has triggered turmoil in the financial markets and drastically increased uncertainty about the recovery of the global economy. The conflict threatens to squeeze energy and other commodity markets. Russia is among top 5 producers of oil, natural gas, steel, nickel aluminum, and wheat. On its side, Ukraine is the key producer of corn, wheat, sunflowers, sugar beet, barley, soybeans and rapeseed. Higher commodity prices intensify the threat of high long-lasting inflation which increases the risk of stagflation and social unrest. Other sectors such as automotive, transport, and chemicals are likely more vulnera-

ble. The exposure to imported inflation and trade disruptions varies across regions. For instance, European economies are more at risk due to its high dependence on Russian oil and natural gas.

This chapter has policy implications for investors and authorities. From the investors' perspective, they have at disposal a reliable instrument to appreciate price uncertainty in global commodity markets as well as the macroeconomic mechanisms of diffusion. More specifically, an appropriate portfolio diversification strategy for risk-averse investors might consist of mitigating the uncertainty spillover effects with a combination of precious metals and one of other assets' groups. From the authorities' perspective, we could draw both short and long-term challenges: Short-term challenges would involve policymakers to cushion price increases that could create an inflationary spiral in order to protect households with low income. Long-term challenges would consist of promoting a supply diversification strategy to reduce the dependence for net importers. For instance, while northern countries are more concerned by energy security, southern countries are betting for food security. Hence, governments could rely on trade and storage policies to insulate their domestic markets from external commodity shocks. This fosters price stability through transaction costs. Moreover, regional trade agreements might prevent the exposure to global commodity markets' linkages.

Finally, this chapter is not devoid of possible improvements since they might set path to future research works, such as the economic policy driver of commodity price uncertainty.

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Appendix A

Uncertainty diffusion across commodity markets

Contents

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A.1 Tables

Table A.1: Commodity monthly prices data from January 1995 to December 2018.

Markets	Description	Units	Weights	Source
Energy				
Oil	Average oil price	\$/bbl	0.84	World Bank
Gas	Average gas price	\$/mmbtu	0.05	World Bank
Coal	Average coal price	\$/mt	0.11	World Bank
Precious Metals				
Gold	Gold spot price	\$/troy oz	0.78	World Bank
Platinum	Platinum spot price	\$/troy oz	0.03	World Bank
Silver	Silver spot price	\$/troy oz	0.19	World Bank
Agriculture				
Cocoa	Cocoa spot price	\$/kg	0.10	World Bank
Coffee	Average coffee price	\$/kg	0.12	World Bank
Maize	Maize spot price	\$/mt	0.14	World Bank
Cotton	Cotton spot price	\$/kg	0.06	World Bank
Lumber	Average Logs price	\$/cubic meter	0.26	World Bank
Soybeans	Soybeans spot price	\$/mt	0.12	World Bank
Sugar	Sugar spot price	\$/kg	0.12	World Bank
Wheat	Average wheat price	\$/mt	0.08	World Bank
Industry				
Aluminum	Aluminum spot price	\$/mt	0.27	World Bank
Copper	Copper spot price	\$/mt	0.38	World Bank
Lead	Lead spot price	\$/mt	0.02	World Bank
Nickel	Nickel spot price	\$/mt	0.08	World Bank
Tin	Tin spot price	\$/mt	0.02	World Bank
Zinc	Zinc spot price	\$/mt	0.04	World Bank
Iron	Iron spot price	\$/mt	0.19	World Bank

Source: World Bank.

Table A.2: **Variables description.**

Variables	Labels	Description
Agriculture	AGRIU1	one-month agriculture uncertainty
Industry	INDUSTU1	one-month industry uncertainty
Energy	ENERGYU1	one-month energy uncertainty
Precious Metals	PMU1	one-month precious metals uncertainty
Volatility	VIX	one-month implied volatility index
Uncertainty	MACROU1	one-month macroeconomic uncertainty

Table A.3: **Market uncertainty - Correlation matrix.**

	AGRIU1	INDUSTU1	ENERGYU1	PMU1	VIX	MACROU1
AGRIU1	1.000 (0.000)					
INDUSTU1	0.550 (0.000)	1.000				
ENERGYU1	0.349 (0.000)	0.349 (0.000)	1.000			
PMU1	0.487 (0.000)	0.728 (0.000)	0.222 (0.000)	1.000		
VIX	0.631 (0.000)	0.263 (0.000)	0.460 (0.000)	0.222 (0.000)	1.000	
MACROU1	0.662 (0.000)	0.703 (0.000)	0.644 (0.000)	0.583 (0.000)	0.566 (0.000)	1.000

Note: AGRIU1 (one-month agriculture market uncertainty), INDUSTU1 (one-month industry market uncertainty), ENERGYU1 (one-month energy market uncertainty), PMU1 (one-month precious metals market uncertainty), VIX (implied volatility), and MACROU1 (one-month macroeconomic uncertainty). The probability values are in parenthesis.

Table A.4: **Market uncertainty - Descriptive statistics.**

	AGRIU1	INDUSTU1	ENERGYU1	PMU1	VIX	MACROU1
Mean	0.717	0.446	0.473	0.629	0.333	0.654
Median	0.713	0.407	0.452	0.603	0.306	0.632
Max	1.000	1.000	1.000	1.000	1.000	1.074
Min	0.598	0.291	0.251	0.344	0.159	0.554
Std dev	0.074	0.132	0.131	0.155	0.130	0.089
Jarque-Berra	0.000	0.000	0.000	0.000	0.000	0.000
Obs	288	288	288	288	288	288

Note: AGRIU1 (one-month agriculture market uncertainty), INDUSTU1 (one-month industry market uncertainty), ENERGYU1 (one-month energy market uncertainty), PMU1 (one-month precious metals market uncertainty), VIX (implied volatility), and MACROU1 (one-month macroeconomic uncertainty). The probability values are in parenthesis.

Table A.5: **Zivot-Andrews unit root test with structural breaks.**

One-month uncertainty	P_{value}	Break dates
Agriculture	0.013	08/2012
Industry	0.001	05/2010
Energy	0.041	06/2009, 08/2014
Precious Metals	0.002	09/2011

Table A.6: **FEVD (Forecast Error Variance Decomposition of industry).**

Period	AGRIU1	ENERGYU1	INDUSTU1	PMU1
2	0.33	0.08	99.48	0.11
4	1.64	0.39	96.87	1.1
6	2.91	0.62	93.16	3.31
8	3.68	0.68	88.90	6.74
10	6.18	0.65	84.36	11.04
12	3.86	0.61	79.80	15.73
14	3.60	0.57	75.45	20.08
16	3.29	0.55	71.43	24.73
18	3.04	0.54	67.79	28.63
20	2.86	0.56	64.54	32.04
22	2.75	0.60	61.66	34.99
24	2.71	0.65	59.10	37.54

Note: AGRIU1 (1-month agriculture market uncertainty), INDUSTU1 (1-month industry market uncertainty), ENERGYU1 (1-month energy market uncertainty), PMU1 (1-month precious metals market uncertainty).

A.2 A brief technical construction of the macroeconomic uncertainty index

Like commodity market uncertainty, Jurado et al. (2015)'s macroeconomic uncertainty is linked to predictability but differs in its estimation methodology. To present the empirical approach, we denote y_{jt} a single time series in a set of variables $Y_t(y_{jt} \in Y_t = (y_{1t}, \dots, y_{N_y t}))$, the h-period uncertainty in that series is defined as the conditional volatility $U_{jt}^y(h)$ of the purely unforecastable component of the future value of the series.

$$U_{jt}^y(h) = \sqrt{E [(Y_{jt+h} - E(Y_{jt+h}|J_t))^2 | J_t]} \quad (\text{A.1})$$

where $j = 1, \dots, N_y$ and $E(\cdot|J_t)$ is the conditional expectation of the variable. The variable J_t is the set of information available at date t. The uncertainty linked to the variable Y_{jt+h} is therefore defined as the expectation of the squared error

forecast. If we consider j individual measures of uncertainty, then we can proceed to an equally weighted aggregation (w_j being the weight) of the latter and obtain the following expression of macroeconomic uncertainty:

$$U_t^y(h) = p \lim_{N_y \rightarrow \infty} \sum_{i=1}^{N_y} w_j U_{jt}^y(h) \equiv E_w [U_{jt}^y(h)] \quad (\text{A.2})$$

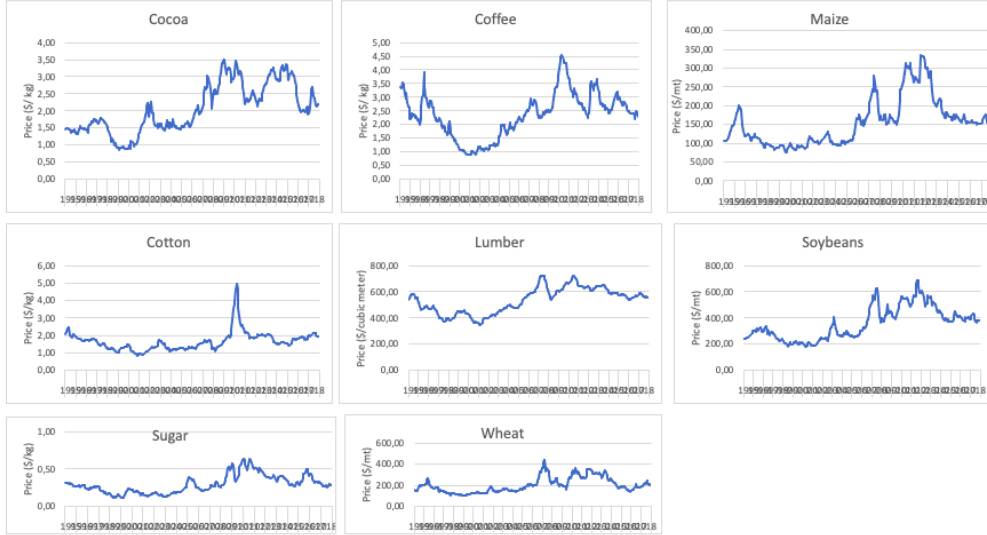
Jurado et al. (2015) propose the estimation of equations (A.1) and (A.2) in three steps. The first step is to substitute the conditional expectation $E(Y_{jt+h}|J_t)$, in equation (A.1), by a forecast in order to compute forecast errors. To do so, they used a factors model with large N predictors X_{it} , $j = 1, \dots, N$ that takes the approximated form:

$$X_{it} = \Lambda_i^{F'} F_t + e_{it}^X + V_t \quad (\text{A.3})$$

where F_t is a $r_f \times 1$ is a vector of latent common factors, Λ_i^F is the vector latent factor loadings and e_{it}^X is the vector of idiosyncratic errors that considers some cross-sectional correlations. The second step is defining the h -step ahead forecast $V_{jt+h}^y = Y_{jt+h} - E(Y_{jt+h}|J_t)$, and estimating the associated conditional volatility, notably $E \left[(V_{t+h}^y)^2 | J_t \right]$ with $h \geq 1$. In the final step, macroeconomic uncertainty $U_t^y(h)$ is constructed from individual uncertainty measures, $U_{jt}^y(h)$ through an equally weighted average.

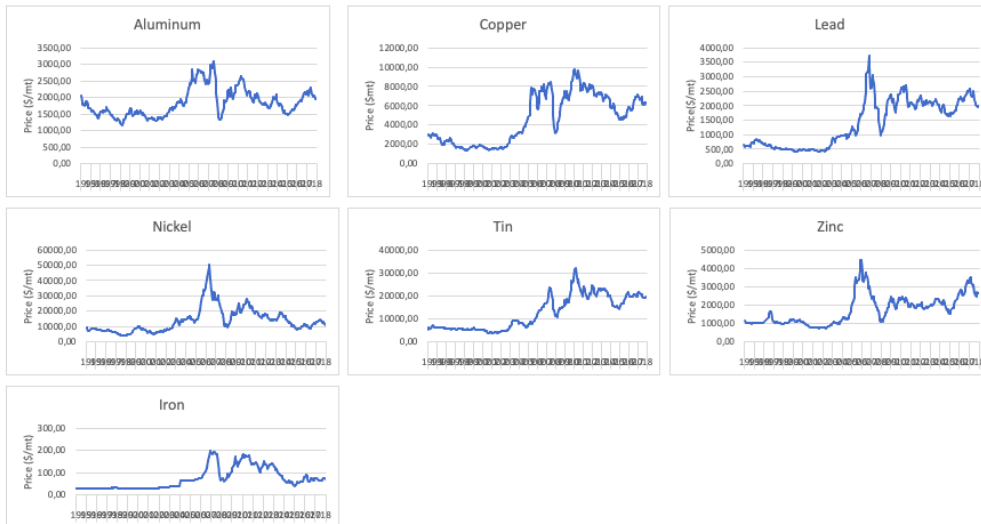
A.3 Figures

Figure A.1: Agriculture markets (monthly seasonally adjusted prices).



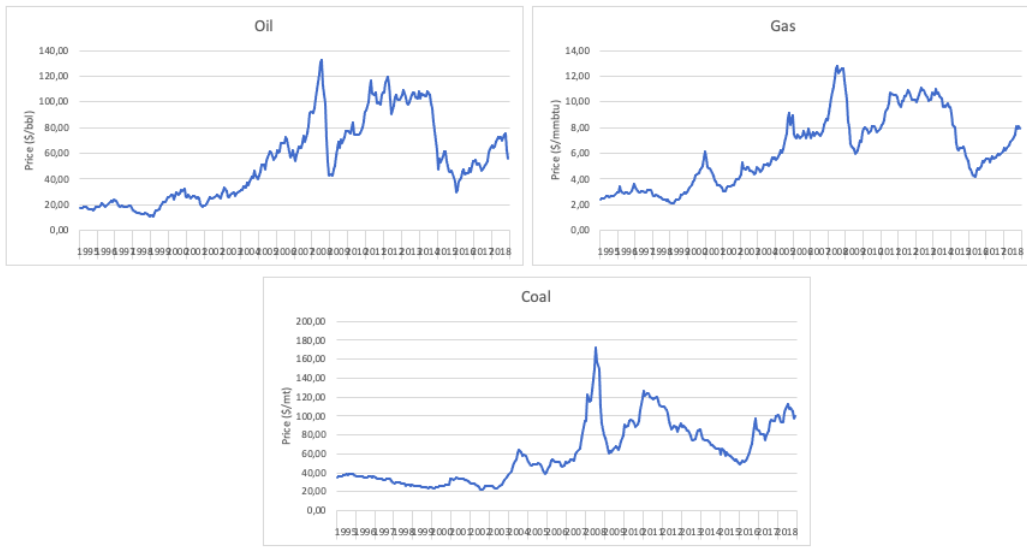
Source: World Bank from January 1995 to December 2018.

Figure A.2: Industry markets (monthly seasonally adjusted prices).



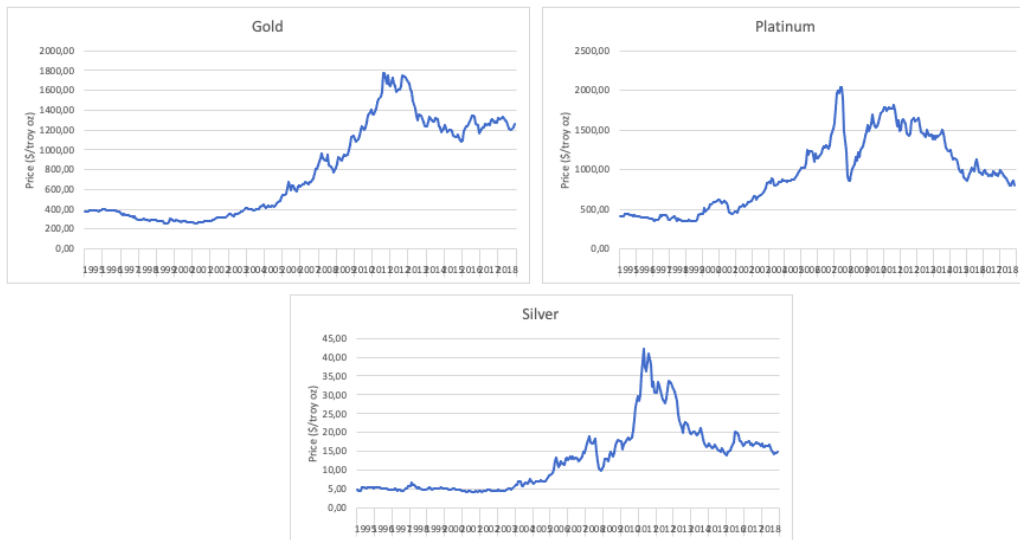
Source: World Bank from January 1995 to December 2018.

Figure A.3: Energy markets (monthly seasonally adjusted prices).



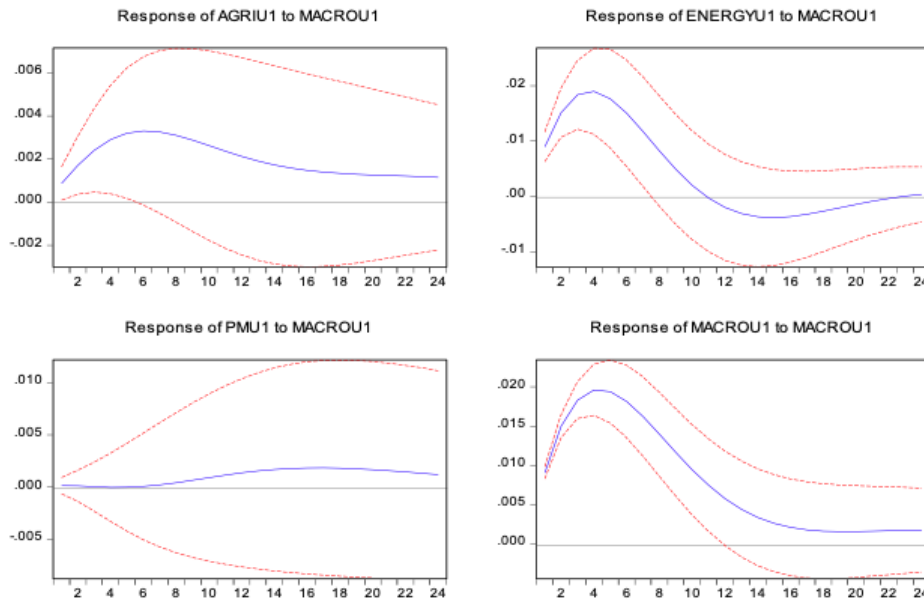
Source: World Bank from January 1995 to December 2018.

Figure A.4: Precious metals markets (monthly seasonally adjusted prices).



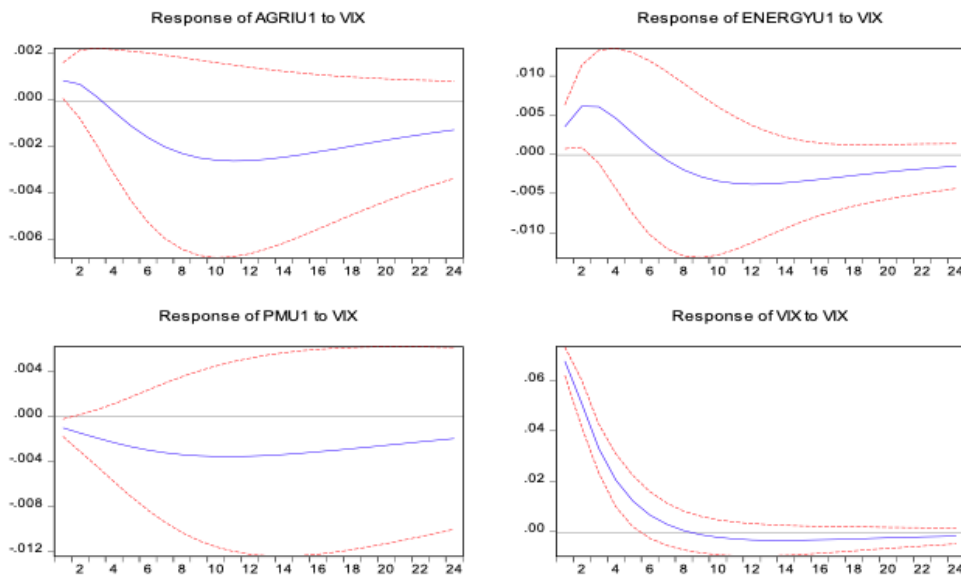
Source: World Bank from January 1995 to December 2018.

Figure A.5: **One-month macroeconomic uncertainty effect on commodity markets uncertainty.**



Note: AGRIU1 (one-month agriculture market uncertainty), ENERGYU1 (one-month energy market uncertainty), PMU1 (one-month precious metals market uncertainty), and MACROU1 (one-month macroeconomic uncertainty).

Figure A.6: **One-month VIX effect on commodity markets uncertainty.**



Note: AGRIU1 (1-month agriculture market uncertainty), ENERGYU1 (1-month energy market uncertainty), PMU1 (1-month precious metals market uncertainty), VIX (1-month implied volatility index).

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Chapter 2

Uncertainty in oil and copper prices: Does Economic Policy Uncertainty matter?¹

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Summary

Disentangling demand and supply shocks has been widely explored in the literature in order to explain commodity price dynamics, especially in crude oil and copper markets. Meanwhile, the literature on the role of Economic Policy Uncertainty (EPU) in predicting commodity price and volatility has also emerged. However, in commodity markets, investors are more concerned with price uncertainty and how it interacts with macroeconomic factors (supply, demand and economic policy changes). Therefore, this chapter aims to investigate the endogenous relationship between oil and copper price uncertainty and the EPU. Our empirical framework relies on a structural vector autoregressive (SVAR) approach with short-run restrictions. Our main finding is that both oil and copper price uncertainty display a significant increase to EPU shocks. The impact is stronger and more persistent in the oil market.

Keywords: Commodity markets, commodity price uncertainty; Oil shocks; Economic Policy Uncertainty, structural VAR.

Classification JEL: Q02, E44, E60, C32.

1 Introduction

For decades, commodity markets have been of primary importance for the sustainability of global economic activity. In addition to the interconnections across markets highlighted in chapter 1, this chapter pays particular attention to investigating the dynamics of price uncertainty in oil and copper markets. The oil market is widely explored because of energy needs and energy transition purposes. Likewise, the copper market plays an important role because it contributes to a significant part of the industry sector.

The global economic engine is sputtering as it struggles to move forward under the heavy burden of the war in Ukraine, mass supply chain disruptions, questions about energy and food security, the consequences of the COVID-19 pandemic, and the highest inflation in 40 years. In this atmosphere of high uncertainty, the oil market has undergone major distortions that require policymakers to react, involving changes in government policy direction. Baker et al. (2016) developed an indicator of Economic Policy Uncertainty (EPU) based on the coverage frequency of press articles discussing major topics related to the economy, policy and uncertainty. According to its authors, the EPU refers to the risk of changes to existing policies that define the parameters of the decision-making process for economic agents, such as consumers, investors, firms and banks. High policy uncertainty affects the economy and delays agents' decisions on spending, investment and employment. The authors also point out that, at the macro level, innovations in policy uncertainty foreshadow declines in output, investment and employment in the United States (US). In addition, as long as global prices, which affect relative prices, continue to impact macroeconomic variables (inflation, consumption, production, investment and welfare), policymakers should draw interest by providing an appropriate and timely response. In the same vein, in the last decade we witnessed the advent of numerous empirical studies investigating the relationship between the EPU, macroeconomic aggregates, and financial and commodity markets. For instance, Bloom (2009) highlights that both political and economic shocks to business cycles result in economic uncertainty.

This chapter stems from two empirical strands of the literature. The first divides sources of oil price shocks into supply, aggregate demand and oil-specific shocks, and identifies their effects on economic activity (Kilian, 2009, Wang et al., 2013, Pedersen, 2019, Cross et al., 2020). This literature identifies drivers in commodity price

dynamics, especially in the oil and copper markets. However, the aforementioned literature is insufficient since it does not explicitly highlight the EPU as a determinant of commodity price. This is where the second strand of the literature comes into play: it encompasses a group of studies that indicate the exogenous effect of the EPU on stock-commodity markets (Kang and Ratti, 2013, Brogaard and Detzel, 2015, Bekiros et al., 2016, Dakhlaoui and Aloui, 2016, Ahmed and Sarkodie, 2021). More recent studies give an extension to the relationship between dynamic stock-commodity market correlations and the EPU (Fang et al., 2017, 2018, Badshah et al., 2019).

This chapter aims to model endogenously oil and copper price uncertainties while considering the EPU, amid supply and demand factors, using a structural vector autoregressive (SVAR) model. In particular, this study relies on a more refined measure of price uncertainty for each market, following the predictability-based approach of Ludvigson et al. (2015) and Jurado et al. (2015) described in chapter 1. This measure helps more reliable decision-making in commodity markets. Therefore, reasoning in terms of price uncertainty and embedding the EPU provide a new insight into identifying shocks in the oil and copper markets.

Using a structural vector autoregressive (SVAR) framework, our analysis shows that oil and copper price uncertainty exhibits a positive and significant response to EPU shocks. In particular, oil and copper price uncertainty reacts instantaneously and a few months after a shock in the EPU with news on policymakers' ongoing economic decisions. The effect is larger and more persistent in the oil market. In addition, the EPU's greatest contribution to oil and copper price uncertainty shocks is recorded in the short run at about 11% and 6% on average, respectively. It should be noted that aggregate demand appears to be the main driver of copper price uncertainty since it accounts for 33% in the long run. Reciprocally, when analyzing the reverse channel of causality, we find that an oil price uncertainty shock significantly increases the EPU. Moreover, the contribution of oil price uncertainty to EPU shocks amounts to 17% on average, whereas copper price uncertainty is only 8%, all in the short run. Finally, the oil price uncertainty shock drops the aggregate demand, as does copper price uncertainty. Once more, it confirms that the oil and copper markets are closely linked to economic activity, so any sudden unfavorable or unexpected shift in the oil or copper price results in sluggish economic activity.

The remainder of the chapter is organized as follows: Section 2 reviews the studies related to the current research on drivers. Section 3 shows the methodology.

Sections 4 and 5 report data and empirical results, respectively. Finally, the last section concludes the chapter with some policy recommendations.

2 Literature review on oil and copper price drivers

As mentioned in section 1, we rely on two strands of the literature to analyze the drivers of oil and copper prices. The first focuses on demand and supply shocks, and the second on the EPU.

2.1 Demand and supply shocks

Numerous empirical studies on the underlying drivers of commodity prices are available for the oil and copper markets. Oil market insights explain the real price of oil and the effects of oil price shocks on macroeconomic aggregates. Kilian (2009) and Kilian and Murphy (2014) propose a structural vector autoregressive framework in the oil market to identify oil price drivers. They find out three main sources of oil price fluctuations: (i) aggregate demand shock (unexpected demand associated with the business cycle), (ii) supply shock (unexpected changes of oil being extracted from the ground), and (iii) storage demand shock (unexpected demand for above-ground oil inventories arising from expectations about demand and supply). Likewise, when analyzing storage demand, Kilian (2009) points out that shifts in oil inventories capture unobservable shifts in expectations about future oil supply and demand. However, a relevant issue to be ascertained is whether the behavior of economic agents drives inventory fluctuations. When buyers strive to look forward or anticipate the oil market's future conditions, they adopt speculative actions. In addition, if agents face heightened oil price uncertainty, they react by increasing their precautionary demand. On the one side, Alquist and Kilian (2010) highlight that this precautionary demand increases the real price of oil, whereas Cross et al. (2020) find that precautionary demand is the primary driver of the real price of oil. This seems to be true as long as agents increase their oil inventory holdings under oil market uncertainty to hedge against potential shortages. On the other side, Kilian and Murphy (2014) argue that speculative demand also increases future oil prices, because speculators buy vast oil inventories that signal to producers to expect the

price to rise. In a domino effect, producers also increase their oil stocks to benefit from the anticipated upturn in the oil price. According to Cross et al. (2020), these identified components of storage demand have a different effect on US macroeconomic aggregates. For instance, they find that precautionary demand shocks reduce the real GDP, whereas speculative demand shocks increase CPI inflation.

Following the thread in chapter 1, Kilian's setting in the oil market serves as a basis for many empirical studies dealing with interrelationships between oil price and other commodity prices. As Kilian (2009) argues, the effects of oil price shocks on economic variables are more consistent when the decomposition of oil price changes is considered, and researchers started to be aware of this. The link between oil and agricultural markets (corn, sorghum, barley), which were often analyzed in terms of volatility spillover from oil prices to several agricultural prices, is now embedded from a supply-demand shock perspective. For instance, Wang et al. (2014) investigate the decomposed oil price shock effects on agricultural prices. This new approach helps to differentiate the effect of oil price shock sources. This seems to be beneficial, as their findings indicate that after the food crisis in 2006-2008, the contributions of oil-specific factors were higher than the aggregate demand contributions in agricultural price variations. Similarly, Vu et al. (2019) explore the reverse effect of agricultural price shocks on the oil price in the US. They discover that agricultural price shocks have different effects on the oil price. In fact, corn use in ethanol (biofuel) plays a prominent role in the impact of corn demand shocks on the oil price. They also identify two main channels through which the impact is noticeable: (i) the indirect cost-push effect (higher corn price induces higher ethanol (or biofuel) price, and (ii) the direct biofuel effect (the expansion of biofuel may trigger the fossil fuel-dependency of the economy).

In the same vein, other empirical studies, such as Uddin et al. (2018), examine the effect of the oil price on metal returns (copper, gold, palladium, platinum, silver) using a non-linear model. They show evidence of the positive effect of demand and supply shocks and the negative effect of risk shocks on precious metal returns. Furthermore, only the influence of risk shocks on metal returns is strongly regime-dependent. The copper market has not escaped the framework of modeling price dynamics. To explain copper price dynamics, Pedersen (2019) emphasizes copper price variations in terms of demand, supply, and specific demand shocks and their effects on Chilean macroeconomic aggregates. They indicate that (i) demand shock increases inflation and thus the monetary policy rate; (ii) supply shock lowers growth

but does not have an effect on inflation or the monetary policy rate; and (iii) specific copper demand shock depreciates the foreign exchange rate, increasing inflation and in the end also a higher monetary policy interest rate.

This part mainly puts into perspective the importance of price fluctuation sources on the oil market and, by extension, the implications for other commodity markets. However, the above commodity setting presents shortcomings. Among others, it does not take into account the EPU as a factor that could affect commodity price dynamics.

2.2 Economic Policy Uncertainty and commodity markets

As stated in section 1, the EPU index developed by Baker et al. (2016) captures events associated with uncertainty about US economic policy in the press. Therefore, its value is proportional to the share of newspaper articles that discuss economic policy uncertainty in a given month. In fact, in addition to the high-frequency coverage of information in the press, newspapers report on conjunctural events on various topics related to *risk* or *uncertainty*. For instance, Baker et al. (2016), when describing the EPU in newspapers consider the concept of *uncertainty* encompassing that of *risk*. In this sense, this view is appealing since it reinforces the idea of equivalence to a certain extent. The authors clearly assert that the EPU reflects: *"uncertainty about who will make economic policy decisions, what economic policy actions will be undertaken and when, and the economic effects of policy actions (or inactions) – including uncertainties related to the economic ramifications of ‘non-economic’ policy matters, e.g. military actions. Our measures capture both near-term concerns (e.g. how to fund entitlement programs), as reflected in newspaper articles."* However, commodity markets are closely linked to financial markets, which fluctuate with policy challenges and investor behavior. These latter need to be considered when investing in commodity markets. Therefore, in the aftermath, we present studies that explore the EPU-commodity price nexus.

Most of the literature has widely explored the effect of the EPU on stock market returns (Pástor and Veronesi, 2013). Some of them highlight the negative effect of the EPU on stock market returns, which contributes to increasing stock market volatility (Arouri et al., 2016, Liu et al., 2017). Other findings indicate the existence of a linear and non-linear causal relationship between the EPU, oil, and the currency market after the gold financial crisis (Albulescu et al., 2019). At the world

level, Antonakakis et al. (2014) stressed that the EPU affects the global oil price through a spillover effect across countries, including the US and China. Likewise, Yin and Han (2014) and Ahmed and Sarkodie (2021) emphasize the time-varying relationship between the EPU and commodity markets to predict volatility in commodity returns. Moreover, Zhu et al. (2020) show evidence that EPU shocks have a significant negative effect on agricultural future returns in bearish markets and a significant positive effect on metal future returns in bullish markets. Reciprocally, the literature also provides insights into the role of commodity prices in predicting the pattern of the EPU (Wang et al., 2015). For instance, Lin and Bai (2021) reveal that oil prices and EPU nexus matter for both oil-exporting and importing countries. Their results report that oil price shocks have a larger effect on the EPU index of oil exporters than on that of oil importers. In contrast, the causal link between the EPU and commodity prices is not always proven. In particular, several studies find a non-significant effect of the EPU on commodity markets returns (Andreasson et al., 2016, Reboredo and Uddin, 2016).

To sum up, this section sheds light on drivers in the commodity markets under consideration and how the EPU interacts with commodity markets. In addition, this chapter contributes to the literature insofar as we endogenously investigate the interdependence between the EPU and commodity price uncertainty. In other words, the novelty lies in two points: (i) we reason in terms of commodity price uncertainty (instead of price), and (ii) we explore reciprocally the role of the EPU in commodity markets. The next section is devoted to the methodology.

3 Methodology

This section is subdivided into two parts: the construction of commodity price uncertainty in the oil and copper markets and the specification of the SVAR model.

3.1 Measuring commodity price uncertainty

In this chapter, the construction of commodity price uncertainty is developed from the monthly inflation-adjusted commodity price obtained as the nominal price over the US CPI (also called real commodity price), and references the predictability-based approach of Jurado et al. (2015). As announced in chapter 1, we refine the measurement using a more flexible predictability model to better highlight specific

events across markets. For each commodity market, the computation process involves three steps:

(i) A fixed rolling window estimation of a seasonal autoregressive integrated moving average (SARIMA) model on the commodity price. Let's consider that Com_t denotes the time series of the real commodity price. To help tackle the non-stationary issue of the real commodity price, we introduce an integration operator Δ^d where d is the order of differencing used. The general form of a SARIMA $(p, d, q)(P, D, Q)$ model is given as follows:

$$\Phi(L)^p \phi(L^s)^P \Delta^d \Delta_s^D op_t = \Theta(L)^q \theta(L^s)^Q \Delta^d \Delta_s^D \epsilon_t \quad (2.1)$$

D takes on a similar meaning to d , but instead applies to seasonal lags of order s . Therefore, Δ_s^D is the differencing operator for seasonal lags in the times series of the commodity price. $\Phi(L)^p$ and $\Theta(L)^q$ represent the including-constant lag polynomials of the non-seasonal AR and MA part of the model, respectively. By analogy, $\phi(L^s)^P$ and $\theta(L^s)^Q$ correspond to including-constant lag polynomials of the AR and MA seasonal part of the model.²

(ii) The previous step allows, for each rolling window estimation, the extraction of a one-step ahead out-of-sample forecast $E(Com_{t+1}|I_t)$ defined as the expectation of the commodity price with respect to the information available at time t . The associated forecast error w_{t+1} is given by:

$$w_{t+1} = Com_{t+1} - E(Com_{t+1}|I_t) \quad (2.2)$$

(iii) The estimation of the stochastic volatility of the series of the one-step ahead forecast error. The estimation of the moving average stochastic volatility model references the works of Chan and Jeliazkov (2009) and Chan and Hsiao (2013). Commodity prices generally exhibit clustering phenomena amid volatility, which justifies this particular modelling method. The series of the one-step ahead forecast error w_t is defined by the following equation:

$$w_t = \mu + v_t \quad (2.3)$$

²The model determines the optimal order of the SARIMA model (according to Akaike (1974) and Schwarz (1978) information criteria) to perform valuable forecasts. In our case, we chose a SARIMA (2,1,2) with a common seasonal autoregressive and moving average component of order 12 for the oil market, and an ARIMA (3,1,3) for the copper market.

where μ represents the mean of the forecast error and v_t is the vector of errors that are serially dependent and assumed to follow a MA(q) process of the form:

$$v_t = \varepsilon_t + \psi_1 \varepsilon_{t-1} + \dots + \psi_q \varepsilon_{t-q} \quad (2.4)$$

$$\theta_t = \mu_\theta + \phi_\theta (\theta_{t-1} - \mu_\theta) + \varsigma_t \quad (2.5)$$

where $\varepsilon_t \sim N(0, e^{\theta_t})$ and $\varsigma_t \sim N(0, \sigma_\theta^2)$ are independent of each other. The variable θ_t is the log-volatility of ε_t and is assumed to follow an AR (1) process, μ_θ is the level of the log-variance and $|\phi_\theta| < 1$ represents the persistence of the log-variance. Note that this variance is not allowed to vary unrestrictedly with time. The feature of this model fundamentally differs from GARCH-type models where the time-varying volatility is assumed to follow a deterministic, rather than stochastic, evolution. The stochastic volatility model is thus conveniently expressed in hierarchical form and is center-parameterized. According to Chan and Hsiao (2013), under the assumption of a moving average extension, the conditional variance of the series w_t is given by:

$$V(w_t | \mu, \psi, \theta) = e^{\theta_t} + \psi_1^2 e^{\theta_{t-1}} + \dots + \psi_q^2 e^{\theta_{t-q}} \quad (2.6)$$

Equations (2.4) and (2.5) capture the moving average and log-volatility, respectively. Equation (2.6) that derives from the latter provides the estimation of the stochastic volatility process so that the series of the one-period ahead commodity price uncertainty ($Comu_t$) satisfies the condition $Comu_t = V(w_t | \mu, \psi, \theta)$.³

3.2 Structural VAR model

The famous critique of Sims (1980) over developing sophisticated econometric models identified by non-justified exclusionary restrictions has given a path to consider more economic theory-based empirical analysis. Due to this new econometric framework, some relevant questions (demand and supply shocks in the business cycle, monetary policy concerns, the recessionary effect of oil price shocks, etc.) have started to be accurately addressed. As previously highlighted, the main contri-

³See Chan and Jeliazkov (2009) and Chan and Hsiao (2013) for deeper details on the model. The Matlab code required for the estimation of the moving average stochastic volatility is available from Joshua Chan's homepage. For each variable, we obtain 20000 loops or draws from the posterior distribution using Gibbs sampler after a burn-in period of 1000. This methodology also helps to compute price uncertainty at 3, 6 and 12 months horizon.

bution of the SVAR model is to investigate hypotheses from the economic theory among the endogenous variables. Generally, the short-run identification process is captured through a common SVAR AB model. This holds as long as we handle the AB model as equivalent to the A model when restricting the B matrix to an identity matrix. This model requires imposing exclusive restrictions on short-run relationships among variables. These restrictions are set towards structural shocks' identification.

The identifying assumptions in the recursive SVAR approach require knowledge of how certain variables react in an instantaneous way to certain shocks. Sometimes, because some variables are "sluggish" or information about them is only available with a lag, we can be pretty confident about these restrictions. However, they are pure guesswork. Therefore, the economic theory could give very little guidance. In fact, the economic theory usually tells us a lot more about what will happen in the long run, rather than exactly what will happen today. For instance, the theory tells us that whatever positive aggregate demand shocks do in the short run, in the long run, they have no effect on the output and a positive effect on the price. In this chapter, we endeavor to give caution to short-run recursive restrictions.

Following Kilian (2009), let's consider the vector Y_t of the endogenous variables in any commodity market given by: $Y_t = (\Delta com_sup, agg_dem, epu, cop_unc, oil_unc)$.⁴ For each commodity market, the terms in parenthesis represent the logarithm of commodity supply, the aggregate demand (Kilian's index for global economic activity), the logarithm of the EPU, the copper price uncertainty, and the oil price uncertainty, respectively. The operator Δ indicates the first-order difference. Accordingly, we estimate two 5-factor SVAR models with each market's specific variable (commodity supply) and common variables (aggregate demand, EPU, copper price uncertainty, and oil price uncertainty).⁵ The specification of the SVAR is defined as follows:

$$\Gamma Y_t = B(L)Y_t + \varepsilon_t \quad (2.7)$$

where Γ is the vector of contemporaneous interconnections among variables. $B(L)$ is the lag polynomial of endogenous variables. We assume that $E(\varepsilon_t \varepsilon_t') = \Pi_k$,

⁴The three-factor benchmark oil market is replicated in Appendix B.2.

⁵The optimal lag length is obtained from FPE and AIC information criteria and is set to 3 for both oil and copper markets (see tables B.1 and B.2 in Appendix B.1). Our results are robust to higher lag order to handle autocorrelation and heteroskedasticity issues in the model.

where Π_k is a k-dimensional diagonal matrix that restricts the structural shocks hitting the system to mutually uncorrelated innovations and k is the number of variables in the vector. The reduced form of the structural representation is given by:

$$Y_t = B^*(L)Y_t + u_t \quad (2.8)$$

The lag polynomial is pre-multiplied by Γ^{-1} to obtain: $B^*(L) = \Gamma^{-1}B(L)$. The relationship between the reduced form errors u_t and the structural innovations ε_t is: $u_t = \Gamma^{-1}\varepsilon_t$. Thus, the variance-covariance matrix of the structural innovations $\Pi_k = \sum_{\varepsilon} = \Gamma \sum_u \Gamma$. In other words, $\sum_{\varepsilon} = E(\varepsilon_t \varepsilon_t')$ and $\sum_u = E(u_t u_t')$.

Following Kilian (2009) and Wang et al. (2013), we first determine the structural innovations by imposing short-run exclusive restrictions on the lower triangular matrix Γ^{-1} as follows:

$$\begin{bmatrix} u_t^{\Delta com_sup} \\ u_t^{agg_dem} \\ u_t^{epu} \\ u_t^{cop_unc} \\ u_t^{oil_unc} \end{bmatrix} = \begin{bmatrix} \gamma_{11} & 0 & 0 & 0 & 0 \\ \gamma_{21} & \gamma_{22} & 0 & 0 & 0 \\ \gamma_{31} & \gamma_{32} & \gamma_{33} & 0 & 0 \\ \gamma_{41} & \gamma_{42} & \gamma_{43} & \gamma_{44} & 0 \\ \gamma_{51} & \gamma_{52} & \gamma_{53} & \gamma_{54} & \gamma_{55} \end{bmatrix} \begin{bmatrix} \varepsilon_t^{com_sup_shock} \\ \varepsilon_t^{agg_dem_shock} \\ \varepsilon_t^{epu_shock} \\ \varepsilon_t^{cop_unc_shock} \\ \varepsilon_t^{oil_unc_shock} \end{bmatrix} \quad (2.9)$$

The Γ^{-1} matrix specification is subject to discussion regarding economic theory. The benchmark model of Kilian (2009) has already set a breach to understand short-term interdependences in the oil market. Other studies (Peersman and Van Robays, 2009, 2012, Cunado and de Gracia, 2014, Wei, 2019) also evoke some assumptions that govern short-term relations in the oil market. Note that the global oil market scheme holds for the copper market, given that both commodities interact with the same macroeconomic factors (Pindyck and Rotemberg, 1990, Pedersen, 2019). Hence, we revisit the stylized facts in the oil market while inserting the copper price uncertainty as follows:

(i) An oil supply shock is an exogenous shift in oil production. In the oil market, the monopolistic structure embodied by OPEC implies the oil supply is exogenously controlled by a small group of large producers. Besides, the oil supply adjustment to oil price shocks only occurs in the long run due to OPEC's quotas, geopolitical events, military conflicts and intensive capital requirements. In such an environment, oil production witnesses a sharp decrease that leads to an increase in oil prices. In contrast, the recent shale revolution drives oil production expansion and reduces the

oil price. We assume the aggregate demand, the EPU and the copper and oil price uncertainties do not contemporaneously affect oil supply. This implies that the last four elements of the first row of Γ^{-1} are zeros.

(ii) An aggregate demand shock represents a sudden boost in global real economic activity. Real economic activity reacts more contemporaneously to oil supply shock but with a lag to commodity price shocks (Hamilton, 1983) as well as the EPU and the copper and oil price uncertainties. This assumption implies that the last three elements of the second row of Γ^{-1} are set to zeros.

(iii) The EPU shock indicates the news-based effects of policymakers' economic decisions. We suppose that oil supply shock and aggregate demand shock instantaneously impact the EPU. However, the copper price uncertainty only affects the EPU with a delay. Thus, the last two elements of the third row of Γ^{-1} are equal to zero.

(iv) According to chapter 1, copper price uncertainty refers to the disaggregated measure of industry uncertainty which serves as a proxy for macroeconomic uncertainty. In this sense, we assume that a copper price uncertainty shock has a contemporaneous effect on oil price uncertainty. Thus, copper price uncertainty is predetermined relative to oil price uncertainty, implying γ_{45} .

(v) Finally, the oil price uncertainty shock reflects an unpredictable shift in the oil price. Therefore, we assume that oil supply, aggregate demand, EPU, and copper price uncertainty have contemporaneous relationships with oil price uncertainty. Likewise, $\gamma_{51}, \gamma_{52}, \gamma_{53}, \gamma_{54} \neq 0$.

4 Data

4.1 Commodity prices: measure of oil and copper price uncertainties

As mentioned in chapter 1, we collected monthly nominal price data of crude oil and copper over the period 1960-2020 from the World Bank website.⁶ These markets represent the main components of the energy and industrial metals sectors. While Brent crude oil (followed by the WTI crude oil) has long been established as the most commonly used worldwide benchmark for pricing sweet crude oil, sour crude

⁶Commodity-prices-pinksheets.

oil, which represents a large share of Middle Eastern crude oil exports, has been less considered. Therefore, in this study, the crude oil price is given by the equally-weighted average of the Brent, WTI, and Dubai crude oil prices. Meanwhile, our database provides a unique international price for copper. Thereafter, the commodity prices are deflated by the monthly US Consumer Price Index (US CPI is assumed to be a proxy of world CPI) to obtain the real prices.⁷ The advantage of using real prices is to check for inflationary shocks of monetary policies on commodity prices. This helps isolate the specific effects of commodity price shocks from the common monetary factor shock.⁸

4.2 Macroeconomic factors

The traditional factors that determine the commodity price are supply and demand. However, economic policy is somehow neglected. Given that this chapter aims to identify factors of price uncertainty, we collect supply-demand variables and the EPU index of Baker et al. (2016).

The monthly world crude oil production including lease condensate production data (in millions of barrels pumped per day averaged by month) are obtained from the Energy Information Administration (EIA) of the US Department of Energy.⁹ The monthly world copper production data (in millions of metric tons) are extracted from the Bloomberg's World Bureau of Metals Statistics.

The demand factor is assumed to represent global economic activity. Most empirical studies often use either real gross domestic production (Hamilton, 1983, Rotemberg and Woodford, 1996) or industrial output (Papapetrou, 2001) to capture global economic activity. However, Kilian (2009) and Baumeister and Hamilton (2019) have separately developed an index of world industrial production, which is still far from reaching a consensus. This is due to the trickiness of accurately measuring global economic activity or worldwide industrial production. Kilian (2009) argues that there are at least three reasons for the weakness of the world economic activity measure based on GDP: (i) first, the unavailability of data at a regular frequency

⁷The US Consumer Price Index for all urban consumer data is extracted from the FRED of St Louis (CPI-FRED). Its base is 1982-1984=100 which means that the computed real prices are stated in terms of average prices over the 1982-1984 period.

⁸Figure B.1 reports the commodity price uncertainty per market.

⁹Energy-International-Association

of small industrialized and emerging countries compared to developed countries, (ii) second, the economic dynamics of each country over time changes its weighting or contribution in the world output, and (iii) third, the divergence of economies' backbones in terms of value added: On the one side, emerging countries are industrial commodity-dependent, while on the other side, industrialized countries rely on industrial services. Therefore, Kilian (2009) proposes an index (updated version in 2018) that reflects the changes in global demand for industrial commodities based on ocean freight rate. The author measures the growth rates of a panel of single voyage bulk dry cargo (grain, oilseeds, coal, ore, iron, fertilizer, and scrap metal) ocean shipping freight rates. In this chapter, the global demand is represented by Kilian's index.¹⁰

We use the US EPU index developed by Baker et al. (2016).¹¹ This news-based index is composite and covers a range of US economic policies such as monetary policy, fiscal policy, taxation, government spending, healthcare, national security, entitlement programs, regulation, financial regulation, trade policy, sovereign debt, and currency crises. However, this chapter does not go through each policy subcategory and is limited to the aggregate US EPU index.

This chapter deals with restrictions on data availability. Namely, according to our data source, the copper supply variable is available from January 1995 to August 2018. Given that each market's analysis is independent of one another, we choose to specify different period ranges among markets. Therefore, the oil market analysis, being mostly data unconstrained, covers the period 1985:3-2020:3. Similarly, the sample in the copper market is limited to 1997:1-2018:8.¹²

4.3 Preliminary analysis

A prefatory insight into our data consists of three steps: a simplistic graphical evolution of the EPU and commodity price uncertainty nexus, descriptive statistics, and some stationarity tests.

First, figure 2.1 lays out the historical evolution of price uncertainty in the oil and copper markets (blue line), together with the evolution of corresponding prices (red line) and the EPU (green line). The vertical gray bands are identified as

¹⁰Data available on Kilian-global-real-economic-activity

¹¹Data available on US-EPU-index

¹²Figure B.2 (in Appendix B.3) plots the time-varying macroeconomic factors.

periods where heightened commodity price uncertainty coincides with sociopolitical or economic disturbances. From the oil market, we note that the general trend is for the uncertainty index to display clear spikes around significant events, such as the OPEC disbandment in 1986 and the Persian Gulf War in 1990. While the former led to a drop in the oil price by \$7 per barrel, the latter raised the oil price from \$34 to \$77 per barrel. Moreover, the conjunction of the Libyan War in 2011 and the Iranian oil embargo in 2012 resulted in a slight but limited increase in oil price uncertainty. As stressed by Barsky and Kilian (2004), an explanation for the surge of oil price uncertainty during war episodes lies in the rise of the precautionary demand for oil. It is worth noting that the oil market also witnessed a significant increase in price uncertainty following the 2007-2009 great recession, the 2014-2016 oil price plunge, and on the onset of the 2020 Covid-19 outbreak followed by the collapse of the OPEC+ agreement on oil production cuts. These disturbances fuelled the downward dynamics of the oil price as the supply glut failed to boost demand as expected. According to this graph, we observe that the EPU relates to heightened oil price uncertainty episodes during three major events: the Persian Gulf War, the great recession, and the Covid-19 outbreak. Furthermore, the EPU reached an unprecedented peak in the early stages of the pandemic in March 2020. Table B.1 reports a significant linear correlation coefficient between the EPU and oil price uncertainty of around 13%. Regarding the copper market, we notice that copper price uncertainty records higher levels during events associated with global economic activity. For instance, the economic booms of the late 1980s and early 2000s led to sharp spikes in the copper price as well as price uncertainty in the copper market. However, like in the oil market, the great recession event triggered an unexpected slowdown in prices while keeping the level of uncertainty high. Except during the 2007-2009 recession period, the comovement between the EPU and copper price uncertainty is less apparent. Moreover, table B.2 does not report any significant linear correlation between both variables.

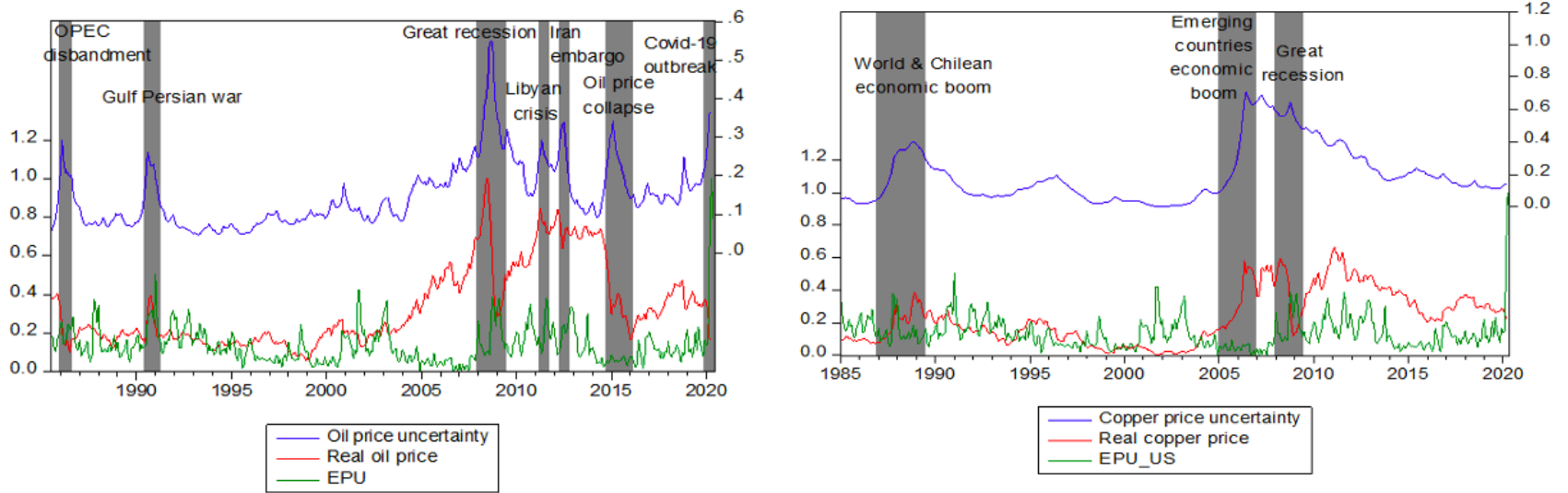
Second, table 2.1 displays the descriptive statistics of the aggregate demand index, the EPU, and price uncertainty for each commodity market. Series are not normally distributed given the Jarque and Bera (1980) statistics. We reject the null hypothesis of normal distribution for all the variables suggesting that price uncertainty is asymmetric and fat-tail distributed (non-zero skewness and positive excess kurtosis).

Third, table 2.2 presents the unit root tests performed with zero, intercept, trend,

and both intercept and trend options. We report the statistics that fit best with the data characteristics. ADF, PP, KPSS, P and ZA denote the statistics of Dickey and Fuller (1979), Phillips and Perron (1988), Kwiatkowski et al. (1992), Perron (1994), and Zivot and Andrews (1992), respectively. The optimal lag length of the ADF and Perron test is chosen based on the Schwarz information criterion (SIC) (Schwarz, 1978), and the bandwidth of the PP unit root test and KPSS stationarity test are determined based on the Newey-West criterion (Newey and West, 1994). The null hypothesis of the ADF, PP, P and ZA tests is a unit root and that of the KPSS test is stationarity. According to unit root tests, the aggregate demand, the EPU, and commodity price uncertainty are stationary in level and in first difference. Only oil and copper supply variables are non-stationary in level and need to be transformed in first difference to comply with stationarity tests.¹³

¹³It is worth noting, that we also consider the seasonality issue in some variables before the estimation.

Figure 2.1: Uncertainty in oil and copper prices and economic policy uncertainty (EPU).



Note: This figure depicts for each commodity market a 1-month price uncertainty measure (on the right axis) along with real price and EPU (on the left axis). The gray bands represent specific events affecting each market and global economic events. For scaling convenience, we apply min-max normalization of the series.

Table 2.1: **Descriptive statistics of variables.**

Variables	Mean	Std.Dev	Max	Min	Skewness	Kurtosis	Jarque-Berra
Kilian index	0.129	53.868	190.728	-159.644	0.892	4.217	121.969***
EPU	103.738	52.722	503.012	32.266	2.685	15.643	3388.661***
Oil price uncertainty	0.127	0.109	1.000	0.000	2.440	14.828	4250.633***
Copper price uncertainty	0.240	0.196	1.000	0.000	1.185	4.165	181.157***

Note: The Jarque-Bera (1980) statistic tests for the null hypothesis of Gaussian distribution. *, **, *** denote the rejection of the standard null hypothesis at 10%, 5% and 1% significance levels.

Table 2.2: **Unit root tests.**

	ADF		PP		KPSS		P		ZA
	level	first diff	level	first diff	level	first diff	level	first diff	level
Kilian index	-4.551***	-18.823***	-3.814***	-18.135***	0.137	0.040	-5.202***	-19.990***	-5.458***
EPU	-6.608***	-17.763***	-6.498***	-31.497***	0.165	0.265	-9.997***	-21.042***	-6.226***
Oil supply	-0.824	-25.934***	-0.278	-28.899***	2.886***	0.091	-2.603	-26.449***	-4.144*
Oil price uncertainty	-6.126***	-14.978***	-4.419***	-9.083***	0.102	0.023	-8.224***	-17.479***	-6.526***
Copper supply	-0.328	-5.196***	-1.368	-46.713***	1.961***	0.035	-1.943	-26.672***	-4.306*
Copper price uncertainty	-3.722***	-7.603***	-2.840*	-7.534***	0.353	0.032	-4.848***	-8.445***	-5.339**

Note: ADF, PP, KPSS, P and ZA denote the statistics of ?, Phillips and Perron (1988), Kwiatkowski et al. (1992), Perron (1994), Zivot and Andrews (1992) unit root test, respectively. The optimal lag length of the ADF and the Perron test is chosen based on the Schwarz (1978) information criterion (SIC), and the bandwidth of the PP unit root test and KPSS stationarity test are determined based on the Newey and West (1994) criterion. It should be noted that the P and ZA tests account for significant structural break points in both intercept and trend. The null hypothesis of the ADF, PP, P and ZA tests is a unit root and that of the KPSS test is stationarity. *, **, *** denote the rejection of the null hypothesis at 10%, 5% and 1% significance levels, respectively.

5 Empirical results

The outcomes of the model are presented as impulse response functions (IRFs) in each commodity market. It is recalled that the purpose of IRFs is to track the responses of variables in the system to a one-unit specific shock. In other words, we expect to know how the dynamic endogenous system responds to some external change at the time of the shock and over subsequent points in time. In our case, the IRFs indicate the impact of an upward unanticipated one-unit standard deviation change in the impulse variable on the response variable over the next several periods.¹⁴ Next, we will successively comment on our findings in the oil and copper markets.

5.1 Oil market results

From figure 2.2, we can highlight the main findings.¹⁵ First, the EPU shock has a positive and significant effect on oil price uncertainty in the medium term after the initial shock. In fact, economic policy disturbances account not only for potential geopolitical risks (commercial wars, military conflicts, etc), but also for the duration of deadlines on making economic policy decisions by governments, which could give rise to speculative actions. In this context, the oil price dynamics are mostly governed by uncertainty. To some extent, this finding goes to several empirical studies, which highlight the positive effect of the EPU on the volatility of oil market returns (Ahmed and Sarkodie, 2021).

Second, a negative oil supply shock indicating an unexpected decrease in global oil supply contributes to increasing oil price uncertainty at an upward point in the short run following the initial shock. Afterwards, this positive effect is slightly reduced in the long run. The dynamics of oil price uncertainty in response to a negative oil supply shock highlights the role of expectations in the crude oil market. Indeed, investors appear to be more concerned by the uncertainty of future supply conditions than perceiving the exogenous drop in oil supply as a turmoil event (geopolitical tensions, trade wars and OPEC's monopoly power) that could affect

¹⁴IRFs are bounded with 95% confidence intervals obtained using the Monte Carlo simulation method.

¹⁵We also report on the recursive restrictions matrix of structural shock responses in table B.5 (in Appendix B.1). Note that the results displayed by this matrix hold for the optimal lag order identified by the information criteria.

the global value chain. In addition to the well-known effect of rising prices resulting from insufficient supply (Kilian, 2009), this implies that the uncertainty driven by agents acting in the oil market is strongly reflected in the oil price.

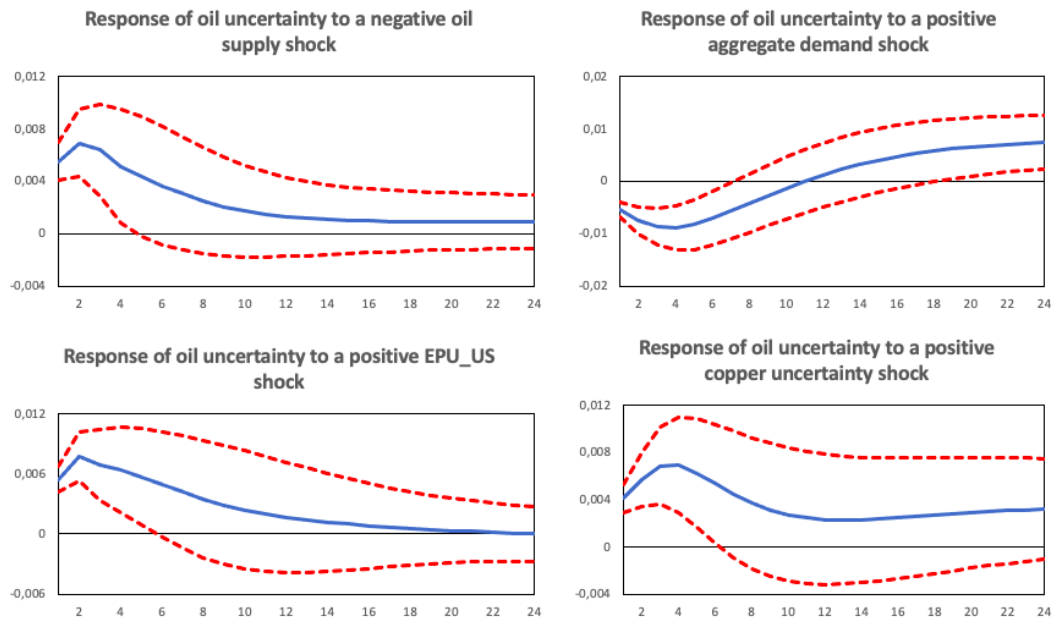
Third, a positive aggregate demand shock leads to a significant decrease in oil price uncertainty in the medium run following the initial shock, the impact being less persistent than that of an oil supply shock. This could be interpreted as a near-term unexpected demand shock. One possible explanation is that if an aggregate demand shock occurs, sharp spikes in oil prices are more likely to generate volatility but not uncertainty because demand shocks are more predictable in the short-run; thus, the effect on oil price uncertainty is limited.

Fourth, we observe the transmission of copper price uncertainty shocks onto the oil market. This result confirms at the micro level what we observed at the macro level in chapter 1.

Figure 2.3 provides the reverse effect of the oil price uncertainty shock on other variables. We note a long-lasting positive and significant effect (up to 10 months) of oil price uncertainty on the EPU. This finding emphasizes the high and persistent sensibility of the policymakers' economic decisions to oil price fluctuations. Besides, aggregate demand shrinks after an oil price uncertainty shock (Bloom, 2009, Colombo, 2013, Jurado et al., 2015, Baker et al., 2016, Henzel and Rengel, 2017, Meinen and Roehle, 2017). In particular, this result is in line with Triantafyllou et al. (2019), who investigate the impact of commodity price volatility-based uncertainty on the US economic activity. The authors highlight that uncertainty in energy, agriculture and metals depresses US economic activity and acts as a harbinger for US recessions. As an early warning signal of unfavorable economic conditions, a prior shock of oil price uncertainty reveals a downward trend in global activity in subsequent months. In our case, the negative effect lies within 12 months.

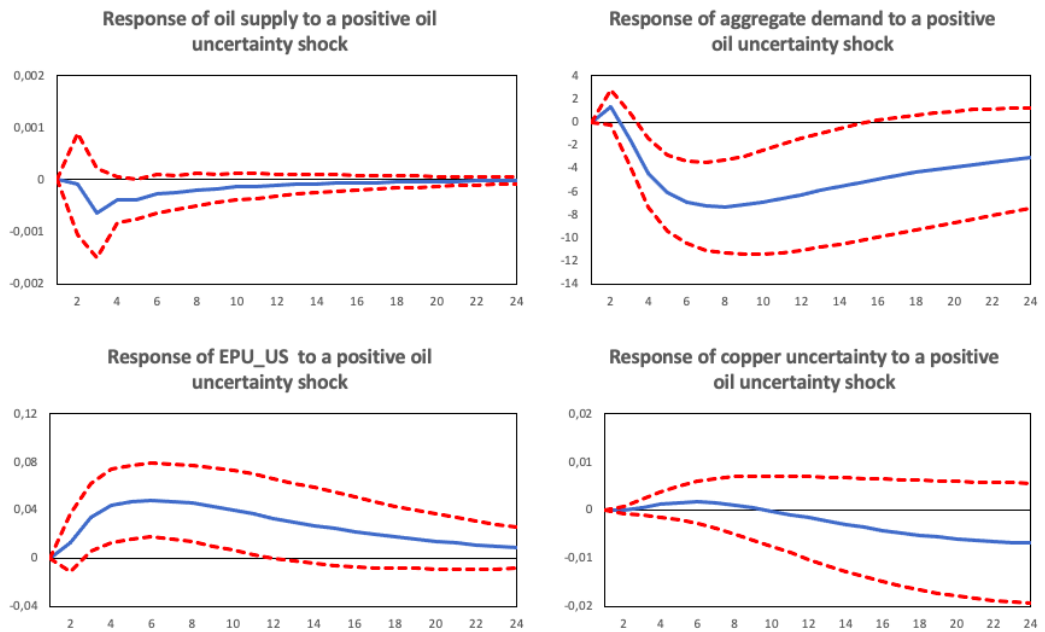
Table B.6 (in Appendix B.1) reports the Forecast Error Variance Decomposition (FEVD) estimates of oil price uncertainty. It provides evidence that oil price uncertainty contributes to about 60% of its own shocks in the short run, reaching 75% in the long run. Meanwhile, it is also notable that the highest contribution of EPU to the oil uncertainty variance is recorded for about 11% on average in the short run, decreasing to 6% in the long run. Finally, EPU shocks are solely more important in the oil price uncertainty variance during the first quarter. Likewise, the oil price uncertainty shocks account for 17% in the short run to the EPU variance (see table B.7 in Appendix B.1).

Figure 2.2: Responses of oil price uncertainty.



Note: These figures depict the responses of oil price uncertainty.

Figure 2.3: Responses to oil price uncertainty shocks.



Note: These figures depict the responses of other variables to oil price uncertainty shocks.

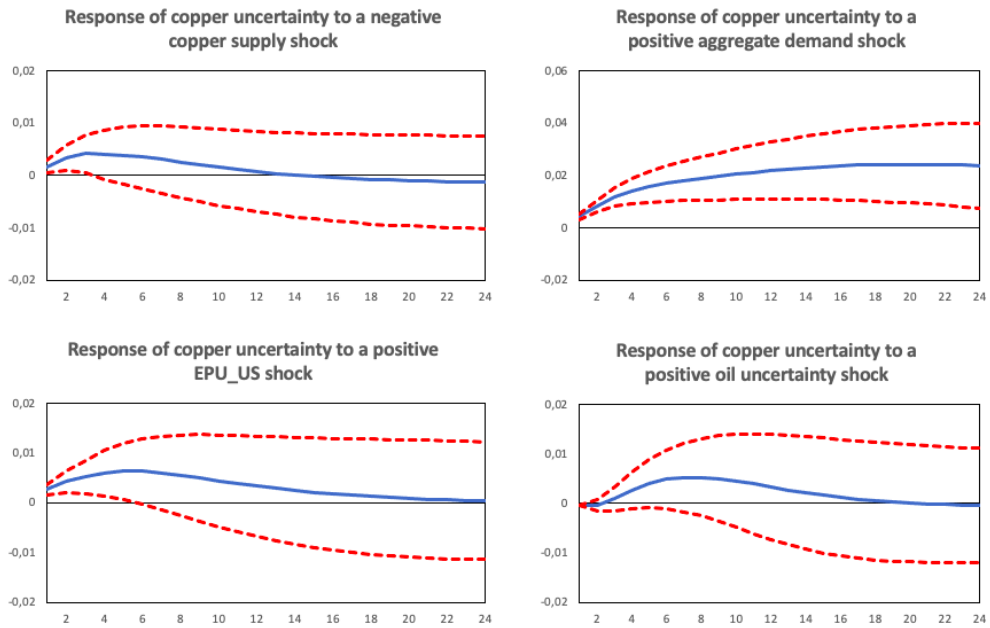
5.2 Copper market results

By analogy, we analyze the underlying dynamics in the copper market.¹⁶ From figure 2.4, at first glance, we notice that the EPU displays a positive and significant effect on copper uncertainty, which lasts in the medium term after the initial shock. Unlike the oil market, the effect is weaker and shorter but remains significant. It is noteworthy that disturbances arising from major copper mining producers (e.g. Chile, Peru) would penalize countries that are highly copper-dependent for their industries. Such unfavorable conditions could lead to increased uncertainty in the copper price, thus drastically hitting global real economic activity. Afterwards, the comovement of copper uncertainty with the aggregate demand is reinforced over time. Hence, aggregate demand shocks are more reliable to explain copper price uncertainty fluctuations (Pedersen, 2019). The copper market, as a leading indicator of real economic activity, reacts almost contemporaneously to changes in global demand. If the copper price drops due to canceled or delayed copper orders, it is a signal a recession is at hand. Conversely, if the copper price rises when the orders increase, industrial jobs benefit from the healthy state of the economy. On both sides, copper price uncertainty increases in response to sudden unexpected changes in aggregate demand. In the same vein, international trade is at play inasmuch as China (the world's largest copper importer) pushes Chile (the world's largest copper producer) to be on the lookout to face this highly intensive demand. The aforementioned explanation holds for short and long-run restrictions frameworks.

Figure 2.5, in turn, displays how other variables react to copper price uncertainty shock. We point out the negative impact of copper price uncertainty on copper supply, real economic activity and the EPU. Since the effect on supply and demand seems to be less surprising, that on the EPU needs to be clarified. The negative effect on the EPU diminishes over time. As we rely on Bakas and Triantafyllou (2018), one explanation is that once the copper price uncertainty shock takes place, the future state of the economic policy becomes less foggy as a result. In particular, this result suggests that there might exist a memory effect of economic policies, which makes them easily predictable by economic agents after the occurrence of macroeconomic uncertainty.

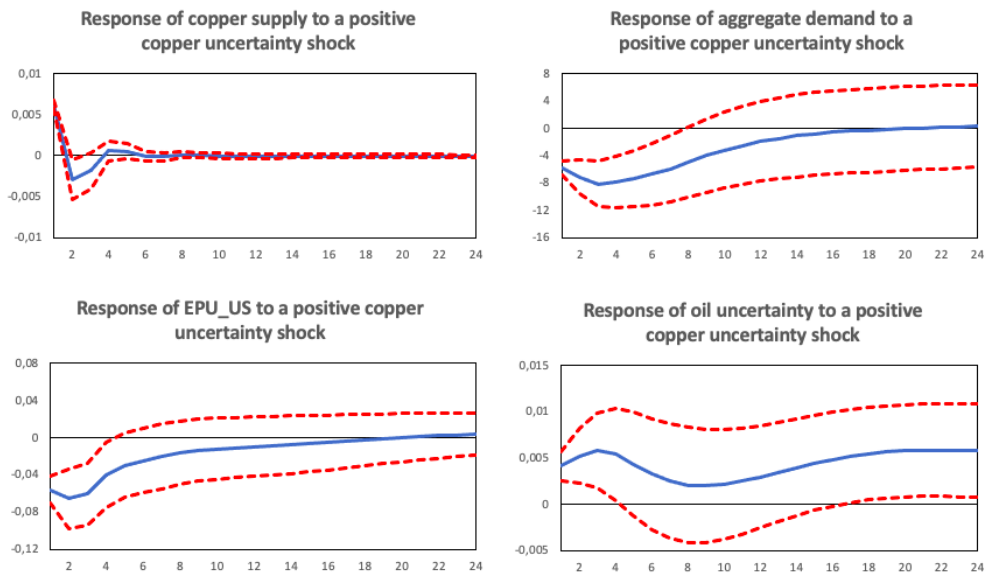
¹⁶The recursive matrix is reported in the table B.8 (in Appendix B.1)

Figure 2.4: Responses of copper price uncertainty.



Note: This graph illustrates the copper price uncertainty responses.

Figure 2.5: Responses to copper price uncertainty shock.



Note: This graph illustrates the copper price uncertainty responses.

The variance decomposition estimates of copper price uncertainty (Table B.9, in Appendix B.1) show that EPU shock accounts for only 6% in the short run and fades as the horizon recedes, whereas the aggregate demand contribution increases with the horizon to reach 33% in the long run. Regarding this finding, the copper uncertainty and the aggregate demand display a long-run pattern. In the same vein, table B.10 (in Appendix B.1) indicates that the share of the copper price uncertainty shocks in the EPU variance is about 8% in the short run.

6 Concluding remarks and policy implications

We investigated price uncertainty drivers in the oil and copper markets. Following the benchmark framework in the oil market developed by Kilian (2009), we proposed to address the oil price uncertainty shocks along with the EPU factor. To successfully carry out this study, we called on an SVAR model with short-run exclusive restrictions to obtain recursive impulse response functions. This approach seemed more appropriate to capture the endogenous relationships between the oil-copper price uncertainty changes with global factors (aggregate demand and supply shocks) and the non-market EPU factor. This chapter uncovered that oil-copper price uncertainties interact positively with the EPU. In other words, an exogenous EPU shock magnifies the effects of each market's price uncertainty. While the EPU recorded almost similar contributions with oil supply and aggregate demand components in the variance of oil price uncertainty, copper uncertainty is mainly driven by aggregate demand shocks. Likewise, oil and copper price uncertainty had a negative impact on aggregate demand. The various negative shocks could stem from the lack of economic decisions synchronization. The political wrestling driven by selfish interests to garner areas of influence is counterproductive. Thus, on the one hand, political authorities have to be aware of the consequences of their actions on international commodity markets and should promote actions on a multi-level oil reserve management system. On the other hand, investors' incentives for diversification and hedging strategies across commodity markets could help mitigate the effects of the EPU. In conclusion, a further insight that might be great of interest is to consider a specific aspect of the EPU in identifying price shocks in commodity markets.

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Appendix B

Uncertainty in oil and copper prices: Does the Economic Policy Uncertainty matter?

Contents

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B.1 Tables

Table B.1: **Correlation matrix in the oil market.**

	1.	2.	3.	4.
1. Oil supply	1.000 (0.000)			
2. Aggregate demand	0.016 (0.691)	1.000		
3. EPU	-0.173 (0.000)	-0.172 (0.000)	1.000	
4. Oil price uncertainty	0.360 (0.000)	0.341 (0.000)	0.133 (0.006)	1.000

Note: The table gives the value of the linear correlation coefficient and the probability values (in parenthesis).

Table B.2: **Correlation matrix in the copper market.**

	1.	2.	3.	4.
1. Copper supply	1.000 (0.000)			
2. Aggregate demand	-0.233 (0.000)	1.000		
3. EPU	0.082 (0.000)	-0.172 (0.000)	1.000	
4. Copper price uncertainty	0.304 (0.000)	0.495 (0.000)	-0.033 (0.492)	1.000

Note: The table gives the value of the linear correlation coefficient and the probability values (in parenthesis).

Table B.3: **Lag length information criteria in the oil market.**

Lag	LogL	LR	FPE	AIC	SC	HQ
0	-403.15	-	5.01e-06	1.98	2.03	2.00
1	1861.42	4463.03	9.27e-11	-8.91	-8.61	-8.79
2	2138.05	538.47	2.73e-11	-10.13	-9.59*	-9.92*
3	2164.10	50.06*	2.71e-11*	-10.14*	-9.35	-9.83
4	2181.40	32.83	2.82e-11	-10.10	-9.07	-9.69
5	2199.93	34.70	2.91e-11	-10.07	-8.80	-9.56
6	2210.66	19.83	3.12e-11	-10.00	-8.48	-9.40
7	2225.01	26.20	3.29e-11	-9.95	-8.19	-9.25
8	2238.03	23.42	3.49e-11	-9.89	-7.88	-9.10

Note: The table illustrates the optimal lag order according to various information criterion.

Table B.4: **Lag length information criteria in the copper market.**

Lag	LogL	LR	FPE	AIC	SC	HQ
0	-514.77	-	3.75e-05	3.99	4.06	4.02
1	451.44	2864.78	5.75e-10	-7.08	-6.67	-6.92
2	1134.55	350.71	1.70e-10	-8.30	-7.55*	-8.00*
3	1161.62	50.81	1.68e-10*	-8.32*	-7.22	-7.87
4	1183.94	41.02	1.71e-10	-8.29	-6.86	-7.72
5	1204.17	36.41	1.78e-10*	-8.26	-6.48	-7.54
6	1218.19	24.70	1.94e-10	-8.17	-6.05	-7.32
7	1240.06	37.68*	2.00e-10	-8.15	-5.68	-7.16
8	1257.37	29.16	2.13e-10	-8.09	-5.28	-6.96

Note: The table illustrates the optimal lag order according to various information criterion.

Table B.5: Recursive coefficients in the oil market.

$$C_{oil}^*(L) = \begin{bmatrix} 0.008(0.000) & 0 & 0 & 0 & 0 \\ 13.275(0.543) & 447.407(0.000) & 0 & 0 & 0 \\ -0.306(0.000) & -0.593(0.000) & 1.103(0.000) & 0 & 0 \\ -0.252(0.002) & 1.451(0.000) & -0.066(0.129) & 0.900(0.000) & 0 \\ -0.098(0.000) & 0.401(0.000) & -0.034(0.053) & 0.266(0.000) & 0.253(0.000) \end{bmatrix}$$

Note: P-values at 10%, 5% and 1% significance levels are in parenthesis.

Table B.6: Forecast error variance decomposition of oil price uncertainty.

FH	Oil supply	Aggregate demand	EPU	Copper uncertainty	Oil uncertainty
1	12.21	11.36	11.98	6.72	57.73
2	10.30	11.14	11.73	6.45	60.38
3	8.34	11.27	9.58	6.72	64.09
4	6.86	11.33	8.40	6.81	66.60
5	5.98	11.19	7.66	6.66	68.51
6	5.41	10.88	7.15	6.44	70.12
7	5.03	10.47	6.78	6.22	71.50
8	4.76	10.03	6.51	6.04	72.66
9	4.57	9.60	6.32	5.90	73.61
10	4.43	9.22	6.17	5.81	74.37
11	4.34	8.92	6.05	5.75	74.94
12	4.26	8.73	5.97	5.72	75.32

Note: FH= Forecast horizon. Data are in percentage.

Table B.7: **Forecast error variance decomposition of EPU in the oil market.**

FH	Oil supply	Aggregate demand	EPU	Copper uncertainty	Oil uncertainty
1	2.52	3.60	71.68	3.49	18.71
2	2.63	4.89	71.51	3.41	17.56
3	2.50	6.23	72.76	2.97	15.54
4	2.92	7.32	73.00	2.70	14.05
5	3.18	8.40	72.89	2.51	13.02
6	3.33	9.44	72.52	2.38	12.33
7	3.40	10.37	72.06	2.29	11.88
8	3.45	11.17	71.55	2.22	11.61
9	3.47	11.85	71.04	2.18	11.46
10	3.50	12.41	70.57	2.14	11.38
11	3.50	12.88	70.14	2.12	11.36
12	3.50	13.26	69.77	2.10	11.37

Note: FH = Forecast Horizon. Data are in percentage.

Table B.8: **Recursive coefficients in the copper market.**

$$C_{cop}^*(L) = \begin{bmatrix} 0.011(0.000) & 0 & 0 & 0 & 0 \\ 113.483(0.002) & 489.796(0.000) & 0 & 0 & 0 \\ -0.386(0.002) & 0.176(0.006) & 1.042(0.000) & 0 & 0 \\ 0.085(0.508) & 1.649(0.000) & 0.061(0.432) & 1.259(0.000) & 0 \\ 0.032(0.428) & 0.523(0.000) & 0.077(0.001) & 0.366(0.000) & 0.148(0.000) \end{bmatrix}$$

Note: P-values at 10%, 5% and 1% significance levels are in parenthesis.

Table B.9: **Forecast error variance decomposition of copper price uncertainty.**

FH	Copper supply	Aggregate demand	EPU	Copper uncertainty	Oil uncertainty
1	3.16	19.64	7.83	69.23	0.14
2	3.56	22.40	6.42	67.55	0.07
3	3.42	24.35	5.64	66.46	0.13
4	2.86	25.29	5.32	66.02	0.51
5	2.43	26.03	5.05	65.51	0.98
6	2.10	26.83	4.78	64.91	1.38
7	1.82	27.76	4.48	64.27	1.67
8	1.60	28.81	4.18	63.57	1.84
9	1.41	29.97	3.88	62.82	1.92
10	1.24	31.22	3.60	62.01	1.93
11	1.11	32.53	3.33	61.16	1.87
12	0.99	33.86	3.09	60.28	1.78

Note: FH = Forecast Horizon. Data are in percentage.

Table B.10: **Forecast error variance decomposition of EPU in the copper market.**

FH	Copper supply	Aggregate demand	EPU	Copper uncertainty	Oil uncertainty
1	6.28	5.72	61.48	5.46	21.06
2	8.24	5.44	57.12	8.25	20.95
3	10.24	4.82	55.55	10.20	19.19
4	10.32	4.93	56.38	10.59	17.78
5	10.53	5.28	56.93	10.58	16.68
6	10.73	5.72	57.21	10.50	15.84
7	10.86	6.18	57.24	10.39	15.33
8	10.87	6.66	57.13	10.24	15.10
9	10.84	7.10	56.89	10.10	15.07
10	10.78	7.49	56.58	9.98	15.517
11	10.70	7.82	56.26	9.89	15.33
12	10.63	8.07	55.98	9.81	15.51

Note: FH = Forecast Horizon. Data are in percentage.

B.2 Resolving the benchmark oil market

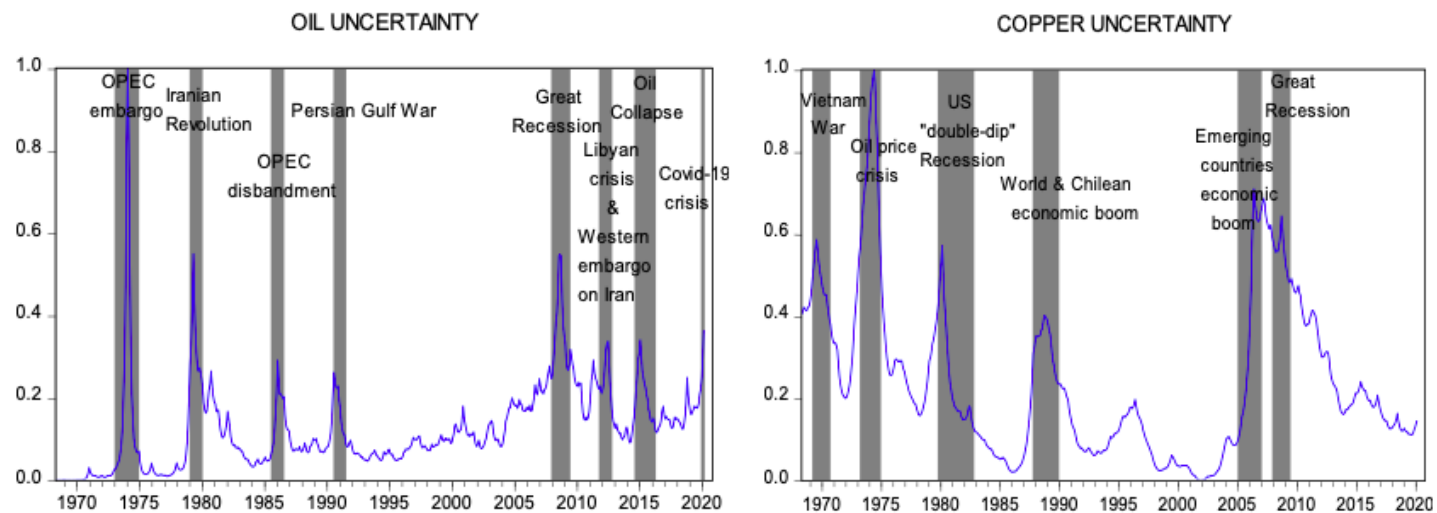
As we expect to propose a common global framework for our commodity markets, we first replicate the results of Kilian (2009) in a three-factor SVAR benchmark model (with oil supply, aggregate demand and real oil price) as endogenous variables. Variables are ordered as listed above. Contemporaneous effects among variables (with P-values at 10%, 5% and 1% significance levels in parenthesis) are given by:

$$\Gamma^{-1} = \begin{bmatrix} 69.023(0.000) & 0 & 0 \\ 2.708(0.351) & 0.075(0.000) & 0 \\ -0.767(0.792) & -0.008(0.005) & 10.765(0.000) \end{bmatrix}$$

From Figure B.3 (in Appendix B.3), we observe that short-run restrictions on oil price dynamics result in negative and not significant response of oil price to oil supply shocks. Nevertheless, oil price shock reacts in a positive, significant and persistent way to aggregate demand shocks and oil-specific demand shocks. The response to aggregate demand shocks seem to vanish over time from the initial shock whereas that of oil-specific shocks is more persistent. The first three aspects (effects of supply shock, aggregate demand shock, oil-specific demand shocks) are consistent with the results of Kilian (2009), Kilian and Park (2009). Indeed, following earlier empirical studies, Wang et al. (2014) explains this non-significance of oil supply shocks on the oil price is due to the fact that global oil production is driven by offsetting flows between oil-producing countries around the world. For instance, when the oil disruption effect occurs in a region it could trigger an oil expansion effect somewhere else so that the global effect on price remains unchanged. Although the first decade of the 2000s was dominated by OPEC's leadership attitude to reduce oil production coupled with geopolitical tensions (Venezuela strike in 2002, second Gulf War in 2003), the oil production has been less by reserves and exploration fields. In the same vein, the finding of Kilian (2008) holds as supply shocks play a lower impact in predicting the real price of oil. On the other side, the aggregate demand shock has a positive impact at 5% level the oil price showing once more that business cycle fluctuations play a major role in oil price changes. The oil-specific shocks in the short-run still have a predominant effect in forecasting oil real price. However, oil-specific shocks could be identified in a workhorse model developed by Kilian and Murphy (2014) and Cross et al. (2020).

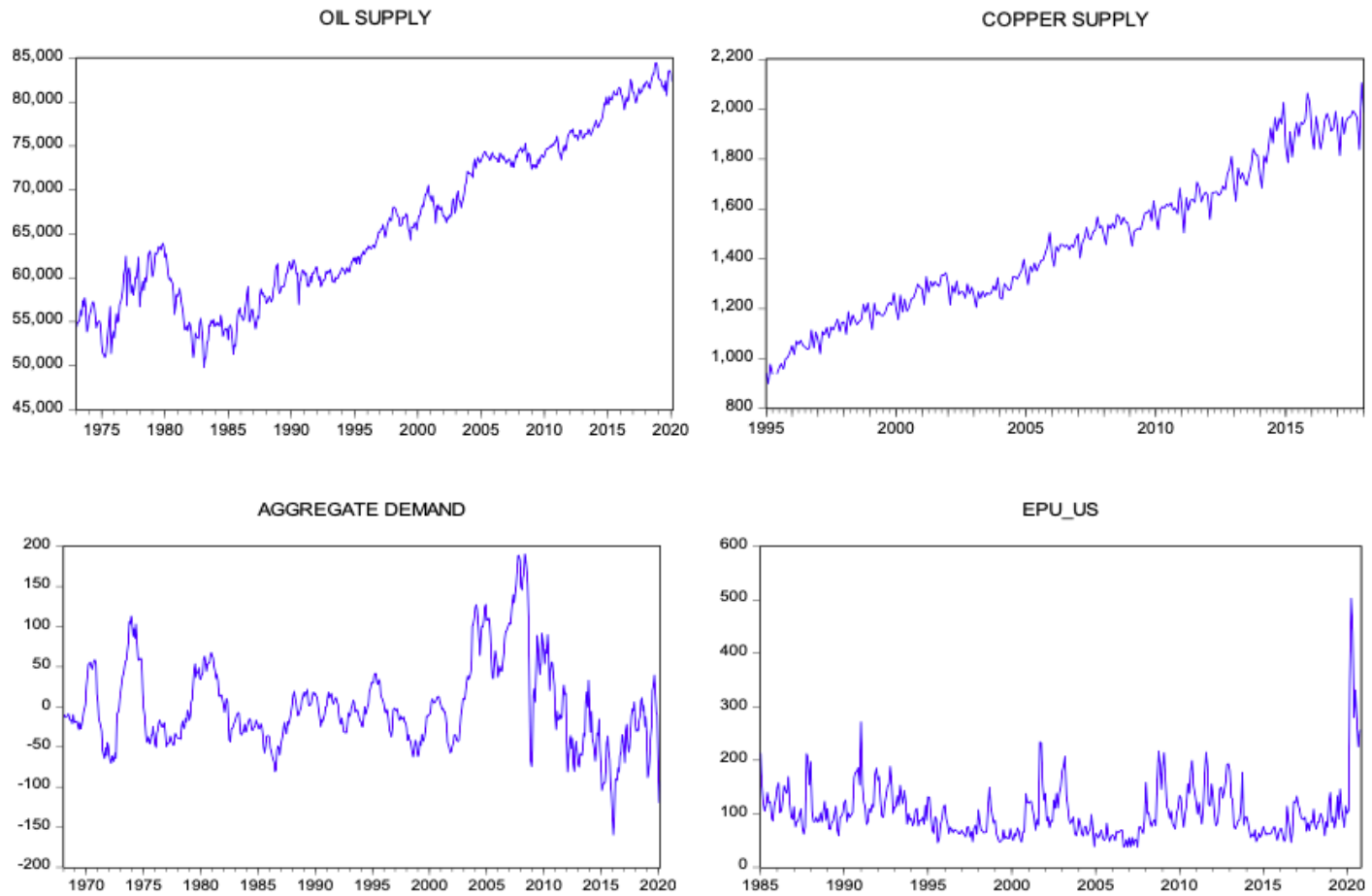
B.3 Figures

Figure B.1: Uncertainty in commodity prices.



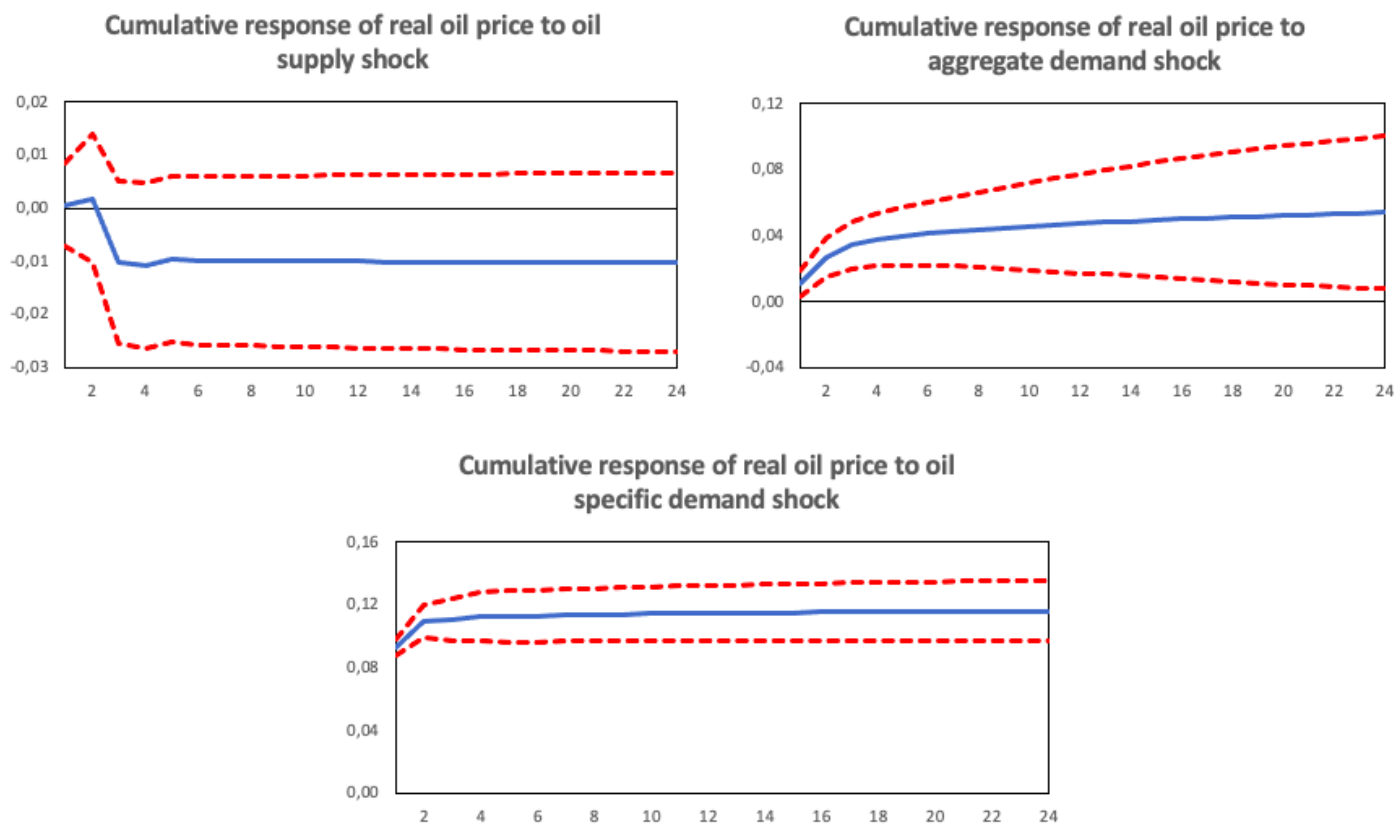
Note: These figures depict for each market a one-month price uncertainty measure along with major macroeconomic or specific events (represented by the grey bands across each commodity market). For convenience, we use min-max normalization to obtain the same interval values for each uncertainty variable so that the lowest and the largest value equals 0 and 1, respectively.

Figure B.2: Macroeconomic variables in oil and copper markets.



Note: These figures depict oil supply (in thousand barrels metrics), copper supply (in thousand tons metrics), the EPU and the aggregate demand variables.

Figure B.3: Oil price dynamics in the benchmark oil market.



Note: These figures depict oil real price responses to supply, aggregate demand, oil specific demand and price uncertainty shocks.

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Chapter 3

Does the European Low-Carbon Policy impact price uncertainty in fossil energy markets?¹

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¹This chapter is a single-authored work. Parts of this chapter were presented at: 8th International MACroeconomics Workshop (Rennes, France), December 1-2, 2022; 3rd World Conference on Climate Change and Global Warming (Prague, Czech Republic), March 10-12, 2023; Doctoriales Macrofi (Poitiers, France), April 6-7, 2023; Commodity and Energy Markets Association Conference (Budapest, Hungary), June 20-21, 2023.

Summary

This chapter aims to appraise the potential effects of an energy-related environmental policy on price uncertainty in fossil energy markets. For this purpose, we propose text-as-data methods relying on unsupervised machine-learning algorithms applied to European Union (EU) laws and newspapers. These are used to construct two monthly indices over the reference period 1997-2021: (i) a news-based index that reflects two underlying components: uncertainty about the global context and regulations on energy and environment as they are relayed in the press, and (ii) a law-based index that reflects structural changes in European energy and environmental regulations. The main findings suggest that both indices display, to some extent, a common evolutionary pattern around salient events in the history of EU energy and environmental policy. Moreover, the news-based index appears to be more volatile and is wider than the law-based index. The support for this carbon phase-out policy leads to further examine the extent to which each index relates to price uncertainty dynamics in fossil energy markets (oil, gas, and coal). As a result, we uncover that an increase in the news-based index displays a dual effect on price uncertainty across markets. Notably, a slight positive short-run effect followed by a permanent dampening effect. Each effect, as described, is considered as a result of the news-based underlying components, namely uncertainty about the global context and the regulations, respectively. Similarly, we find a significant and negative short-run and persistent impacts of law-based index shocks on price uncertainty across markets. Thus, stabilizing price uncertainty dynamics by regulations is a way to gauge the efficacy and resilience of European energy and environmental policy.

Keywords: Energy and Environment Policy; News and media; Text-mining; Unsupervised machine learning; Commodity markets, Structural VAR.

Classification JEL: Q58, C55, C80, D80, Q02, C32.

1 Introduction

Developments in economic policies are of increasingly great interest when analyzing price fluctuations in commodity markets. In line with chapter 2 which explores the empirical evidence of economic policy uncertainty, this chapter addresses the central issue of the European energy-related environmental policy (also called low-carbon policy) and its implications for fossil energy markets.

Global warming has become a major concern for governments around the world. To address it, countries have entered into national, regional and international agreements involving more responsible energy transition policies. For instance, the European Union (EU) identifies climate change as one of the biggest challenges of the forthcoming decades. This objective stems from the fact that the EU is willing to play a crucial role in negotiations and the implementation of the Kyoto Protocol and its latest version, the Paris Agreement (Oberthür and Roche Kelly, 2008). To fulfill this position, environment and climate policy has become more embedded into EU sectoral policies including energy, as confirmed by the Energy Union framework (Biermann et al., 2009, Jordan et al., 2011, Maltby, 2013). Therefore, major developments in EU energy policy are required (Damro et al., 2008, Solorio, 2011). The awareness of European authorities about climate and environmental concerns results in legislation on the bulk of related laws, which are subsequently relayed in the newspapers. The salience of energy and environmental policy on the political agenda tends to fluctuate over time, leading numerous economic players (producers and consumers) to shift their incentives towards green energy securities.

The cycle of energy and environmental policy is subject to periods of increasing stringency and sudden rollbacks. In particular, in early 2017, Trump's administration initiated the US withdrawal from the Paris Agreement. In 2018, France also revoked the fuel tax after the Yellow Vest protests. China and Australia also backpedaled their respective coal regulations. Such changes trigger a surge in uncertainty about the future state of regulations. Policymakers often face the dilemma of balancing competing long-run environmental goals and short-run economic and electoral priorities. Moreover, lobbies, legislative battles, protests and legal challenges constitute, among others, barriers to the establishment and implementation of regulations. Hence, such unpredictable swings induce uncertainty in energy and environmental policy, making it difficult to foresee how the regulatory framework will unfold in the future. Both regulation and uncertainty about regulation on en-

ergy and the environment influence the transition to a low-carbon economy. Indeed, agents' decision-making to postpone or withdraw investments relies on policy assumptions under uncertainty. In the same vein, the European Investment Bank (EIB, 2021) highlights in a survey that 43% of European institutional investors consider uncertainty about regulation as a hindrance to undertaking climate-related investment.

The novelty of this chapter is to explore the nexus between energy-related environmental regulations and price uncertainty in fossil energy markets. To this end, using textual analysis, we propose a quantitative assessment of energy and environmental policy through newspapers and law publication activity by the EU Commission. The procedure involves the use of two distinct datasets on news and laws, respectively. Unlike the seminal EPU index developed by Baker et al. (2016), our news dataset focuses on a broader perspective to capture both uncertainty about the global context and energy and environmental regulations as discussed in the European press. At the same time, our law dataset lists the legal acts frequently published by the EU Commission. In other words, while the press highlights the uncertain environment regarding international conditions and the way the regulations are embedded in newspapers, laws solely describe the evolution of the adoption and/or implementation of legal acts. The former is more susceptible to being volatile since newspapers cover high-frequency information. The latter is relatively stable and displays a seasonal pattern. In general, regulations are introduced as a package of proposals with multifaceted aspects, such as the Green Deal or regulations on pollutants used by industries and households. Each index is an aggregation of topic-specific indices, allowing the multidimensionality of energy-related environmental policy to be addressed. The composite indicator is available on a monthly basis. As stated by Brunel and Levinson (2020), the construction of a meaningful aggregate index in empirical works is a very tricky and challenging task. Thanks to machine learning techniques, we have the opportunity to disentangle latent information from a rich amount of text and elaborate subclusters to build up topic-specific indices. In the end, this process helps us track the salience of energy and environmental policy.

Our indices of energy-related environmental policy provide complementary insights into existing quantitative environmental policy measures. First, in contrast with one of the pioneering works of Noailly et al. (2021) constructing a news-based index of US environmental policy, our news-based index describes the global context of the evolution of environmental policy as reported in European newspapers. News-

papers have the advantage of giving additional information about the regulatory context, namely details on sentiment, controversies, and implementation processes (Noailly et al., 2022). Second, our law-based index approach appears to be original since it captures the legislative cycle of energy and environmental regulations in the EU. The latter provides a different way of considering the regulatory framework in addition to (Botta and Koźluk, 2014), who developed an OECD environmental policy stringency index computed on an annual basis at a country level.

The dynamics of energy and environmental regulations strengthen the reduction of fossil energy in favor of healthy alternatives; this is not without any consequence on fossil energy markets. In addition, one might argue that the EU, as one of the world's largest importers of fuels for its industrial production system, could generate exogenous shocks on fossil energy markets by taking substantial actions on energy-related environmental regulations.

Following the standard empirical approach in the literature, we use a Bayesian Vector Autoregressive (BVAR) model to investigate the implications of energy-related environmental policy on the price uncertainty dynamics in fossil energy markets (namely oil, gas, and coal markets). Our findings show that shocks on the news-based composite indicator display a two-way pattern on oil and coal price uncertainty: (i) a slight upward trend occurring in the short run, which is attributable to either uncertainty about the global context or announcement effects; and (ii) a persistent detrimental effect that follows to stabilize the price uncertainty dynamics is attributable to the regulations. It is worth noting that the downward momentum of gas price uncertainty begins earlier and sets in permanently after the shocks in the news-based index. Likewise, we observe a negative and significant impact of increases in the law-based composite indicator on oil and coal price uncertainty. The impact is particularly long-lasting in the coal market. Furthermore, we observe that the bearish effect on gas price uncertainty is unveiled when analyzing environment-specific regulation shocks. To sum up, we draw from these outcomes that the news and law-based energy-related environmental policy indices contribute, at various time horizons, to cushioning the dynamics of price uncertainty across fossil energy markets. Additionally, we assess the effects of our indices on markets' prices. As a result, we find that the news-based index solely plummets prices as markets foreshadow regulations.

The rest of the chapter is organized as follows. Section 2 reviews the related literature. Section 3 describes the methodology of the textual analysis. Section

4 provides the construction of news and law-based indices, respectively. Section 5 explores how both indices relate to fossil energy markets and section 6 concludes the chapter.

2 Related literature

The significance of this study is owed to two main strands of the literature. First, this work builds on the growing interest in the textual analysis of news in economic analysis to construct meaningful indicators (Gentzkow and Shapiro, 2010). For instance, Baker et al. (2016) developed a methodology to build a news-based index of economic policy uncertainty (EPU) from 10 leading newspapers in the United States (US). Similarly, Bybee et al. (2020) used a topic modeling approach to unveil specific topics from a set of 80,000 articles published in the *Wall Street Journal* over the period 1987-2017. They discovered that news topics track a wide range of economic activity measures and are also powerful incremental predictors of economic outcomes, namely for output and employment in recession times. Beyond the aforementioned macroeconomic developments of the textual analysis, less attention is given to environmental economics Baylis (2020), Dugoua et al. (2022). Only a few research papers in the financial literature have reviewed some aspects of environmental concerns, such as pollution news Hamilton (1995), Dasgupta et al. (2001) or the impact of investors' Twitter sentiment on renewable energy stocks (Reboredo and Ugolini, 2018, Song et al., 2019). Relatedly, studies using text-mining methods to measure climate risks and perceptions in newspapers have emerged (Sautner et al., 2020, Kölbel et al., 2020, Engle et al., 2020). This literature has so far solely reported the salience of the climate change and environmental issues nexus to public attention. In addition, this work also emphasizes the regulatory actions of public authorities to mitigate concerns about the energy-environment-climate triptych. Thus, a sophisticated methodology is mobilized to identify and classify relevant documents using automated text-mining techniques.

Second, this chapter is related to the literature addressing the effects of economic policies on various economic variables. In environmental economics, both theoretical and empirical studies have investigated this issue. Theoretical models mainly focus on uncertainty arising from environmental and climate shocks. This uncertainty tends to raise precautionary savings and capital adjustments (e.g. away

from capital prone to climate shocks). As a result, the works of Bakkensen and Barrage (2018) and Cai and Lontzek (2019) point out a possible drop in productivity, growth and welfare. According to the theory-supported economic mechanism, firms postpone investments when the regulatory framework becomes uncertain. Such a wait-and-see behavior is first characterized by pent-up investment which induces a subsequent investment boom, reinforcing the cycle of economic activity (Stokey, 2016). Another handful of theoretical papers underscores, in relation to uncertainty about environmental policy, firms' investment strategies in relation to pollution controls (Viscusi, 1983), assets portfolios (Bretschger and Soretz, 2021) and risk level (Blyth et al., 2007, Fuss et al., 2008). In the same vein, corresponding empirical studies in environmental economics are taken from the seminal literature on the impact of policy uncertainty on investment. A major contribution is the work of Baker et al. (2016) to construct a monthly news-based EPU index. At the micro-level, these authors show evidence that the EPU is associated with lower investments and higher volatility for firms most exposed to policy uncertainty. At the macro level, the EPU shrinks industrial production and employment. In other words, empirical investigations into environmental economics mostly rely on event studies exploring how uncertainty about environmental policy affects investments. Sen and von Schickfus (2020) conducted an analysis of the effect of German climate policy on firms' fossil energy utilities. They uncovered that such a policy exposes energy-sector assets at risk of becoming stranded so that investors would expect financial compensation to avoid the abrupt devaluation of firms. Moreover, some research papers involving the US experience regarding unexpected shifts in climate policy report spikes in coal prices and inventories (Lemoine, 2017) as well as compliance costs across states (Dorsey, 2019). Regarding the precedent, central to the insight of the existing literature is the impact of environmental policy uncertainty on investment. However, to the best of my knowledge, no study has explored the implications of energy-related environmental policy on fossil energy markets. Yet, this idea is crucial when considering a transition to a low-carbon economy.

3 Topic modelling

The textual analysis methodology used to construct both news and law-based indices consists of a hands-off unsupervised machine learning algorithm called Latent

Dirichlet Allocation (LDA) developed by Blei et al. (2003). The language of text collections refers to entities such as "words", "documents", and "corpora". This is helpful to keep in mind since it helps to guide intuition, particularly when further introducing latent variables which aim to capture abstract notions such as topics. Formally, we define these entities as follows:

- A *word* is a basic unit of discrete data, defined as an item of a vocabulary V indexed by $1, \dots, V$. Note that words are represented using unit-basis vectors that have a single component equal to one and all other components equal to zero. Thus, using superscripts to denote components, the v_{th} word in the vocabulary is represented by a V -vector w such that $w^v = 1$ and $w^u = 0$ for $u \neq v$.
- A *document* is a sequence of N words denoted by $w = (w_1, w_2, \dots, w_N)$, where w_n is the n^{th} word in the sequence.
- A *corpus* is a collection of M documents denoted by $D = (d_1, d_2, \dots, d_M)$.

LDA is considered a probabilistic model that looks for high-probability assignments in documents and similarities across them in the corpus. The algorithmic process aims to uncover latent (hidden or unknown) structures in the corpus. The latent thematic structure, expressed as per-word topics and per-document topic proportion assignments, is represented by hidden variables that LDA points onto the corpus. The nature of LDA describes an imaginary random process based on probabilistic sampling rules, from which we assume documents come from. Nevertheless, while we only observe words within documents, we need to infer hidden structures by applying statistical inference techniques. Besides, it is clearly an unsupervised algorithm because it learns these two latent distributions of the model without prior information regarding their themes. This process helps to answer the question: Which hidden structure or topic model is most likely to have generated these documents? In doing so, one can capture the posterior distribution of the hidden structure given to the observed documents.

One way to understand LDA is to consider that the model recovers two unknown distributions by obtaining parameters that maximize the probability of each word appearing in each document given the total number of topics K . The probability of each word w_i appearing in a document is then given by the formula:

$$P(w_i) = \sum_{k=1}^K P(w_i|z_i = k)P(z_i = k) \quad (3.1)$$

where z_i is a latent variable that indicates the topic from which the i^{th} word was drawn. $P(w_i|z_i = k)$ is the probability of word w_i being drawn from topic k , and $P(z_i = k)$ is the probability of drawing a word from topic k in the current document. More precisely, $P(w|z)$ refers to which words are important to a topic, while $P(z)$ indicates which of these words are important to a document.

An alternative way to get the algorithm is to have a look at the generative process defined as follows:

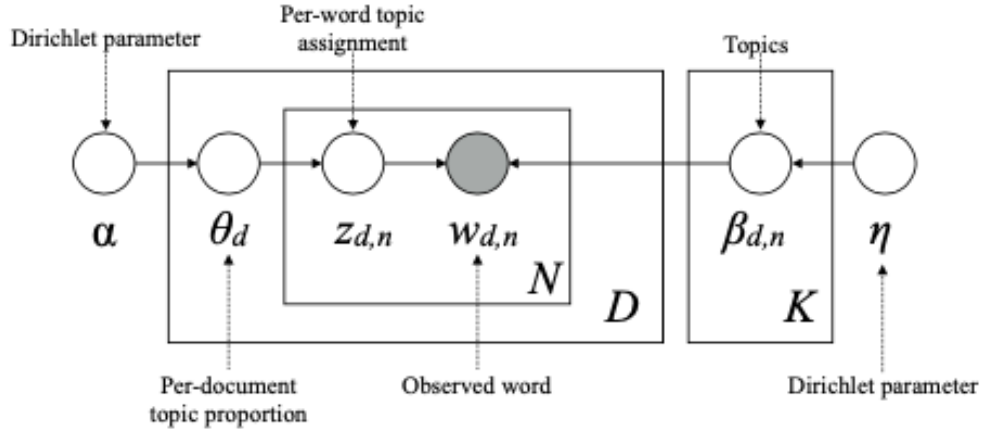
- 1) For every topic $k \in 1, \dots, K$
 - Draw each topic $\beta_k \sim Dirichlet(\eta)$ as a multinomial distribution over the vocabulary V
- 2) For every document d
 - Draw a distribution over words such as $N \sim Poisson(\xi)$
 - Draw a distribution over topics $\theta_d \sim Dirichlet(\alpha)$ (i.e. per-document topic proportion)
 - For each word w within a document d
 - Draw a topic assignment $z_{d,n} \sim Multinomial(\theta_d)$ where $z_{d,n} \in 1, \dots, K$ (i.e. per-word topic assignment).
 - Draw a word $w_{d,n} \sim Multinomial(\beta_{z_{d,n}})$, where $w_{d,n} \in 1, \dots, V$

α and η denote the smoothing hyperparameters of topics within the documents and words within topics, respectively. These parameters are likely to be adjusted in the model. The joint distribution of all hidden variables β_k (topics), θ_D (per-document topic proportions), z_D (word topic assignments), and observed variables w_D (words in documents) is expressed as follows:

$$P(\beta_k, \theta_D, z_D, w_D | \alpha, \eta) = \prod_{k=1}^K P(\beta_k | \eta) \prod_{d=1}^D P(\theta_d | \alpha) \prod_{n=1}^N P(z_{d,n} | \theta_d) P(w_{d,n} | z_{d,n}, \beta_{d,k}) \quad (3.2)$$

The aforementioned underlying process of the LDA could always be graphically expressed by the figure 3.1 below:

Figure 3.1: LDA generative probabilistic process.



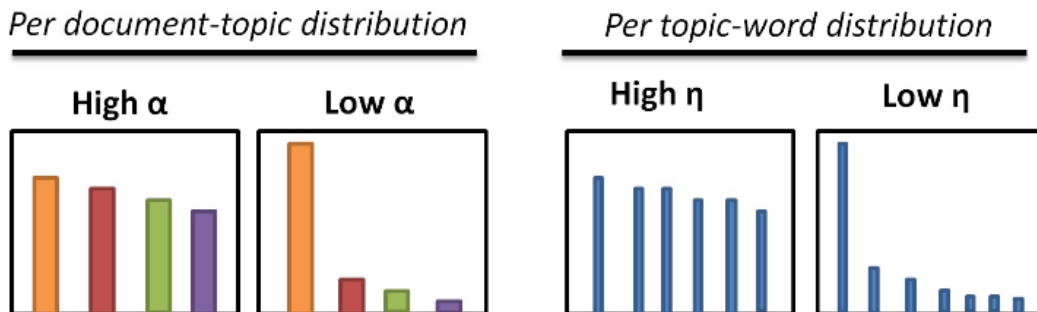
Note: This picture depicts graphical aspect of the LDA model on plate notation. While the shaded nodes represent observed variables, unshaded ones correspond to the hidden random variables. Edges illustrate the conditional dependencies between unshaded nodes. Rectangles (also called plates) denote a replication process (source: LDA-Process).

The graphical representation is roughly equivalent to the joint probability distribution in the equation (3.2). $\prod_{k=1}^K P(\beta_k|\eta)$ represents distributions over words for all K topics. $\prod_{d=1}^D P(\theta_d|\alpha)$ indicates the per-document topic proportion across the corpus D of all documents. Finally, for unique N words, $\prod_{n=1}^N P(z_{d,n}|\theta_d)P(w_{d,n}|z_{d,n}, \beta_{d,k})$ represents the probability of assigning the n^{th} word to a given document. This probability is the product of the two-stage probability selection process: (i) the probability of assigning a given document to topic k ($P(z_{d,n}|\theta_d)$), and (ii) the probability of nominating the n^{th} word to a document selected in step i ($P(w_{d,n}|z_{d,n}, \beta_{d,k})$). This last stage is characterized by the probability of matching a word from the collection of words $w_d = w_1, \dots, w_n$ to a document given a word-to-topic assignment $z_{d,n}$ and the per-corpus topic distribution $\beta_{d,k} = \beta_{1,1}, \dots, \beta_{D,K}$.

Figure 3.2 is an illustration of LDA hyperparameters. High levels of η indicate the probability distribution of words to topics being more even, while a low level of η represents fewer words having a much higher probability of defining that topic than the rest. Similarly, high levels of α indicate documents containing a similar

topic distribution per document while low levels of α represent a more disperse distribution.

Figure 3.2: **LDA hyperparameters.**



Source: Azqueta-Gavaldón (2017).

The maximization of $P(w_i|z_i = k)$ and $P(z_i = k)$ from the equation (3.1) to approximate the posterior distribution $P(z|w)$ requires either sampling methods or variational methods. In this chapter, we use an advanced type of variational method called *online variational Bayes* (Hoffman et al., 2010) which is deemed to be faster and more suitable for large databases.² Eventually, the coherence score C_v of the model is chosen as a relevant criterion to estimate the optimal number of topics K .³ Given that the model runs on two datasets separately, the optimal K is set to 14 for the laws dataset and 29 for the news dataset. Thereafter, we apply the algorithmic process on both news and laws datasets to construct meaningful composite indicators, accordingly.

4 Construction of news and laws-based indices

The handful construction of indices lies in three main points. The first step of the construction process of each index consists of searching documents related to the given topic using a simple keyword approach as in Baker et al. (2016) and Basaglia et al. (2021). In the second step, we use text pre-processing techniques and convert each document into numerical vectors of n-grams (known as the generalized form of a

²See more details on the methodology in Appendix C.1.

³Further elements are reported in Appendix C.2.

bag of words). Then, we derive a term-frequency inverse-document frequency matrix (tf-idf) adjusted for words with low and high occurrence. The last step calls on the methodology proposed by Azqueta-Gavaldón (2017) to run an unsupervised machine learning algorithm in order to classify documents into specific subcategories. The unsupervised nature of the algorithm categorizes documents into topics without the need for previous knowledge of the themes covered in the documents. The algorithm used is called "Latent Dirichlet Allocation" (LDA) and was developed by Blei et al. (2003). It is a generative probabilistic method that recovers two distributions, namely words-to-topic and topic-per-document distributions. The main advantage of this topic modeling algorithm is that the researcher is not required to come up with individual lists of keywords for each topic, but can apply this method to uncover the structural patterns of any text endogenously. However, one of the caveats of this method is that each topic represents a set of most probable words to be interpreted by the researcher.

4.1 Developing a news-based index

4.1.1 News data

The starting point of the experiment is to download a set of 65,807 articles from the archives of 694 European newspapers from January 1997 to April 2022. These are available on the retrieval tool of Nexis, an online database with extensive media articles coverage. Articles are selected from the query using a 'naive' dictionary approach, as in Baker et al. (2016) and Basaglia et al. (2021), which consists of searching articles simultaneously containing keywords such as "regulation", "energy", "environment", "climate", "policy", "risk and/or "uncertainty". More specifically, this keyword-based retrieval method detects two components of the news content, namely global uncertainty and regulations. In addition, narrowing the search for articles with keywords avoids, as much as possible, including a myriad of articles dealing with contexts that are not applicable to energy or environmental regulations (type-I error). Besides, we admit that this strategy is not restrictive enough to avoid missing out on potentially relevant articles by imposing too much structure (type-II error). Therefore, we should strike a balance to be more representative. Since we rely on an unsupervised algorithm, we intend to end up with energy and environmental regulation-related articles recording the highest weight in our sample.

Next, we apply text pre-processing steps to our corpus of 65,807 articles, namely

filtering stop-words (words that do not reveal informative details about the corpus of documents), removing numbers, punctuation and html tags, lowercasing and lemmatizing all words (i.e. taking into account the morphological analysis of the words).⁴ Afterwards, we convert articles into numerical vectors of uni-bi-trigram frequencies using a 'bag-of-words' method. A matrix is then constructed as a term-frequency inverse document frequency (tf-idf) in which words with high and low occurrences are under-weighted because they appear less informative than other words.⁵

Finally, we train our set and its corresponding tf-idf matrix as inputs to the LDA algorithm to assign words and documents into topics, accordingly.

4.1.2 Descriptive statistics

Based on the methodology presented in the section 3, here we lend credence to our LDA classifier algorithm with a number of descriptive statistics such as the optimal number of topics K according to the coherence score C_v and representative words per topic. Regarding these criteria, the best model fits with $K = 29$ and $C_v \simeq 0.48$. Table 3.1 displays dominant topics and their corresponding excerpts of most representative words across articles in the sample. We pay attention to articles the LDA classifier identifies as preeminently talking about energy and environmental regulations from a probability distribution. The algorithm analyzes important text features to determine whether an article falls into a specific topic. Thereby, we label topics according to the words they encompass. For instance, energy and climate issues are illustrated by words such as 'energy', 'emission', 'nuclear', 'power', 'climate', 'change', 'carbon', 'renewable', 'green' and 'target'. It is worth noting that uncertainty features mostly arise from a massive interest given to a topic. Therefore, the number of articles per topic in the sample derived from the LDA classifier provides a signal of the importance of a topic under discussion. The idea is to point out the effect of the mimetic behavior of mass newspapers on reporting a topic that intrinsically generates uncertainty. One another point is to consider the global context characterized by exogenous events-induced uncertainty such as political unrest, military conflicts (e.g. the Russo-Ukrainian war), economic or even health crisis (e.g. COVID-19).

Regarding table 3.1 reporting unveiled topics provided by the LDA algorithm,

⁴The list of stopwords is reported in Appendix C.3.

⁵An overview on N-Gram models and the tf-idf matrix is illustrated in Appendix C.4.

each topic is labeled according to the semantic that governs its most representative words. Else, documents in the sample are classified according to the dominant topic. Amidst, one can target topics (as well as documents in proportion to the entire sample) related to energy and environmental regulations.

Figure 3.3 illustrates the news-based index, which represents the share of articles assigned to energy-related environmental regulations and the global context over all articles in the sample per month. Scaling by the total number of articles is a way to appraise the importance of discussions about energy-related environmental regulations in newspapers. The news-based composite indicator results from the combination of 10 topics defined as subcategories (i.e. topics 4, 5, 6, 8, 11, 14, 15, 25, 27, 29) representing almost 44% of the initial sample. The composite index is then normalized to an average value of 100 and 1 standard deviation. We also annotate significant peaks which capture meaningful increases in the prevalence of uncertainty amid ongoing debates on energy and environmental regulations.

From figure 3.3, we find out that, in the early 2000s, the news-based index was punctuated by several bursts, notably around the Kyoto Protocol adoption and the Bonn climate change conference. Indeed, the EU authorities established a new challenge of fighting against climate change generated by greenhouse gas emissions, in particular CO_2 from anthropological activities. In order to limit Earth's average surface temperature, the EU favored the advent of a 'carbon market' in 2005 to penalize major industrial sectors with the highest CO_2 emissions. The target of the initiative was to ensure a gradual transition from "damageable" fossil energies to 'healthy' renewable energies. In 2008, the European leaders put in place a "climate-energy package". This program was initially targeted for 2020 before it was postponed in 2014 to 2030. Its contribution was threefold: (i) the reduction of greenhouse gas emissions by 20%, (ii) the improvement of energy efficiency by 20%, and (iii) the increase to 20% of the share of renewable energies in the final energy consumption. The success of the 3x20 program was relative because it came up against several economic events including the great recession and the sovereign debt crisis. As in times of crisis, authorities are less concerned with energy-related environmental policy. Therefore, the index plummeted over the 2009-2012 period. Also, we observe along the historical evolution of the index, consecutive major events such as the Paris Agreement in 2015 and the Green Deal in 2019. The purpose of the EU Green Deal is to put an end to net greenhouse gas emissions by 2050. The target is to reduce them by at least 55% by 2030 in comparison with values from 1990.

Thereby, Europe would become the first “climate neutral” continent, i.e. it would achieve “carbon neutrality”. The plan is based in particular on the phasing out of fossil energies, electric mobility, technological innovation, the circular economy, building renovation and sustainable agriculture. Since 2020, the world has faced various energy uncertainty-inducing exogenous events, namely the UK’s exit conditions from the EU, the COVID outbreak, and the Russo-Ukrainian crisis. The latter obliged the EU to put “energy sovereignty” back at the top of its list of concerns by promoting independence from all Russian fossil fuels well before 2030 (given that Russia supplies 49% of coal imports, 38% of natural gas and 25% of oil in the EU).

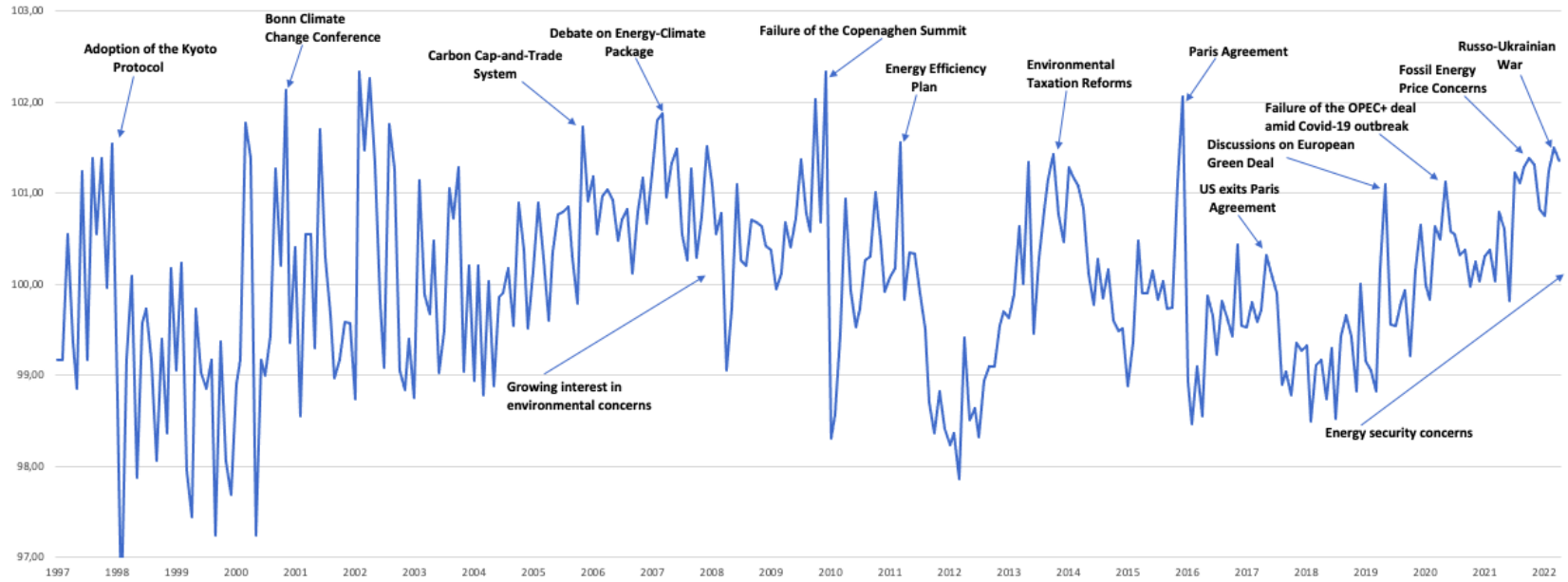
Table 3.1: LDA topics and most representative words.

Topic	Label	Top-10 words ($\lambda = 0.5$)	Percent
T.1	Unknown	<i>say, time, block, minister, publish, people, labour, get, go, government</i>	1.39%
T.2	European security	<i>state, country, European, policy, agreement, member, law, foreign, security, take</i>	6.18%
T.3	Economic crisis	<i>bank, euro, market, financial, debt, government, fund, crisis, economic, risk</i>	5.43%
T.4	Coal and steel	<i>steel, industry, government, coal, plant, Chinese, car, fuel, make, job</i>	1.26%
T.5	Energy supply	<i>company, gas, oil, energy, price, market, group, supply, business, project</i>	5.09%
T.6	Conflicts	<i>Russia, Ukraine, war, military, country, sanction, people, force, time, Ukrainian</i>	1.94%
T.7	Agriculture	<i>food, use, make, say, farmer, people, farm, water, work, many</i>	6.30%
T.8	Energy emission	<i>climate, world, change, global, country, emission, power, nuclear, energy, make</i>	8.60%
T.9	US politics	<i>Trump, time, president, block, state, republican, publish, minister, go, say</i>	0.58%
T.10	Vacation	<i>travel, flight, airline, airport, passenger, time, fly, go, holiday, people</i>	0.78%
T.11	Health report	<i>vaccine, time, report, country, covid, people, coronavirus, case, death, British</i>	0.57%
T.12	UK politics	<i>time, say, parliament, government, vote, Brexit, prime minister, deal, block, minister</i>	1.46%
T.13	Investment	<i>business, economy, work, economic, investment, sector, job, company, need, government</i>	5.78%
T.14	Energy taxation	<i>government, energy, tax, cost, price, nuclear, pay, power, say, go</i>	3.62%
T.15	Environment	<i>time, woman, government, fire, block, people, say, publish, minister, flood</i>	0.36%
T.16	Brexit border debate	<i>Brexit, people, government, border, make, leave, country, migrant, work, trade</i>	2.20%

Topic	Label	Top-10 words ($\lambda = 0.5$)	Percent
T.17	Unknown	<i>go, get, make, take, time, last, first, people, come, play</i>	1.43%
T.18	Unknown	<i>people, make, work, go, many, take, get, life, see, think</i>	6.06%
T.19	Brexit trade debate	<i>deal, Brexit, time, trade, leave, say, agreement, talk, leader, government</i>	3.36%
T.20	Politics	<i>government, Croatia, country, state, company, project, public, report, minister, increase</i>	1.19%
T.21	Entitlement programs	<i>service, community, education, people, chief, executive, covid, officer, child, school</i>	0.26%
T.22	Financial indices	<i>market, month, price, rate, rise, time, block, publish, government, minister</i>	3.37%
T.23	Monetary policy	<i>growth, economy, rate, price, inflation, economic, increase, risk, expect, market</i>	6.35%
T.24	Stock market	<i>cent, point, market, fall, rise, share, index, stock, high, today</i>	2.18%
T.25	Energy-climate policy	<i>energy, emission, climate, change, carbon, renewable, government, green, target, policy</i>	12.21%
T.26	Unknown	<i>time, block, publish, British, minister, say, gmt, government, people, get</i>	0.87%
T.27	Elections	<i>party, election, vote, make, government, political, people, country, leave, policy</i>	8.71%
T.28	Royal family	<i>family, make, royal, take, tell, go, day, last, say, work</i>	0.80%
T.29	Health crisis	<i>case, covid, people, coronavirus, health, time, government, country, day, week</i>	1.69%

Note: The relevance of a term (w) per topic (k) is given by $(w|k) = P(w|k) + (1 - \lambda)P(w|k)/P(w)$. $\lambda \in [0, 1]$, $P(w)$ is the frequency of a word in the corpus (see Sievert and Shirley (2014)).

Figure 3.3: News-based index.



4.2 Developing a law-based index

4.2.1 Laws data

Following the thread in the subsection 4.1, this part focuses on the EU laws database.⁶ First, data collection criteria rely on all laws that contain the words "energy", "environment" and "policy". Second, we extend the sample to laws whose titles are closest semantically to the above three words, such as "propellant", "climate" and "regulation". As a result, the set of laws under consideration gathers 7,657 daily legal acts recorded from January 1997 to May 2021. These are in majority parliament preparatory documents, consolidated texts, treaties, international agreements, and case laws. Authors of regulatory acts are mainly the European Commission, the European Parliament, the European Economic and Social Committee, the Council of the European Union, and the European Commission of Regions. Ultimately, before performing the LDA model, the corpus of documents is filtered to remove stopwords, punctuation, numbers, and other special characters. Then, words are lemmatized and converted to lowercase.

4.2.2 Descriptive statistics

The initial model provides an optimal number of topics $K = 14$. Once the key parameter K is set, we can then run the final model while adjusting hyperparameters α and η to improve the average coherence score as well as the performance of the model. The final model records a $C_v \simeq 0.45$.⁷ Afterwards, we retrieve the distribution of words by topic, as well as the distribution of topics by documents. Once the topics have been identified, it is up to the researcher to label and determine the dominant topic for each document. The construction of each topic's monthly time series goes through the proportion of each dominant topic per month. In other words, we compute for each topic the number of documents it contributes to the most divided by the total number of documents delivered per month. Finally, all series are standardized to mean 100 and 1 standard deviation along the period covered.

Table 3.2 reports the most representative words for the optimal number of topics provided by the model. Figure 3.4 shows the evolution of the European law-based

⁶EUR-LEX

⁷Details about the computation of model's performance criteria are reported in Appendix C.2.

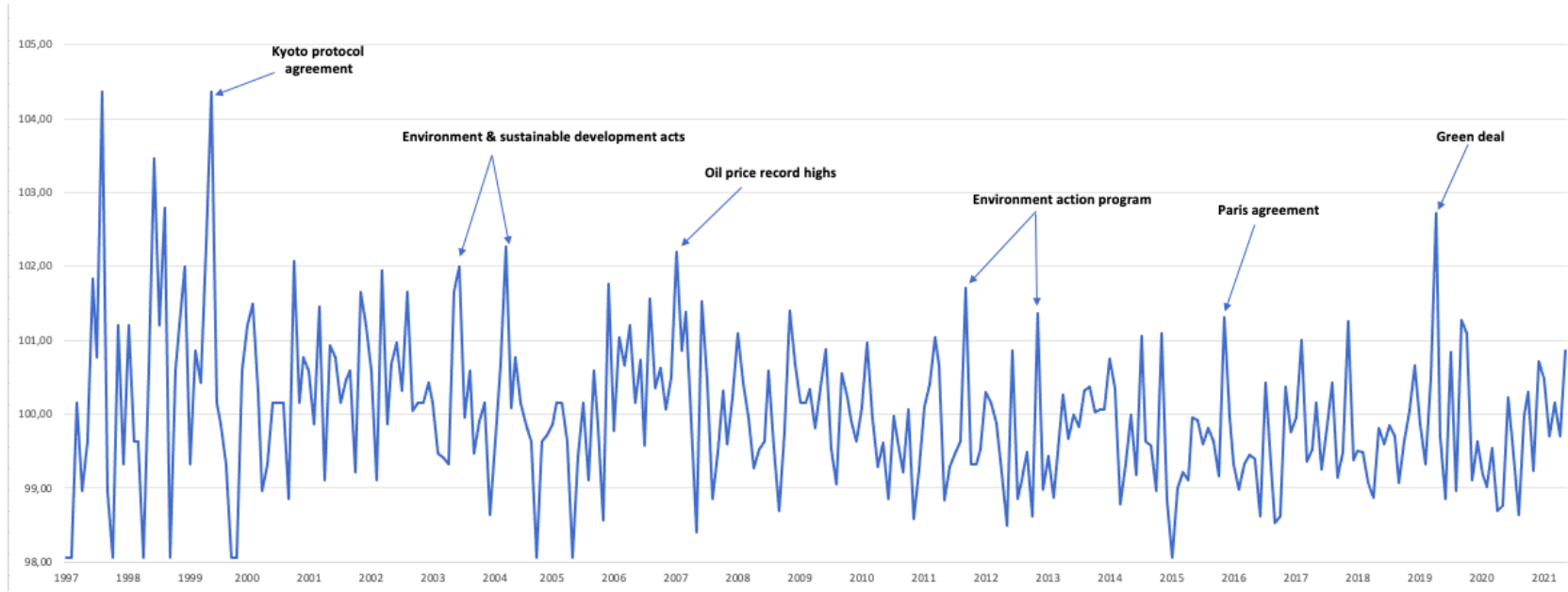
index of energy and environmental policy from January 1997 to May 2021. It is constructed from the table 3.2 as the sum of the monthly normalized time-series of topics 6, 7 and 11 that are assigned to energy and environment concerns (i.e. regulations on energy and climate, energy efficiency and environment, respectively). The latter account for about 30% of the entire sample. These topics are considered law-based subcategories and reflect components behind each law-based index fluctuation. The law-based index exhibits sudden spikes and falls around events that litter the legislation cycles on energy and environmental challenges. For instance, the Kyoto Protocol, adopted and entered into force in 1999 (alongside the Euro area establishment), gave priority to a coordinated resolution of major environmental issues. The early 2000s saw an institutional crisis, namely on the approval of the EU constitution in France and the Netherlands. In 2007, the Treaty of Lisbon was designed to make the EU more democratic, efficient and transparent and thereby able to tackle global challenges such as climate change, security and sustainable development. This process was hindered by a major financial crisis (2008) that hit the world economy. By the end of 2015, despite an influx of war refugees to the EU needing international protection, the United Nations Conference held in Paris (including 195 countries) concluded a new agreement on climate change. This agreement, with the EU playing a pivotal role, comprised an action plan to limit global warming to 2C compared to pre-industrial levels. In 2019, public concern about the climate crisis increased, driven by a growing and active international youth movement. A new commission took office with its sights firmly set on making Europe climate-neutral by 2050 through a new growth strategy: the European Green Deal.

Table 3.2: LDA topics and most representative words for the EU.

Topic	Label	Top-10 words ($\lambda = 0.5$)	Percent
T.1	Development program	<i>program, support, development, country, policy, project, state, action, fund, include</i>	18.35%
T.2	Payment regulation	<i>state, regulation, payment, refer, aid, provide, case, apply, amount, period</i>	4.87%
T.3	Labour and Capital	<i>increase, rate, market, high, growth, sector, investment, labour, GDP, public</i>	6.41%
T.4	Investment efficiency	<i>market, state, service, policy, public, new, level, investment, cost, sector</i>	11.70%
T.5	Unknown	<i>law, report, state, public, implementation, progress, continue, policy, system, area</i>	7.20%
T.6	Energy and Climate	<i>energy, policy, climate, development, research, change, environmental, sustainable, action, transport</i>	15.88%
T.7	Energy efficiency	<i>energy, emission, state, cost, directive, option, impact, measure, product, report</i>	8.88%
T.8	Industry	<i>product, free, material, service, exceed, party, include, year, manufacture, head</i>	6.63%
T.9	Financial regulation	<i>appropriation, regulation, financial, expenditure, payment, Europe, program, result, chapter, commitment</i>	2.65%
T.10	Unknown	<i>system, vehicle, directive, requirement, type, annex, regulation, technical, state, body</i>	1.95%
T.11	Environment	<i>directive, state, water, measure, environmental, aid, regulation, include, information, area</i>	4.93%
T.12	Trade and transport	<i>agreement, party, service, trade, state, transport, cooperation, include, provision, international</i>	5.64%
T.13	Tax strategy	<i>country, tax, trade, policy, increase, state, measure, economic, market, committee</i>	3.92%
T.14	Agriculture regulation	<i>test, animal, substance, chemical, control, method, product, state, concentration, health</i>	0.98%

Note: The term per topic $(w|k) = P(w|k) + (1 - \lambda)P(w|k)/P(w)$, $\lambda \in [0, 1]$, $P(w)$ is the frequency of a word in the corpus (see Sievert and Shirley (2014)).

Figure 3.4: Law-based index of European energy and environmental policy.



Consequently, the assessment of our composite indicators (news and law-based indicators) is to show whether they capture significant events throughout the history of EU energy and environmental regulations. The historical back-testing of indices provides continuous tracking of the evolution of energy-related environmental policy in news and laws. At first glance, the news-based index is more likely to reflect uncertainty about the global context in which policy actions are undertaken. The latter does not only present points of time commitment but also might implicitly take into account the long-lasting dynamics of the policy process (e.g. announcements, delays, revisions and failures) on markets. All these characteristics make the news-based index more volatile with two upsurge periods of environment and climate concerns followed by energy security concerns. Moreover, as we stressed above, the measurement of the news-based index also emphasizes the global context in which regulations evolve. In contrast, the law-based index does not display any trend, it remains dominated by several prominent peaks nested to the adoption of international and regional agreements on climate change (Kyoto Protocol in 1997, Paris Agreement in 2016, and European Green Deal in 2019). Nevertheless, according to the calendar of legislative sessions, the index depicts a seasonal pattern that hides in-between events which potentially appear under-weighted.

4.3 News versus Laws

Another important aspect is to analyze how both indices evolve together.⁸ To this end, each index is transformed into its 3-month moving average to clearly exhibit a momentum with less volatility. Figure 3.5 scales the monthly evolution of the news-based index along with the law-based index. We observe that there is a dynamic correlation across the indices highlighted by episodes of high and low correlation. Therefore, this graphical analysis helps to visualize and to identify periods of common trends. Starting in the early 2000s, it appears, among others, that the relationship is likely significant during phases of action on global warming commitments, energy transition, and environmental taxation. In the same vein, a deeper description of the relationship between both time series could be explored with cross-correlation analysis. Indeed, the cross-correlation function (CCF) is helpful for identifying which variable is leading and which is lagging. For instance, figure

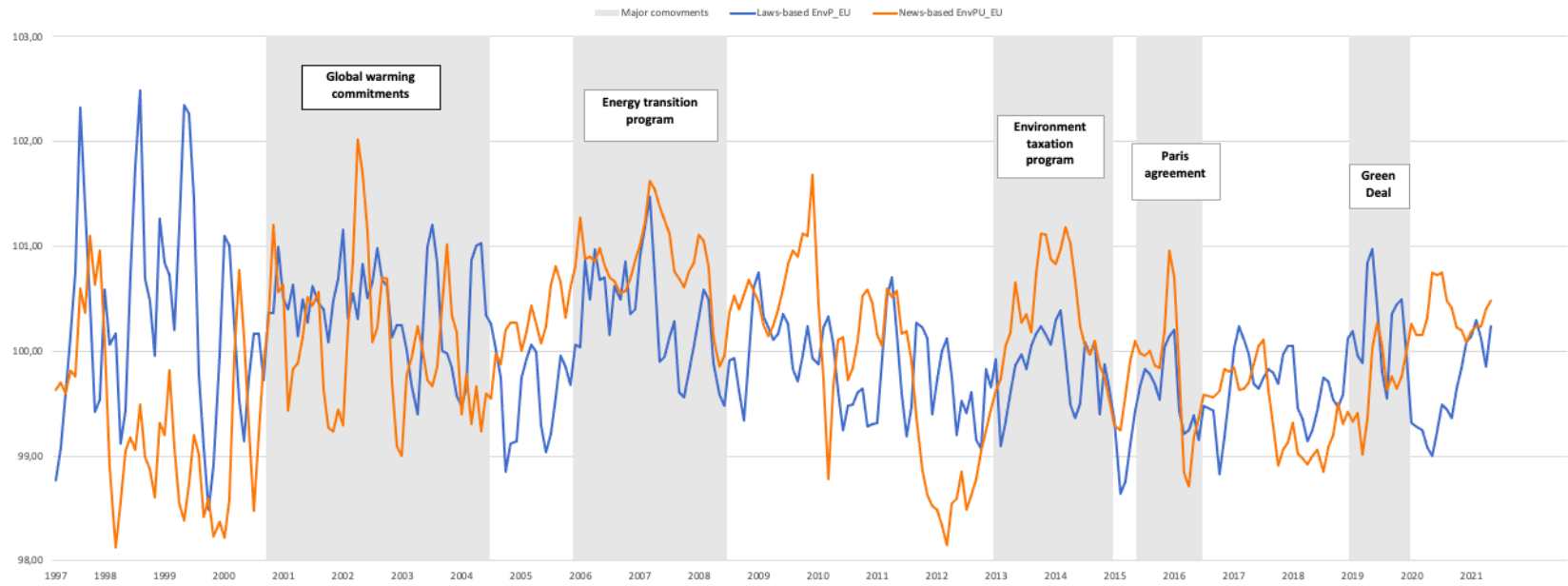
⁸Data on law and news-based indices and subcategories are available upon request.

3.6 illustrates the prediction power between news and law-based indices over time. The result shows that the law-based index has a significant positive prediction on the news-based index in the short run.⁹ This is less surprising as it suggests that laws are quickly integrated into the news as soon as they are voted. At that moment, this mechanism could be perceived by markets as more regulations. This pass-through fades over time, and this justifies the significant negative correlation observed in the medium term. Thereby, by analogy, the markets' perception of regulatory relief is reinforced.¹⁰

⁹Additionally, cross-correlation scatter plots are available in Appendix C.5.

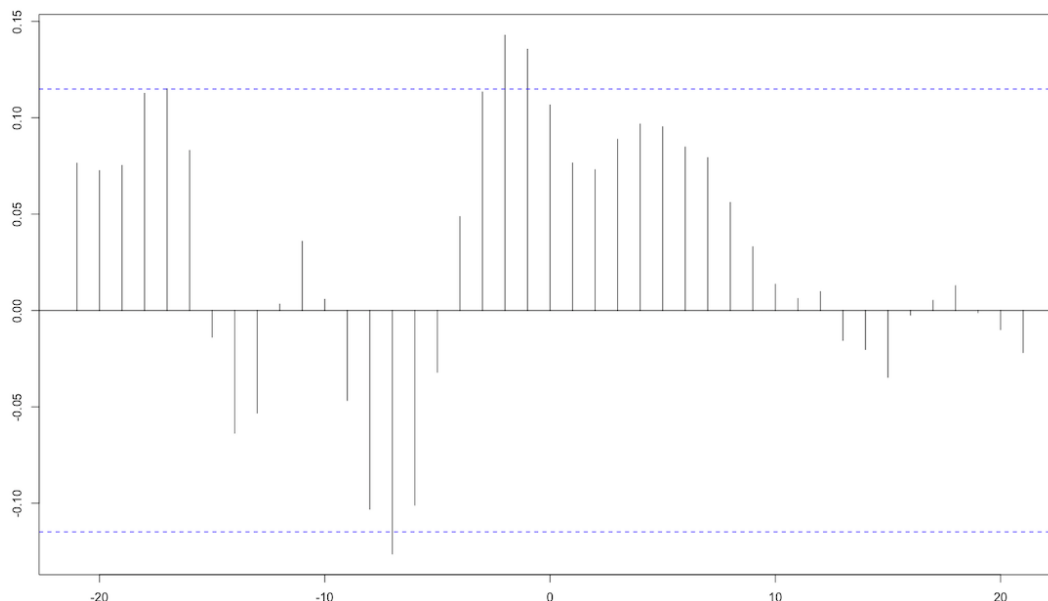
¹⁰In line with this cross-correlation analysis, the dynamic inference of both indices is briefly reported in Appendix C.5 stemming from our empirical model developed in the next section.

Figure 3.5: Law vs News indices, a pairwise 3-month moving average.



Note: This graph represents the common evolution of law-based index (blue line) and news-based index (orange line). Shaded areas are set as periods of major comovements.

Figure 3.6: Cross-correlation function between law and news-based indices.



Notes: This figure presents the lag-leading relation between news and law-based indices. The vertical axis scales the correlation values. Likewise, the horizontal axis shows the time delay factor. When it displays negative values, then lags of the law-based index are predictors of the news-based index and vice-versa. The blue dotted line is set for a 95% confidence interval.

Once these indices are constructed and analyzed, we rely on an empirical framework to test their effects on price uncertainty dynamics in the fossil energy markets.

5 Low-carbon policy and fossil energy markets

5.1 Econometric framework: model specification and identification

This part is devoted to exploring the assumption on the relationship between energy and environmental policy and fossil fuel (oil, gas and coal) price uncertainty in a structural vector autoregressive (VAR) framework to keep in line with the literature approach. The monthly data for each fossil fuel price uncertainty is obtained following the methodology described in chapter 1. Thus, our VAR model includes five variables: the law-based index, the news-based index, and each market's price uncertainty.

Prior to the VAR model estimation, unit root tests are performed for each vari-

able.¹¹ Accordingly, we notice that none of these variables simultaneously pass all the unit root tests. For convenience, we consider the first difference transformation of the logarithm of law and news-based indices along with the market's price uncertainty.

The VAR is run at a monthly frequency. The estimation period is 1997:4-2021:5. A VAR model of a finite order p , referred to as VAR(p) model, is expressed as:

$$Y_t = a_0 + A_1 Y_{t-1} + \dots + A_p Y_{t-p} + \epsilon_t, \epsilon_t \sim \mathcal{N}(0, \Sigma) \quad (3.3)$$

where Y_t is an $M \times 1$ vector of endogenous variables (M being the number of variables), a_0 is an $M \times 1$ intercept vector, A_j ($j = 1, \dots, p$) are $M \times M$ coefficient matrices, and ϵ is an $M \times 1$ vector of exogenous Gaussian shocks with zero mean and variance-covariance matrix Σ .

We rely on a Bayesian hierarchical modeling approach to estimate the VAR model (Giannone et al., 2015).¹² In general, Bayesian estimation techniques are used to tackle over-dimensionality due to the number of coefficients $M + M^2 p$ rising quadratically with the number of variables and linearly in the lag order. However, Bayesian methods are also useful when dealing with short sample periods to overcome "overfitting" issues. According to AIC and FPE information criteria, the preliminary estimation of the VAR model sets the optimal lag length to 6.

The BVAR specification requires a prior specification and hierarchical prior selection procedure. The flexibility of prior setup in the Bayesian framework permits the accommodation of a wide range of economic issues. Following Giannone et al. (2015), prior hyperparameters in a data-based fashion are treated as additional parameters to be estimated. In that sense, hyperparameters are assigned their own hyperpriors as stated by Bayes's law below:

$$P(\gamma|Y) \propto P(Y|\theta, \gamma)P(\theta|\gamma)P(\gamma) \quad (3.4)$$

$$P(Y|\gamma) = \int P(Y|\theta, \gamma)P(\theta|\gamma)d\theta \quad (3.5)$$

where $Y = (Y_{p+1}, \dots, Y_T)'$, θ represents the autoregressive and variance param-

¹¹Table C.3 in Appendix C.6 reports the unit root tests.

¹²For further information on BVAR estimation and inference, we highly recommend interested readers to works of Gelman et al. (2013), Koop et al. (2010) and Kilian and Lütkepohl (2017).

ters of the VAR model, γ is the set of hyperparameters and $P(Y|\gamma)$ is the marginal likelihood (ML). Using the Normal-inverse Wishart (NIW) family for conjugate prior distributions, the equation (3.3) could be approached assuming $A = (a_0, A_1, \dots, A_p)'$ and $\beta = \text{vec}(A)$. Therefore, the conjugate prior setup is given as follows:

$$\beta|\Sigma \sim \mathcal{N}(b, \Sigma \otimes \Omega) \quad (3.6)$$

$$\Sigma \sim IW(\Psi, d) \quad (3.7)$$

where b , Ω , Ψ and d are lower-dimensional vectors of hyperparameters γ . The common practice in the literature is to consider three specific priors: the Minnesota prior (Litterman, 1980) as a baseline where all variables follow random walk processes, the sum-of-coefficients prior and the single-unit-root prior (Sims and Zha, 1998).

The prior for β is defined as a Minnesota-type and is characterized by the following moments:

$$\mathbb{E}[(A_s)_{ij}|\Sigma] = \begin{cases} 1 & \text{if } i = j \text{ and } s = 1, \\ 0 & \text{otherwise.} \end{cases}$$

$$\text{cov}[(A_s)_{ij}, (A_r)_{kl}|\Sigma] = \begin{cases} \lambda^2 \frac{1}{s^\alpha} \frac{\Psi_{ik}}{\psi_j/(d-M-1)} & \text{if } l = j \text{ and } r = s, \\ 0 & \text{otherwise.} \end{cases}$$

Formally, i corresponds to the dependent variable in the i^{th} equation, j to the independent variable in that equation, and l to the lag number. The key hyperparameter λ controls the tightness of the prior. The variance decay with the lag order depends on the degree of shrinkage among distant observations measured by α . Finally, ψ_j representing the j^{th} variable of the matrix Ψ adjusts the prior's standard deviation on lags of variables other than the dependent variable.

In accordance with the Bayesian macroeconomic literature, we set $\lambda = 0.2$ leaving α , ψ on their default values (see Kuschnig and Vashold (2021)). We use the Metropolis-Hastings algorithm as a Markov chain Monte Carlo (MCMC) method for the sampling approach in order to define the posterior hyperparameter space.

Lastly, draws of β and Σ from their respective marginal posterior likelihood are obtained after simulating 50,000 draws with 10% burn-in.¹³

In the end, the dynamics of our VAR system are given by impulse response functions (IRFs) that underlie the structural shock inference and are identified using Cholesky decomposition with the following variable ordering: law-based index, news-based index, oil price uncertainty, gas price uncertainty and coal price uncertainty.¹⁴

5.2 Main results

As a central tool for structural analysis, IRFs are the cornerstone of inference with VAR models. They represent the propagation of shocks hitting the system of variables. Similarly, the proper identification scheme of the model conditions a meaningful interpretation.

Figure 3.7 illustrates the dynamics of fossil energy price uncertainty following the shocks on law and news-based indices at 84% and 68% confidence levels, respectively. Note that a shock in the law-based index indicates an unprecedented increase in laws on energy-related environmental policy voted at the European level. Similarly, a shock in the news-based index stands for an unanticipated spike in news on energy-related environmental policy as discussed in the European press.

Overall, we find that each market's price uncertainty displays specific reactions to shocks in law and news-based indices. In particular, an increase in the law-based index has a negative and significant effect on price uncertainty in oil and coal markets. Especially, the dampening effect is more persistent in the coal market. However, there is no apparent significant response to the law-based index shock on gas price uncertainty. It should be noted that European legislation on energy-related environmental issues is oriented toward green transition. In this sense, the pathway to a greener economy appears as a long-run perspective that substantially affects price uncertainty dynamics, which is considered to be conjuncture-driven. Nonetheless, several lessons could be drawn from these findings. First, according to our results, the perception of the law-based index in the oil and coal markets recalls the concept of "divine coincidence" whereby a green (environmental) policy does

¹³The model indicates an accepted draws rate of 34.5%. In the Appendix C.5, we report hyper-parameters' posterior distributions and the convergence diagnostic of Geweke (1992).

¹⁴The economic intuition behind the order of markets' variables lies in that oil is predetermined relative to gas and coal, respectively.

not come at the cost of higher energy prices, and therefore higher price uncertainty Panetta (2022). This outcome contrasts with negative narratives underscoring that green policies contribute to rising fossil fuel prices as investment in fossil fuels declines due to lower expected demand Dlugosch and Kozluk (2017). Nonetheless, the European authorities need to legislate more on low energy intensity, energy security, and transition funding. Second, though coal is clearly identified as the most polluting fossil fuel, it still faces strong demand for power generation in the EU. The stringency of coal's phase-out plans contributed to a coal diversification strategy in order to reduce adverse effects of the coal price uncertainty.

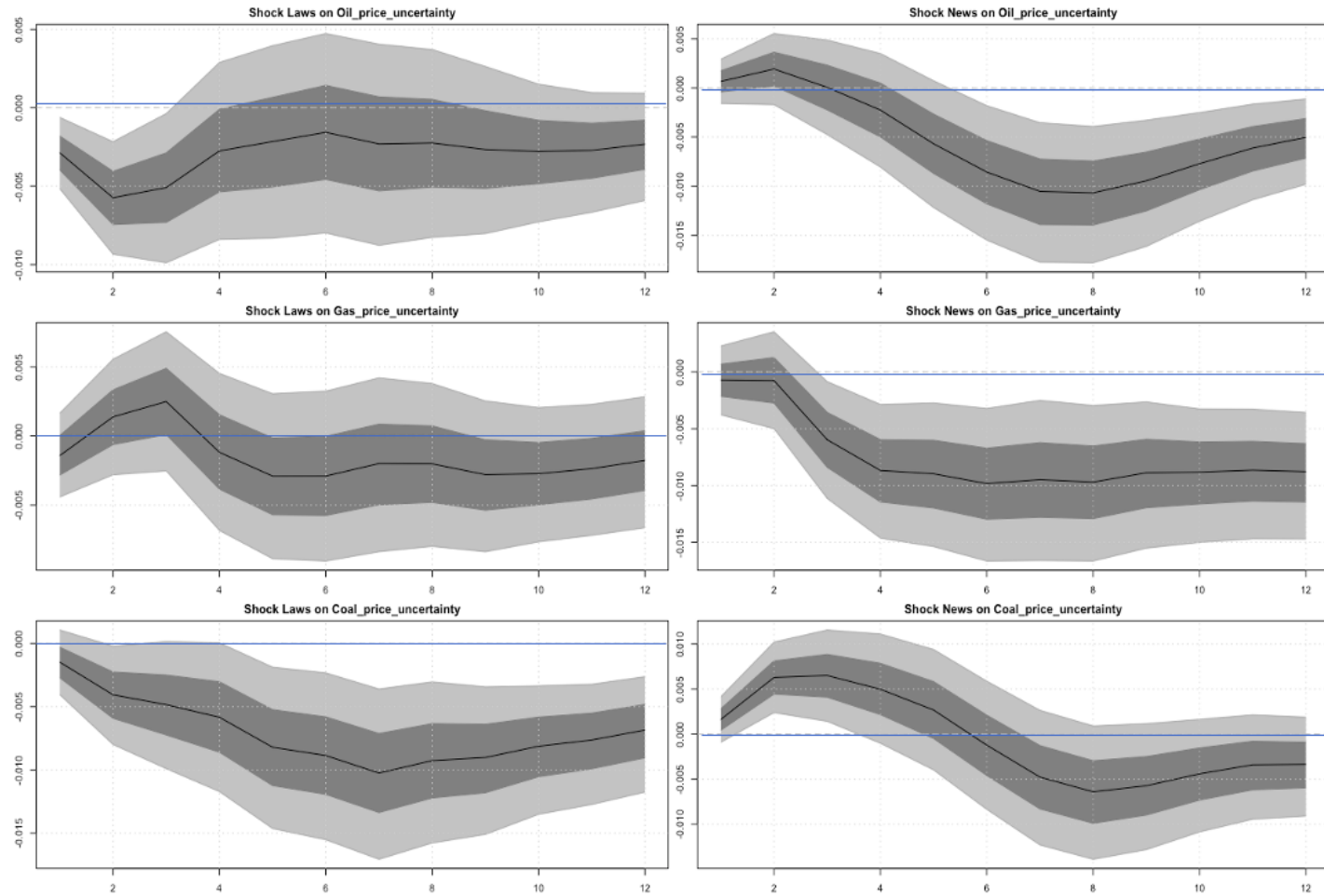
By analyzing the effects of the news-based index shocks on market price uncertainty, some patterns are highlighted in accordance with the news-based index components. First, we uncover that an increase in the news-based index triggers a short-run slight and significant rebound in price uncertainty in oil and coal markets. This upward effect arises from uncertainty about the global context. Actually, sometimes news tends to amplify information about proactive regulations that might generate unexpected market reactions after legal act announcements. From this point of view, our result is in line with what we would expect from a positive shock in the news-based EPU index on price uncertainty as discussed in chapter 2. Afterwards, the positive tendency is reversed by a persistent negative effect on price uncertainty in these markets due to the regulations component. In contrast, we note that the long-lasting shrinking incidence starts earlier for the gas market. Hence, we can conclude that the news-based index exerts a prevailing stabilizing effect on price uncertainty across markets.

In a deeper way, we explore in detail the responses of each market's price uncertainty to law-based sub-index shocks in figure 3.8. We recall that the law-based sub-indices refer to tracking regulations on energy efficiency, climate, and the environment. In general, this figure reports that coal price uncertainty is negatively associated with all law-based sub-index shocks, whereas oil and gas price uncertainty mostly reacts to the specific environment sub-index. Therefore, compared to our finding in figure 3.7, it is highly recommended to give priority to environmental regulations that considerably reduce unpredictable price fluctuations in the gas market.

Altogether, this part sheds light on the potential effects of two major aspects of the European low-carbon policy on price uncertainty in fossil energy markets. The main outcomes of our investigation emphasize that the law-based structural index

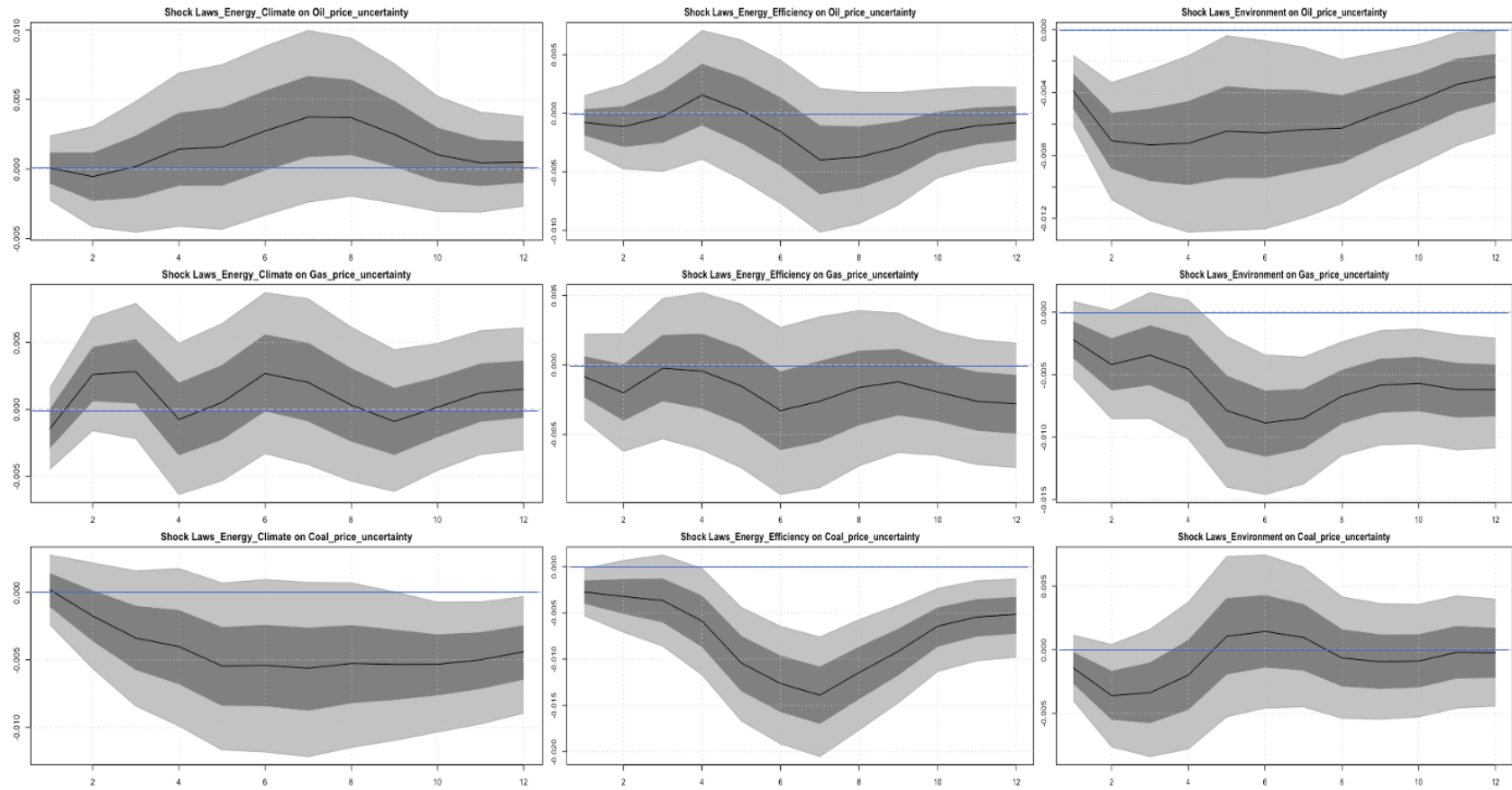
reduces price uncertainty in the oil and coal markets in a more conspicuous and protracted manner. It is also the case in the gas market when considering a shock in the law-based environmental regulations sub-index. Likewise, the news-based index points out a dual effect (positive or negative) on price uncertainty relative to its components. We find out that the negative effect outweighs in the long run, which shows that regulatory efficacy could withstand uncertainty.

Figure 3.7: Responses of fossil energy price uncertainty to shocks in news and law-based indices.



Notes: This figure reports impulse response functions for fossil energy price uncertainty to positive shocks in law and news-based indices (i.e. one standard deviation). The SVAR is estimated with Bayesian methods and shocks are identified using Cholesky decomposition with variables ordered as follows: $\Delta(\log(\text{Laws}))$, $\Delta(\log(\text{News}))$, Oil price uncertainty, Gas price uncertainty, Coal price uncertainty. Gray bands represent 84% and 68% confidence intervals.

Figure 3.8: Responses of fossil energy price uncertainty to shocks in law-based sub-indices.



Notes: This figure reports impulse response functions for fossil energy price uncertainty to positive shocks in law-based sub-categories (i.e. one standard deviation). The SVAR is estimated with Bayesian methods for each sub-category and shocks are identified using Cholesky decomposition with variables ordered as follows: $\Delta(\log(\text{laws sub-category}))$, Oil price uncertainty, Gas price uncertainty, Coal price uncertainty. Bands represent 84% and 68% confidence intervals.

5.3 Complementary results

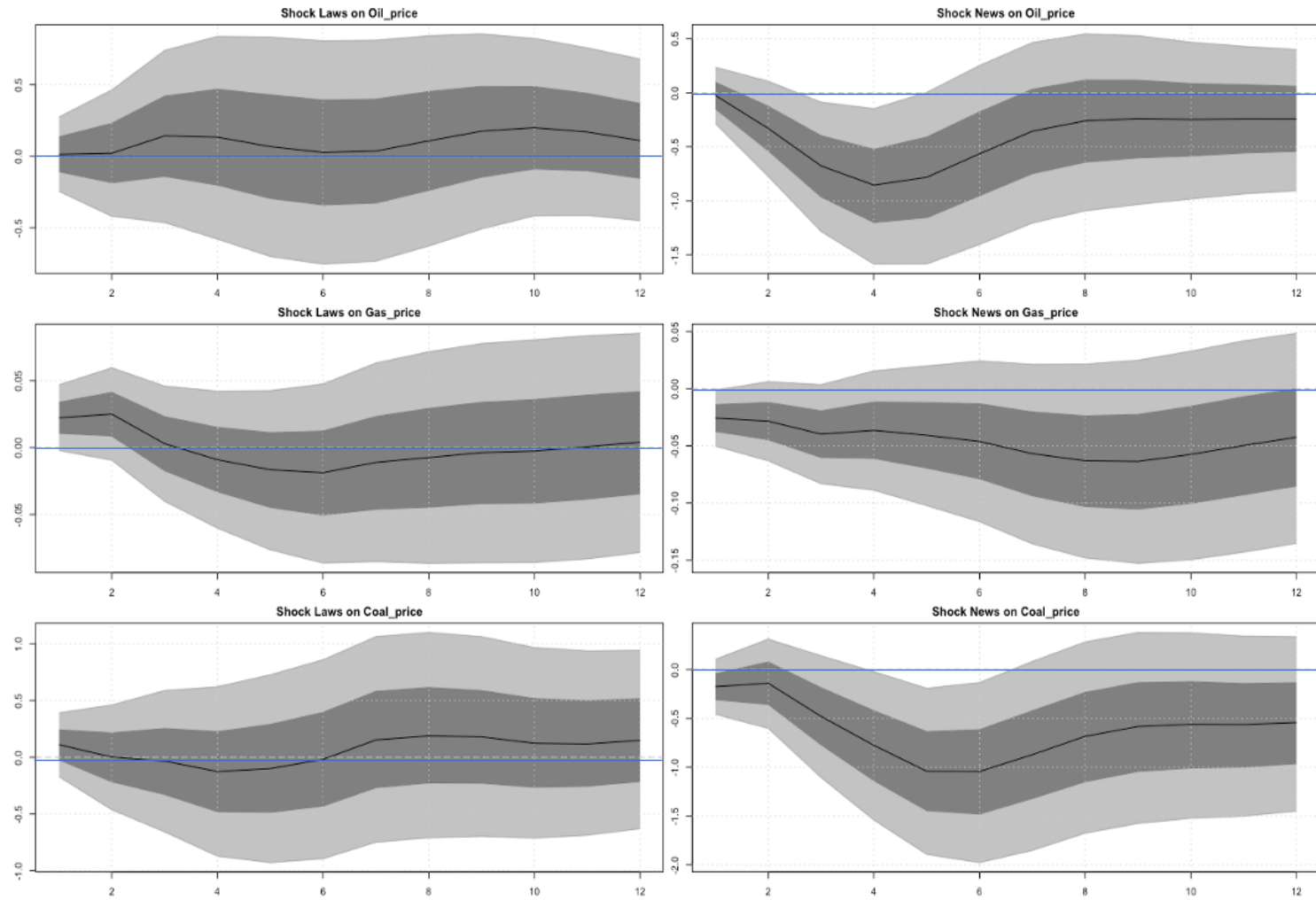
As the construction of price uncertainty arises from prices and is defined as its unanticipated component, another relevant point of this part consists of analyzing market price inference in our model.¹⁵ For this purpose, we re-estimate our model by replacing price uncertainty with price level. Figure 3.9 reveals, on the one side, a non-significant drop in prices across markets after a positive shock increase in the law-based index. This observation brings to the point that, although law-based low-carbon regulations may have an effect on price uncertainty, this does not mechanically lead to a significant impact on the price level. On the other side, news-based index shocks contribute to a drop in prices within markets. For each market, the burst begins earlier than that of price uncertainty and becomes established over time. One interesting explanation is to consider that markets anticipate regulations, therefore prices adjust downward beforehand.

Furthermore, our findings on low-carbon policy effects could also be interpreted as a means to mitigate the energy price-core inflation nexus which tends to be particularly high due to the current economic situation. This inflation has been caused by years of loose monetary policies and profligate spending after the 2008 crisis and to combat Covid-19, and by the recent Russo-Ukrainian War-induced energy crisis. Having a look at the last phenomenon, we observe that energy prices account for a large share of inflation in European net energy importer economies. Therefore, these most advanced countries face worsening terms of trade and the exposure of their energy-intensive industries. Among the two complex channels through which changes in energy prices affect inflation, a distinction is made between first- and second-round effects. The first-round effect refers to the increase in the cost of living and purchasing power as transport and heating, for instance, become more expensive. The second-round effect translates into higher production costs, including for non-energy goods and services, which firms try to pass on to consumers. The larger the second-round effects, the more hawkish central banks are against inflation. However, when governments interfere with pricing mechanisms (i.e. measures on price caps and subsidies) to shield consumers and companies from rising energy costs, it only deepens the problems in the long run as it increases energy consumption in a situation where there is a need to curb it, and subsidies increase liquidity in the

¹⁵Data of monthly nominal prices from the World Bank website: [Commodity-prices-pink-sheets](#).

system and have the potential to fuel inflation Nakhle (2022). Beyond these short-run counterproductive government measures to alleviate the burden of unexpectedly skyrocketing fossil fuel prices that generate high uncertainty, hastening the shift towards green policy is not necessarily at odds with price stability Heemskerk et al. (2022). In other words, the authors emphasize that global energy prices are expected to be reduced in the long run under a green energy policy.

Figure 3.9: Responses of fossil energy prices to shocks in law and news-based indices.



Notes: This figure depicts impulse response functions for fossil energy prices to positive shocks in law and news-based indices (i.e. one standard deviation). The SVAR is estimated with Bayesian methods and shocks are identified using Cholesky decomposition with variables ordered as follows: $\Delta(\log(\text{Laws}))$, $\Delta(\log(\text{News}))$, Oil price, Gas price, Coal price. Bands represent 84% and 68% confidence intervals.

6 Concluding remarks and policy recommendations

This chapter explored the European low-carbon policy through the legislative cycle as well as the resulting uncertainty reflected in news articles. We relied on an unsupervised machine learning algorithm on legal acts and newspapers pertaining to energy and environmental regulations. This methodology yielded two distinct measures: a law-based index of European low-carbon policy and a news-based index. Each index was the result of a bottom-up approach since they appeared as an aggregation of equally-weighted endogenous individual components (also called sub-indices). Whilst the law-based index somehow presented a stable seasonal scheme, the news-based index appeared to be governed by the intrinsic volatility of news articles. Besides, the news-based index made it possible to capture events around law adoption and it emphasized the global context. In this sense, one considers that once laws are voted, their treatment in newspapers per se might also generate an inner uncertainty. Representing both indices side by side, we noticed periods of common dynamics and how laws foreshadow news in the short run. Hence, as designed, the law-based index captures a structural dimension, whereas the news-based index incorporates a conjunctural aspect, reflecting uncertainty.

Afterwards, we conducted an empirical analysis of the relationship between the aforementioned indices and price uncertainty in fossil energy markets. The findings show, in terms of maturity, heterogeneous responses across markets to shocks in law and news-based indices. Especially, regarding the effects of the news-based index shocks, we noted that, except for the gas market which reacted negatively from the outset, the oil and coal markets displayed a dual effect. This dual effect was characterized by a slight increase in price uncertainty in the short term followed by a significant decrease that tended to stabilize price uncertainty permanently. In the same way, looking at shocks in the law-based index, there was a significant decrease in oil and coal price uncertainty, whereas no significant effect was recorded for the gas market except when considering the law-based environment sub-index shock. Additionally, we performed further analysis to appraise the effects of our indices on markets' price levels. We found out that only the news-based index contributed to significantly dampening prices across markets, meaning that markets anticipate the regulations and adjust their prices accordingly.

The results of this chapter have two main implications. First, they lend credence to a wealth-of-words environment based on legal acts and press articles to quantify energy-related environmental policy. In this respect, the usefulness of the LDA algorithm lies in the categorization of individual components to fulfill a bottom-up approach, accordingly. Second, the effects of law and news-based indices on price uncertainty in fossil energy markets could be of great interest to policymakers. The latter should take transparent actions to provide incentives to reduce fossil fuel demand for a given after-tax price. This would cushion the upward pressure on energy prices and the subsequent uncertainty. Authorities also have to ensure energy security since fossil fuel price shocks could lead to overall inflation. Therefore, a coordinated policy at the European level could prevent national beggar-thy-neighbor policies. Finally, policies need to bridge the gap in green investment to diversify energy sources and contain energy prices.

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Appendix C

Does the European Low-Carbon Policy impact price uncertainty in fossil energy markets?

Contents

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C.1 Estimating the LDA

As seen before, LDA as a probabilistic machine learning model consists of the joint distribution of hidden variables $z = (\beta_K, \theta_D, z_D, w_D)$ and observed variables $x = w_D$, such that $P(z|x)$. Inference about this unknown conditional probability, also called the posterior distribution is expressed as follows:

$$P(z|x) = P(\beta_K, \theta_D, z_D|w_D) = \frac{P(\beta_K, \theta_D, z_D, w_D)}{P(w_D)} \quad (\text{C.1})$$

Unfortunately, the computation of the posterior distribution is intractable due to the denominator $P(w_D)$ that represents the marginal probability. To tackle this issue, one appeals to approximation of the posterior distribution, where the denominator is the sum of the joint distribution over all instantiations of the hidden structure. Hence, the newly LDA posterior distribution becomes:

$$P(\beta_K, \theta_D, z_D|w_D) = \frac{P(\beta_K, \theta_D, z_D, w_D)}{\int_{\beta} \int_z P(\beta_K, \theta_D, z_D, w_D)} \quad (\text{C.2})$$

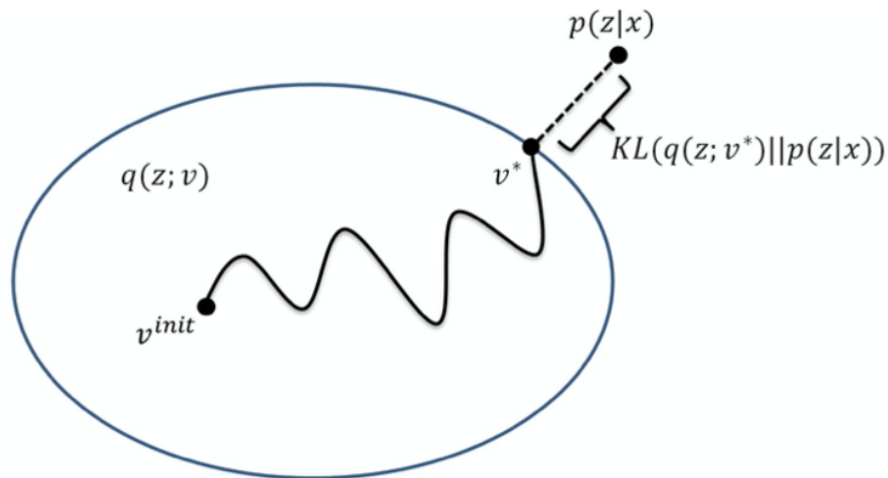
To estimate the posterior distribution, two types inference techniques are discerned:

- Sampling method uses Monte Carlo Markov Chains (MCMC) to generate independent samples from the posterior distribution.
- Optimizing method relies on Variational Bayes (VB), which provides similar accurate results as does the sampling method. It optimizes a simple parametric distribution to be as close as possible in Kullback-Leiber divergence to the posterior distribution (more details about are discussed later).

The main advantage of VB over MCMC is to be faster when dealing with large datasets, as highlighted by Hoffman et al. (2010).

Following Azqueta-Gavaldón (2017), the basic idea behind VB could be graphically described by figure C.1 below:

Figure C.1: Variational Bayes inference.



Note: This graph illustrate a simple process of the variational Bayes inference.

Given the need to replicate as faithful as possible the posterior distribution $P(z|x)$, one postulates a variational family distributions over latent variables $q(z, v)$, with v the variational parameter. In the ellipse, the algorithm takes as a starting point a particular realization of the distribution v^{init} and adjust the free parameter v until it finds the closest value to the posterior distribution v^* . As shown in figure C.1, the optimization process is the curvature path connecting v^{init} to v^* . Finally, the Kullback-Leiber divergence $KL(q(z, v^*) || P(z|x))$ represents the measure of closeness.

There are two versions of VB: the batch version (generally set by default in any LDA estimation), and the Stochastic or online VB. Our study uses a mix of the two, namely the batch VB to get the optimal number of topics and the online VB to estimate the final LDA model. Nonetheless, one admits that the batch VB faces inefficiency problems since for each data point it has to undertake local computations, and then aggregate them to re-estimate the global structure iteratively. To overcome this issue, online VB comes to rescue, hence is highly recommended. Hoffman et al. (2010) provide details about the mathematical formalization of VB versions below.

Batch variational Bayes

According to Hoffman et al. (2010), in the Variational Bayesian inference (VB) the true posterior is approximated by a simpler distribution $q(z, \theta, \beta)$, which is indexed by a set of free parameters (Attias, 1999, Jordan et al., 1999). These parameters are optimized to maximize the Evidence Lower Bound (ELBO). In figure C.1, the ELBO is represented by the optimization path that connects v^{init} to v^* . Formally, the ELBO is given by the following expression:

$$\text{Log } P(w|\alpha, \eta) \geq \mathcal{L}(w, \phi, \gamma, \lambda) \triangleq \mathbb{E}_q[\text{Log } P(w, z, \theta, \beta|\alpha, \eta)] - \mathbb{E}_q[\text{Log } q(z, \theta, \beta)] \quad (\text{C.3})$$

Note that maximizing the ELBO is equivalent to minimizing the *KL* divergence between $q(z, \theta, \beta)$ and the posterior $P(z, \theta, \beta|w, \alpha, \eta)$. Following Blei et al. (2003), we choose a fully factorized distribution q of the following form:

$$q(z_{di} = k) = \phi_{dw_{di}k}; q(\theta_d) = \text{Dirichlet}(\theta_d; \gamma_d); q(\beta_k) = \text{Dirichlet}(\beta_k; \lambda_k) \quad (\text{C.4})$$

It is worth mentioning that this posterior over the per-word topic assignments z is parameterized by ϕ ; the posterior over the per-document topic weights θ is parameterized by γ ; and the posterior over the topics β is parameterized by λ . As a shorthand, we refer to λ as "the topics". Equation (C.4) factorizes to:

$$\begin{aligned} \mathcal{L}(w, \phi, \gamma, \lambda) = & \sum_d \{ \mathbb{E}_q[\text{Log } P(w_d|\theta_d, z_d\beta)] + \mathbb{E}_q[\text{Log } P(z_d|\theta_d)] - \mathbb{E}_q[\text{Log } q(z_d)] \\ & + \mathbb{E}_q[\text{Log } P(\theta_d|\alpha)] - \mathbb{E}_q[\text{Log } q(\theta_d)] + (\mathbb{E}_q[\text{Log } P(\beta|\eta)] - \mathbb{E}_q[\text{Log } q(\beta)]/D) \} \quad (\text{C.5}) \end{aligned}$$

Notice we have brought the per-corpus terms into the summation over documents, and divided them by the number of documents D . This step will help to derive an online inference algorithm. We now expand the expectations above to be functions of the variational parameters. This reveals that the variational objective relies only on n_{dw} , the number of times word w appears in document d . When using

VB -as opposed to MCMC- documents can be summarized by their word counts:

$$\begin{aligned}
\mathcal{L} = & \sum_d \sum_w n_{dw} \sum_k \phi_{dwk} (\mathbb{E}_q[\text{Log } \theta_{dk}] + \mathbb{E}_q[\text{Log } \beta_{dk}] - \text{Log } \phi_{dwk}) \\
& - \text{Log } \Gamma(\sum_k \gamma_{dk}) + \sum_k (\alpha - \gamma_{dk}) \mathbb{E}_q[\text{Log } \theta_{dk}] + \text{Log } \Gamma(\gamma_{dk}) \\
& + (\sum_k -\text{Log } \Gamma(\sum_w \lambda_{kw}) + \sum_w (\eta - \lambda_{kw}) \mathbb{E}_q[\text{Log } \beta_{kw}] + \text{Log } \Gamma(\lambda_{kw})) / D \\
& + \text{Log } \Gamma(K\alpha) - K \text{Log } \Gamma(\alpha) + (\text{Log } \Gamma(W\eta) - W \text{Log } \Gamma(\eta)) / D \\
& \Delta \sum_d \ell(n_d, \phi_d, \gamma_d, \lambda) \quad (\text{C.6})
\end{aligned}$$

where W is the size of the vocabulary and D is the number of documents. $\ell(n_d, \phi_d, \gamma_d, \lambda)$ denotes the contribution of document d to the ELBO. \mathcal{L} can be optimized using coordinate ascent over the variational parameters ϕ, γ, λ (Blei et al., 2003):

$$\phi_{dwk} \propto \exp\{\mathbb{E}_q[\text{Log } \theta_{dk}] + \mathbb{E}_q[\text{Log } \beta_{kw}]\}; \quad \gamma_{dk} = \alpha + \sum_w n_{dw} \phi_{dwk}; \quad \lambda_{kw} = \eta + \sum_d n_{dw} \phi_{dwk} \quad (\text{C.7})$$

The expectations under q of $\text{Log } \theta$ and $\text{Log } \beta$ are the following:

$$\mathbb{E}_q[\text{Log } \theta_{dk}] = \Psi(\gamma_{dk}) - \Psi(\sum_{i=1}^K \gamma_{di}); \quad \mathbb{E}_q[\text{Log } \beta_{kw}] = \Psi(\lambda_{kw}) - \Psi(\sum_{i=1}^W \lambda_{ki}) \quad (\text{C.8})$$

where Ψ denotes the digamma function (the first derivative of the logarithm of the gamma function). The updates in equation (C.8) are guaranteed to converge to a stationary point of the ELBO. By analogy to the Expectation-Maximization (EM) algorithm (Dempster et al., 1977), we can partition these updates into an "E" step-iteratively updating γ and ϕ until convergence, holding λ fixed -and an "M" step-updating λ given ϕ . In practice, this algorithm converges to a better solution if we reinitialize γ and ϕ before each E step. Algorithm 1 outlines batch VB for LDA.

Algorithm 1: Batch variational Bayes for LDA

```

Initialize  $\lambda$  randomly.
while relative improvement in  $\mathcal{L}(w, \phi, \gamma, \lambda) > 0.00001$  do
    E step:
    for  $d = 1$  to  $N$  do
        Initialize  $\gamma_{dk} = 1$ . (The constant 1 is arbitrary.)
        repeat
            Set  $\phi_{dwk} \propto \exp\{\mathbb{E}_q[\text{Log } \theta_{dk}] + \mathbb{E}_q[\text{Log } \beta_{kw}]\}$ 
            Set  $\gamma_{dk} = \alpha + \sum_w \phi_{dwk} n_{dw}$ ;
        until  $\frac{1}{K} \sum_k |\text{Change in } \gamma_{dk}| < 0.00001$ ;
    end
    M step:
    Set  $\lambda_{kw} = \eta + \sum_d n_{dw} \phi_{dwk}$ 
end

```

Online variational inference for LDA

Algorithm 1 has constant memory requirements and empirically converges faster than batch collapsed Gibbs sampling (Asuncion et al., 2012). However, it still requires a full pass through the entire corpus for each iteration. It can therefore be cumbersome to apply to very large data-sets, and is not naturally suited for settings where new data is constantly arriving. We propose instead an online variational inference algorithm for fitting λ , the parameters to the variational posterior over the topic distributions β . Our algorithm is nearly as simple as the batch VB algorithm, but converges much faster for large datasets.

A good setting of the topics λ is one for which the ELBO \mathcal{L} is the highest possible after fitting the per-document variational parameters γ and ϕ with the *E* step defined in algorithm 1. Let $\gamma(n_d, \lambda)$ and $\phi(n_d, \lambda)$ be the values of γ_d and ϕ_d produced by the *E* step. Our goal is then to set λ to maximize the following expression:

$$\mathcal{L}(n, \lambda) \Delta \sum_d \ell(n_d, \gamma(n_d, \lambda), \phi(n_d, \lambda), \lambda) \quad (\text{C.9})$$

where $\mathcal{L}(n, \lambda)$ is the *d*th document's contribution to the variational bound in the equation (C.9). This is analogous to the goal of least-squares matrix factorization, although the ELBO for LDA is less convenient to work with than a simple squared loss function. Online VB for LDA ("online LDA") is described in Algorithm 2. As the *t*th vector of word counts n_t is observed, we perform an *E* step to find

locally optimal values of γ_t and ϕ_t , holding λ fixed. We then compute $\tilde{\lambda}$ the setting of λ that would be optimal (given ϕ_t) if our entire corpus consisted of the single document n_t repeated D times. D is the number of unique documents available to the algorithm, i.e. the size of a corpus. (In the true online case $D \rightarrow \infty$, corresponding to empirical Bayes estimation of β .) We then update λ using a weighted average of its previous value and $\tilde{\lambda}$. The weight given to $\tilde{\lambda}$ is given $\rho_t \Delta (\tau_0 + t)^{-\kappa}$ where $\kappa \in [0.5, 1]$ controls the rate at which old values of $\tilde{\lambda}$ are forgotten and $\tau_0 \geq 0$ slows down the early iterations of the algorithm. The condition that $\kappa \in [0.5, 1]$ is needed to guarantee convergence. We showed above that online LDA corresponds to a stochastic natural gradient algorithm on the variational objective \mathcal{L} (Bottou and Murata, 2002).

Mini-batches. A common technique in stochastic learning is to consider multiple observations per update to reduce noise. In online LDA, this means computing $\tilde{\lambda}$ using $S > 1$ observations:

$$\tilde{\lambda}_{kw} = \eta + \frac{D}{S} \sum_s n_{tsk} \phi_{tskw} \quad (\text{C.10})$$

where n_{ts} is the sth document in mini-batch t . The variational parameters α and η for this document are fit with a normal E step. Note that we recover the batch VB when $S = D$ and $\kappa = 0$.

Hyperparameter estimation. In batch variational LDA, point estimates of the hyperparameters α and η can be fit given γ and λ using a linear-time Newton-Raphson method. We can likewise incorporate updates for α and η into online LDA:

$$\alpha \leftarrow \alpha - \rho_t \tilde{\alpha}(\gamma_t); \quad \eta \leftarrow \eta - \rho_t \tilde{\eta}(\lambda) \quad (\text{C.11})$$

where $\tilde{\alpha}(\lambda)$ is the inverse of the Hessian times the gradient $\nabla_{\alpha} \ell(n_t, \gamma_t, \phi_t, \lambda)$; $\tilde{\eta}(\lambda)$ is the inverse of the Hessian times the gradient $\nabla_{\eta} \mathcal{L}$, and $\rho_t \Delta (\tau_0 + t)^{-\kappa}$ as elsewhere.

Algorithm 2: Online variational Bayes for LDA

```

 $\rho_t \Delta (\tau_0 + t)^{-\kappa}$ 
Initialize  $\lambda$  randomly.
for  $t = 0$  to  $\infty$  do
    E step:
    Initialize  $\gamma_{tk} = 1$ . (The constant 1 is arbitrary.)
    repeat
        | Set  $\phi_{twk} \propto \exp\{\mathbb{E}_q[\text{Log } \theta_{tk}] + \mathbb{E}_q[\text{Log } \beta_{kw}]\}$ 
        | Set  $\gamma_{tk} = \alpha + \sum_w \phi_{twk} n_{tw}$ ;
    until  $\frac{1}{K} \sum_k |\text{Change in } \gamma_{tk}| < 0.00001$ ;
    M step:
    Compute  $\tilde{\lambda}_{kw} = \eta + D n_{tw} \phi_{twk}$ 
    Set  $\lambda = (1 - \rho_t)\lambda + \rho_t \tilde{\lambda}$ 
end

```

C.2 Selecting the optimal number of topics

The estimation of LDA model draws an approximation of a posterior distribution (see more details later) with K topics (represented as multinomial distribution over V). This process infers each topic distribution that contains words with different probability assignment. Generally, words within topics with high probability are those that tend to co-occur more frequently. Moreover, these words are used to interpret and semantically label the topics.¹

Choosing the optimal number of topics K is essential in topic modelling algorithm, including the LDA. Previously, predictive likelihood have been sofar proposed by researchers to determine K . However, such measures had a main drawback to be negatively correlated with human interpretability. In other words, topics with high predictive become less coherent from a human perspective. As a result, coherence measures have emerged, which rely on a qualitative approach to automatically uncover the coherence of a topic. Indeed, a high topic coherence indicate that words which constitute the topic occur in similar contexts. For this study, we mainly focuses on two most popular coherence scores: the C_v coherence score based on a sliding window one-set segmentation of top words in all documents' topics; the C_{Umass} coherence score illustrates the cosine similarity among words co-occurrences

¹One of the caveats of the LDA is that topics recovered most probable words that need to be interpreted by the researcher. But this task seems to be straightforward since the training sample is correctly calibrated.

in documents’ topics. The average C_{Umass} score computes how often two words w_i and w_j appear together in the corpus to draw each topic. It is then defined as follows:

$$C_{Umass} = \frac{1}{K} \sum_{k=1}^K \sum_{i \neq j=1}^n \log \left(\frac{D(w_{i,k}; w_{j,k}) + 1}{D(w_{i,k})} \right) \quad (\text{C.12})$$

While $D(w_{i,k}; w_{j,k})$ indicates how many times words w_i and w_j appear together in documents for a given topic, $D(w_{i,k})$ represents how many times w_i figures alone for a given topic. The greater the score, the better is the coherence score.²

In addition to coherence scores, we appreciate the performance of the final model with the perplexity score. The latter is often used to evaluate models on a held-out training sample and is equivalent to the geometric mean per-word likelihood. Formally, it is given by :

$$Perplexity(w_d) = \exp \left(- \frac{\sum_{d=1}^D \log(P(w_d))}{\sum_{d=1}^D N_d} \right) \quad (\text{C.13})$$

D is the number of documents, w_d denotes words in document d , and N_d the number of words in document d .³

Also in line with the pick up of the optimal number of topics K , we iterate the LDA algorithm for different values of $k = 1, \dots, K$. Thereafter, we retrieve for each time the corresponding coherence and the perplexity scores. We also control for similarity or diversity across each topics’ pairwise using Jaccard Similarity (JS) score. JS score of pairwise i, j ($i \neq j$) is given by:

$$JS = \frac{Topic_i \cap Topic_j}{Topic_i \cup Topic_j} \quad (\text{C.14})$$

A low value of JS score reflects a small topics overlapping structure, which is good for the quality of the model. To sump up, the optimal number of topics is obtained for the LDA model with the highest difference between the average C_v score and the JS score before the two curves flatten out.⁴

² C_{Umass} scores for both news and law-based final models are -0.81 and -0.28 , respectively.

³The perplexity scores for news and law-based final models are -7.19 and -7.07 , respectively.

⁴ JS scores of news and law-based final models are around 0.13 .

C.3 Stopwords

['i', 'me', 'my', 'myself', 'we', 'our', 'ours', 'ourselves', 'you', "you're", "you've", 'you'll', 'you'd', 'your', 'yours', 'yourself', 'he', 'him', 'his', 'himself', 'she', 'she's', 'her', 'hers', 'herself', 'it', "it's", 'its', 'itself', 'they', 'them', 'their', 'theirs', 'themselves', 'what', 'which', 'who', 'whom', 'this', 'that', 'that'll', 'these', 'those', 'am', 'is', 'are', 'was', 'were', 'be', 'been', 'being', 'have', 'has', 'had', 'having', 'do', 'does', 'did', 'doing', 'a', 'an', 'the', 'and', 'but', 'if', 'or', 'because', 'as', 'until', 'while', 'of', 'at', 'by', 'for', 'with', 'about', 'against', 'between', 'into', 'through', 'during', 'before', 'after', 'above', 'below', 'to', 'from', 'up', 'down', 'in', 'out', 'on', 'off', 'over', 'under', 'again', 'further', 'then', 'once', 'here', 'there', 'when', 'where', 'why', 'how', 'all', 'any', 'both', 'each', 'few', 'more', 'most', 'other', 'some', 'such', 'no', 'nor', 'not', 'only', 'own', 'same', 'so', 'than', 'too', 'very', 's', 't', 'can', 'will', 'just', 'don', 'don't', 'should', 'should've', 'now', 'd', 'll', 're', 've', 'ain', 'aren', 'aren't', 'couldn', 'couldn't', 'didn', "didn't", 'doesn', 'doesn't', 'hadn', 'hadn't', 'hasn', 'hasn't', 'haven', 'haven't', 'isn', 'isn't', 'ma', 'mightn', 'mightn't', 'mustn', 'mustn't', 'needn', 'needn't', 'shan', 'shan't', 'shouldn', 'shouldn't', 'wasn', 'wasn't', 'weren', 'weren't', 'won', 'won't', 'wouldn', 'wouldn't', 'official', 'http', 'reg', 'data', 'no', 'page', 'journal', 'article', 'paragraph', 'european', 'union', 'member', 'commission', 'from', 'subject', 'use', 'not', 'would', 'say', 'could', 'be', 'know', 'good', 'go', 'get', 'do', 'done', 'try', 'many', 'some', 'nice', 'thank', 'think', 'see', 'rather', 'easy', 'easily', 'lot', 'lack', 'make', 'want', 'seem', 'run', 'need', 'even', 'right', 'line', 'even', 'also', 'may', 'take', 'come']

C.4 Introduction to N-Gram models

An N-Gram model is a probabilistic language model for predicting the next item in such a sequence in the form of a $(n - 1)$ - order Markov model. The computing task of the model is to determine the probability of a word w (or an entire word sequence W) given some history h defined as $P(w|h)$. Formally, let's consider $P(X_i)$ denoting the probability of a particular random variable X_i taking on a list of values. We represent a sequence of n words either as $w_1 \dots w_n$ or $w_{1:n}$ (so the expression $w_{1:n-1}$ means the string w_1, \dots, w_{n-1}). For the joint probability of each word in a sequence having a particular value $P(X_1 = w_1, X_2 = w_2, X_3 = w_3, \dots, X_n = w_n)$, we use $P(w_1, w_2, \dots, w_n)$. To compute probabilities of entire sequences $P(w_1, w_2, \dots, w_n)$, we

decompose this probability using the chain rule of probability as follows:

$$\begin{aligned} P(X_1, \dots, X_n) &= P(X_1)P(X_2|X_1)P(X_3|X_{1:2})\dots P(X_n|X_{1:n-1}) \\ &= \prod_{k=1}^n P(X_k|X_{1:k-1}) \end{aligned} \quad (\text{C.15})$$

Applying the chain rule to words, we get:

$$\begin{aligned} P(w_{1:n}) &= P(w_1)P(w_2|w_1)P(w_3|w_{1:2})\dots P(w_n|w_{1:n-1}) \\ &= \prod_{k=1}^n P(w_k|w_{1:k-1}) \end{aligned} \quad (\text{C.16})$$

The chain rule shows the link between computing the joint probability of a sequence and computing the conditional probability of a word given previous words. Equation above suggests that we could estimate the joint probability of an entire sequence of words by multiplying together a number of conditional probabilities. Nonetheless, using the chain rule does not really help since it is roughly difficult to calculate the accurate probability of a word given a long sequence of preceding words $P(w_n|w_{1:n-1})$. Moreover, we cannot just estimate it by counting the number of times every word occurs following every long string, because language is creative and any particular context might have never occurred before. Hence, the intuition of the n-gram model is that instead of computing the probability of a word given its entire history, we can approximate the history by only the last few words. For example, predicting the conditional probability of the next word given the history is equivalent to deducing its probability only from the previous word (according to Markov property). Indeed, Markov models are the class of probabilistic models that assume we can predict the probability of some future unit without looking too far into the past. As a result, N-grams models split into subcategories such as bigrams (with $N = 2$ and it looks one word into the past), trigrams (with $N = 3$ and it looks two words into the past) and n-grams (with $N = n$ and it looks $n - 1$ words into the past). The generalization of the probability approximation is given as follows:

$$P(w_n|w_{1:n-1}) \approx P(w_n|w_{1:n-1}) \quad (\text{C.17})$$

Under the bigram assumption, the probability of a complete word sequence that

derives is defined as:

$$P(w_{1:n}) \approx \prod_{k=1}^n P(w_k|w_{k-1}) \quad (\text{C.18})$$

Finally, an intuitive way to estimate probabilities is to call on the maximum likelihood estimation (MLE). This method provides parameters of an n-gram model by getting counts from the corpus, and normalizing them so that they lie between 0 and 1. For instance, to obtain a particular bigram probability of a word w_n given a previous word w_{n-1} , we compute the count of the bigram $C(w_{n-1}w_n)$ and normalize by the sum of all the bigrams that share the same first word w_{n-1} :

$$P(w_n|w_{n-1}) = \frac{C(w_{n-1}w_n)}{\sum_w C(w_{n-1}w)} \quad (\text{C.19})$$

Since the sum of all bigram counts that start with a given word w_{n-1} must be equal to the unigram (or bag-of-words) count for that word w_{n-1} , the equation above becomes:

$$P(w_n|w_{n-1}) = \frac{C(w_{n-1}w_n)}{C(w_{n-1}w)} \quad (\text{C.20})$$

The process described above owes its importance to the construction of lexical fields from a sequence of words. In other way, words associated by their meaning with the same given conceptual idea tend to appear together. Now, moving across documents, we reason in terms of term frequency-inverse document frequency (*tf – idf* for short) which is a numerical statistic reflecting how a word is important to a document in a corpus. The *tf–idf* value increases proportionally to the number of times a word appears in the document and is offset by the number of documents in the corpus that contain the word, which helps to adjust for the fact that some words appear more frequently in general. The *tf – idf* splits into *tf* value and the *idf* value. The term frequency, $tf(w, d)$ is the relative frequency of term w within document d given by:

$$tf(w, d) = \frac{f_{w,d}}{\sum_{w' \in d} f_{w',d}} \quad (\text{C.21})$$

where $f_{w,d}$ is the raw count of a term in a document, i.e., the number of times that term w occurs in document d . Note the denominator is simply the total number of terms in document d (counting each occurrence of the same term separately).

The *idf* is a measure of how much information the word provides, i.e., if it is common or rare across all documents. It is the logarithmically scaled inverse fraction

of the documents that contain the word (obtained by dividing the total number of documents by the number of documents containing the term, and then taking the logarithm of that quotient such as:

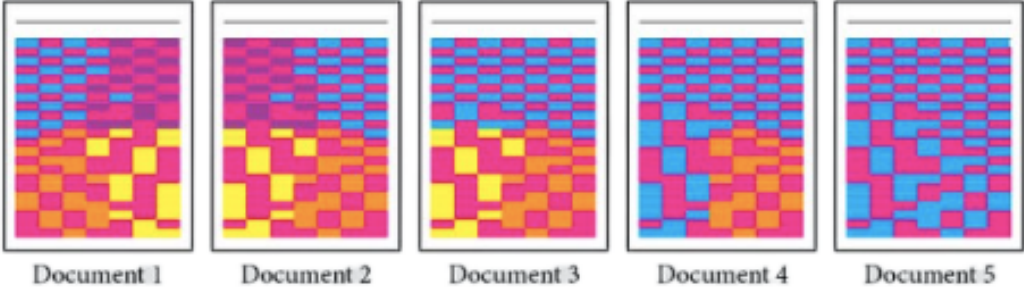
$$idf(w, D) = \text{Log} \frac{D}{|d \in D : w \in d|} \quad (\text{C.22})$$






D is the total number of documents in the corpus. $|d \in D : w \in d|$ is the number of documents where the term w appears (i.e., $tf(w, d) \neq 0$). If the term is not in the corpus, this will lead to a division-by-zero. Therefore, it is common to adjust the denominator to $1 + |d \in D : w \in d|$. Then the $tf - idf$ is calculated as follows:

$$tf - idf(w, d, D) = tf(t, d) \times idf(t, D) \quad (\text{C.23})$$

A practical overview of $tf - idf$ matrix is reported by the figure C.2 below. We can draw from the analysis of this figure that the first two documents are quite similar as their $tf - idf$ values are equal whereas the last document is not unique. Moreover, we remark, for instance, that while the first term is not useful in understanding the unique content of the documents as all its $tf - idf$ values equal to zero, the second term is most useful.

Figure C.2: Term Frequency- Inverse Document Frequency.



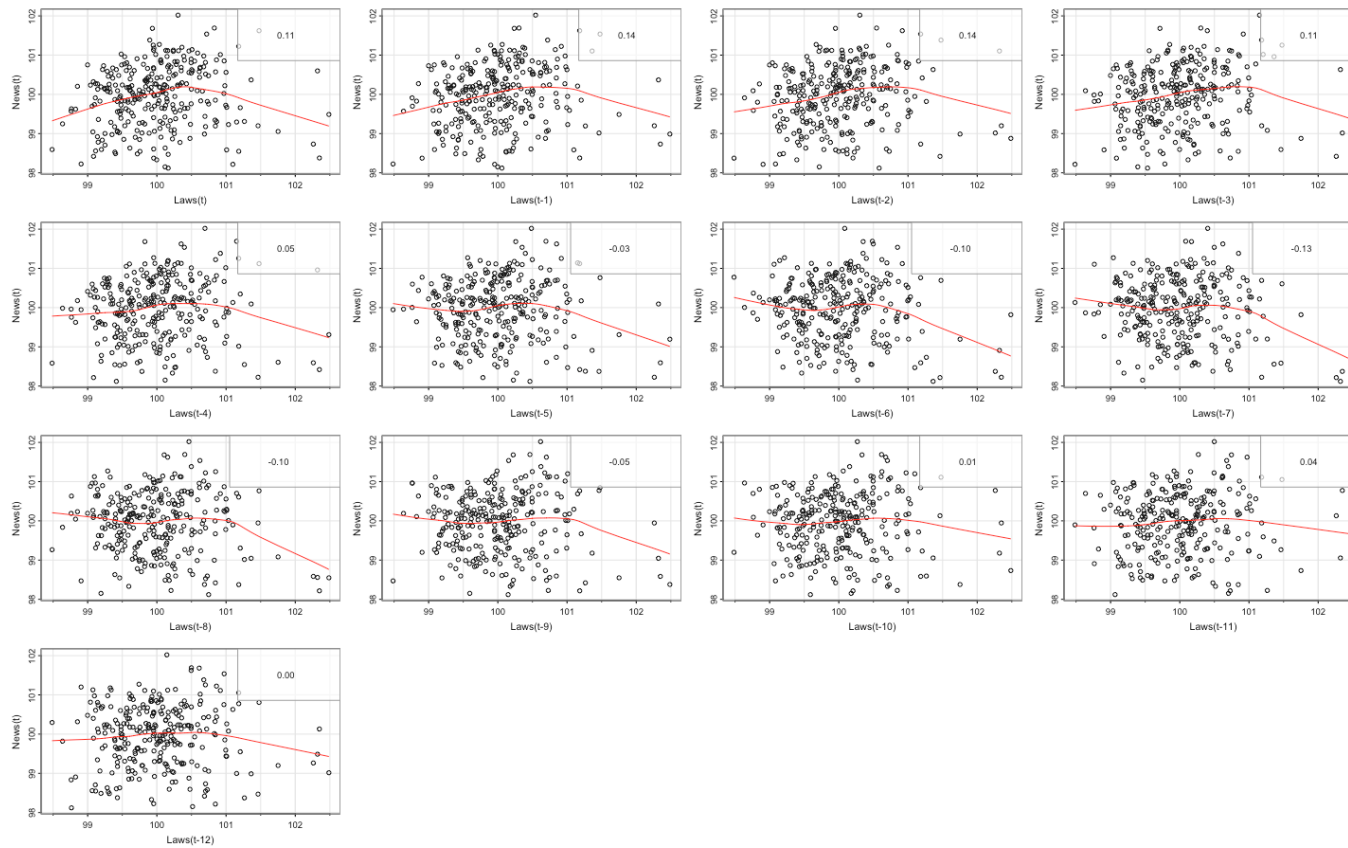
		Corpus TF-IDF Values				
		Terms				
						
Documents	1	0	.05	.027	.012	0
	2	0	.05	.027	.012	0
	3	0	0	.027	.012	0
	4	0	0	0	.012	0
	5	0	0	0	0	0

Source: Garla (2021)

Note: This graph illustrates tf-idf values of five terms extracted from five documents.

C.5 Figures

Figure C.3: Cross correlation scatter plots between law and news-based indices.



Notes: This graph shows scatter plots adjustment between law and news-based indices in a range of 12 months.

Figure C.4: Correlation functions (ACF and PACF) for the news-based index.

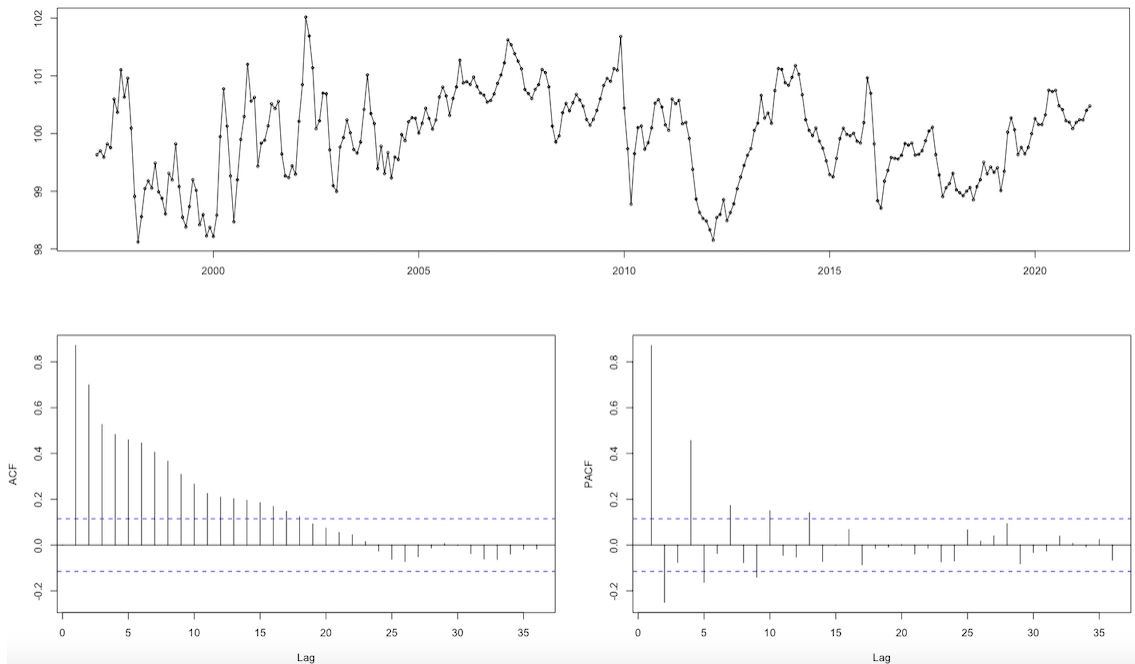


Figure C.5: Correlation functions (ACF and PACF) for the law-based index.

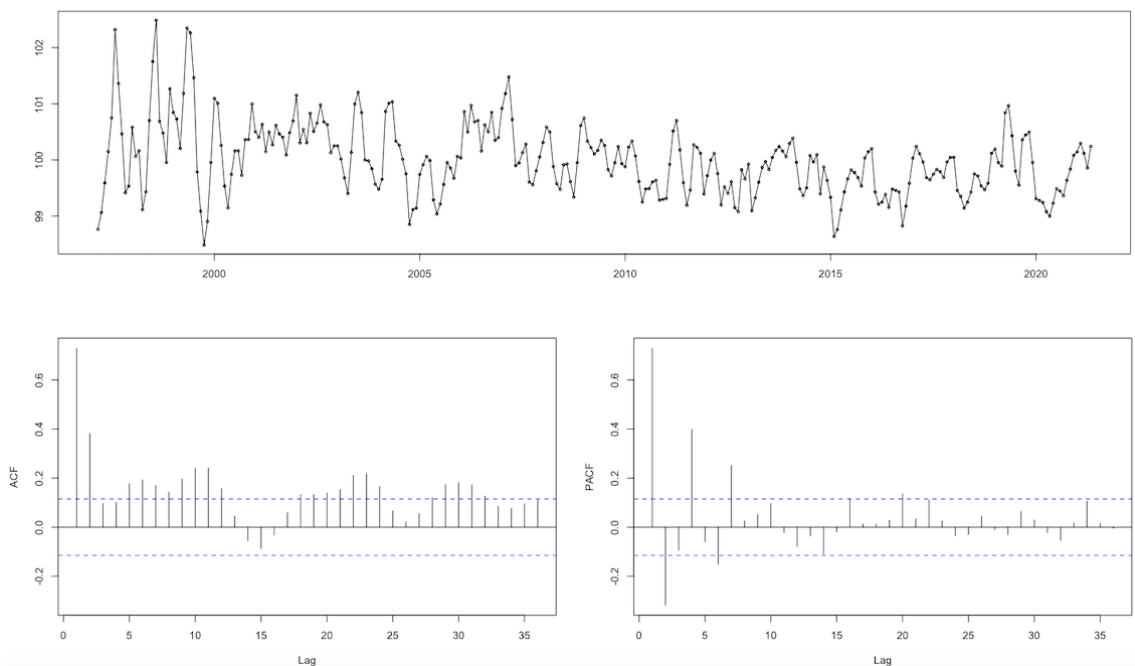
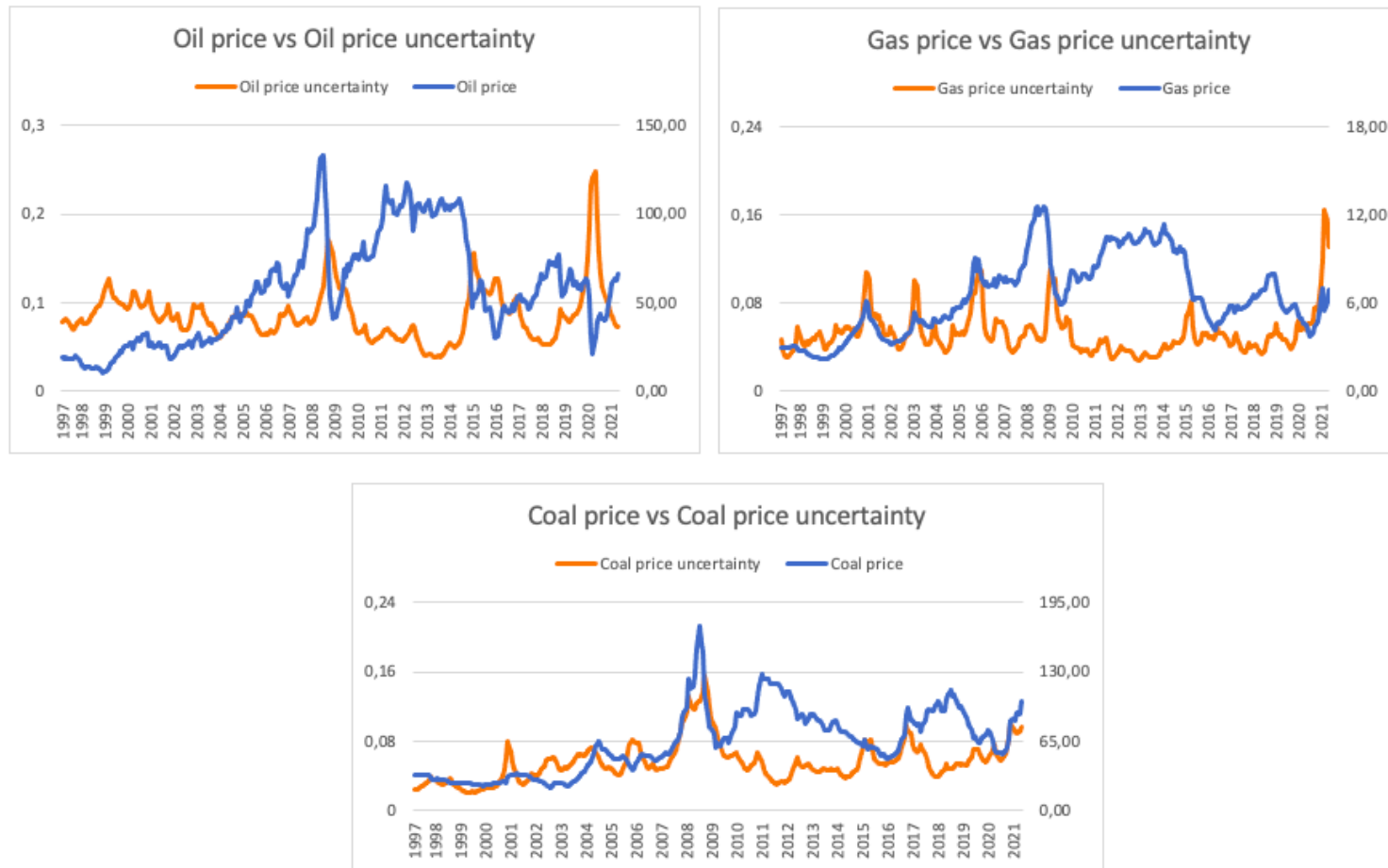
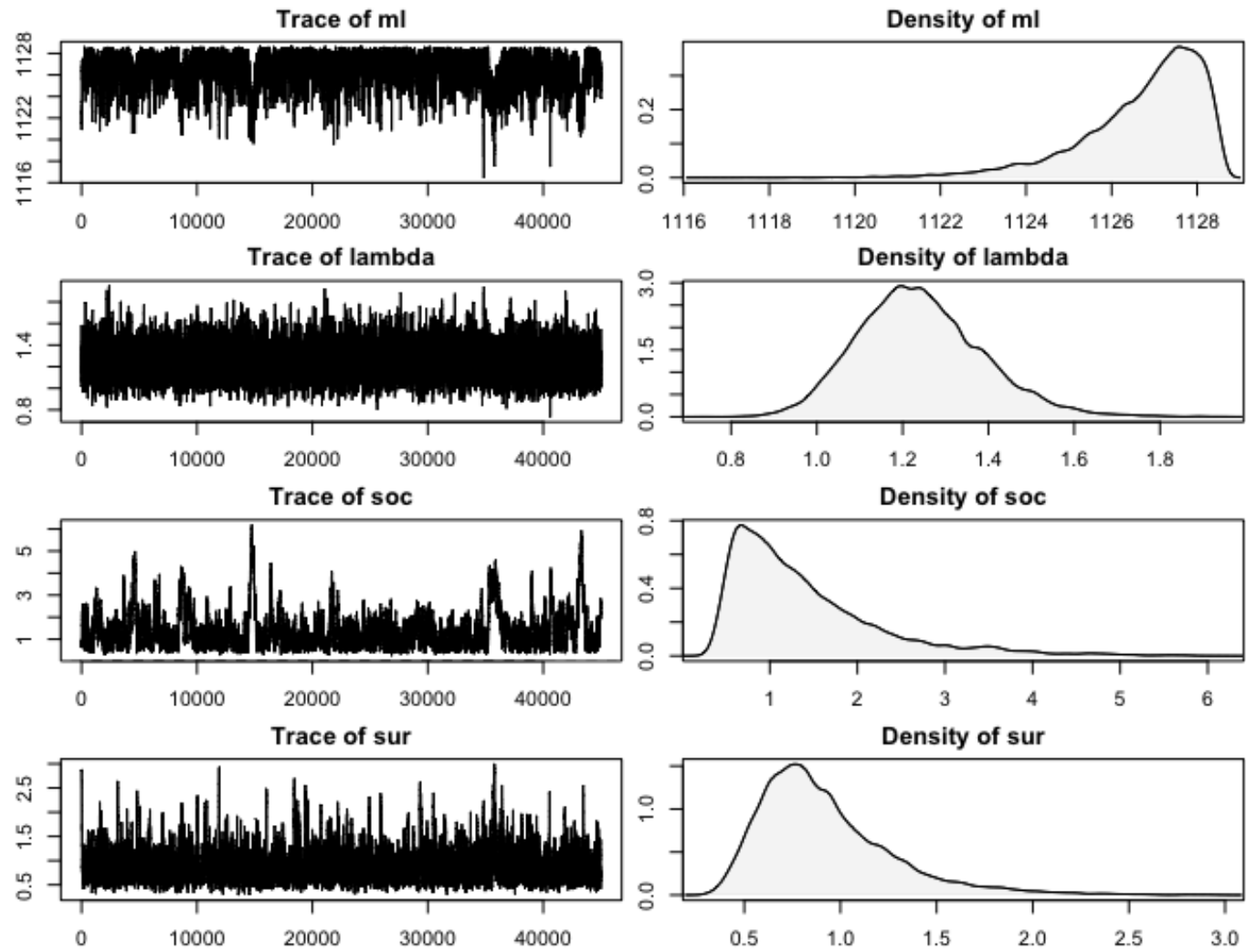


Figure C.6: Price uncertainty in fossil energy markets.

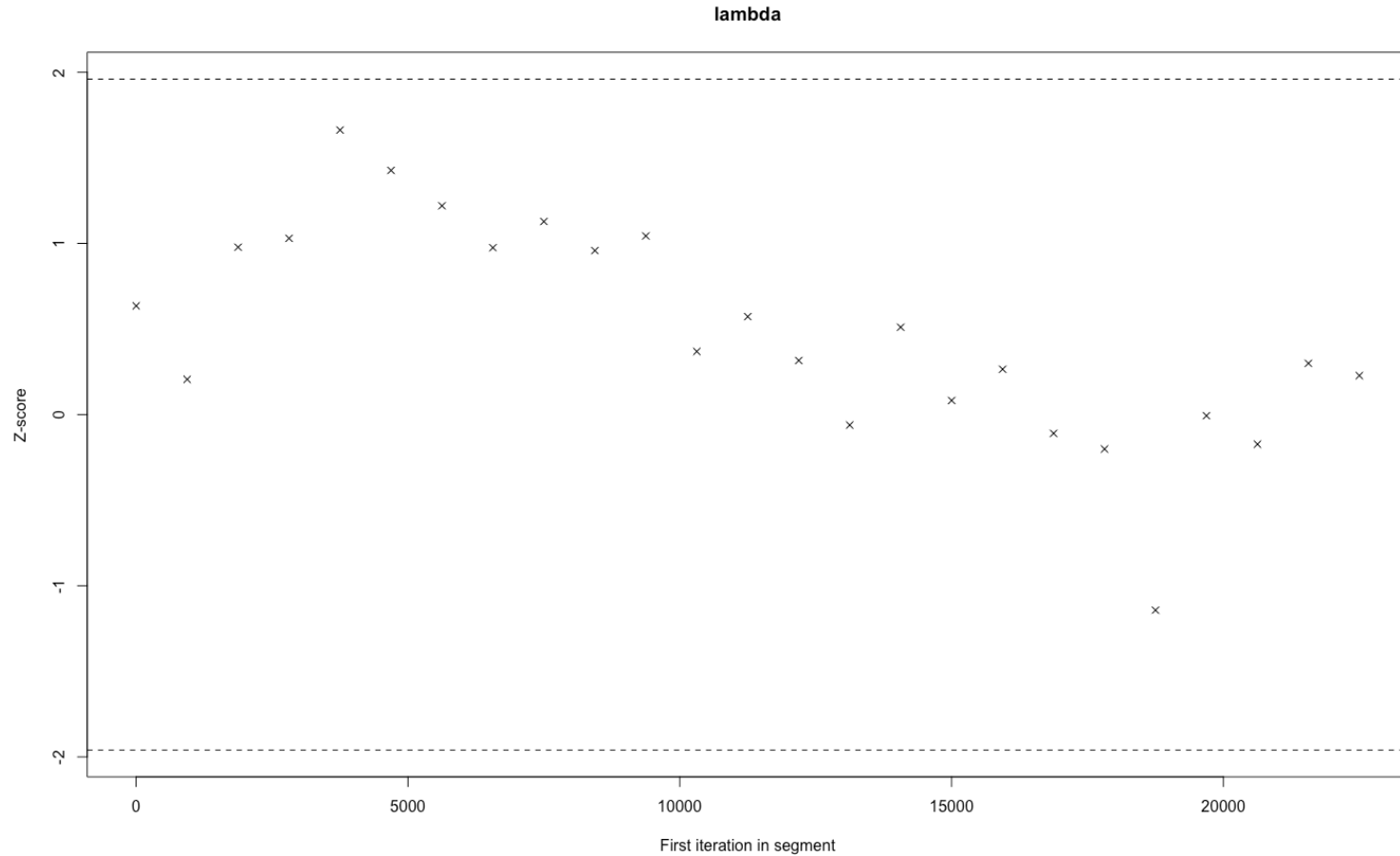


Notes: The figure plots the price uncertainty (orange line scaled on the left axis) along with the price (blue line scaled on the right axis) in oil, gas and coal markets.

Figure C.7: Estimates of hyperparameters' posterior distribution of the BVAR model.

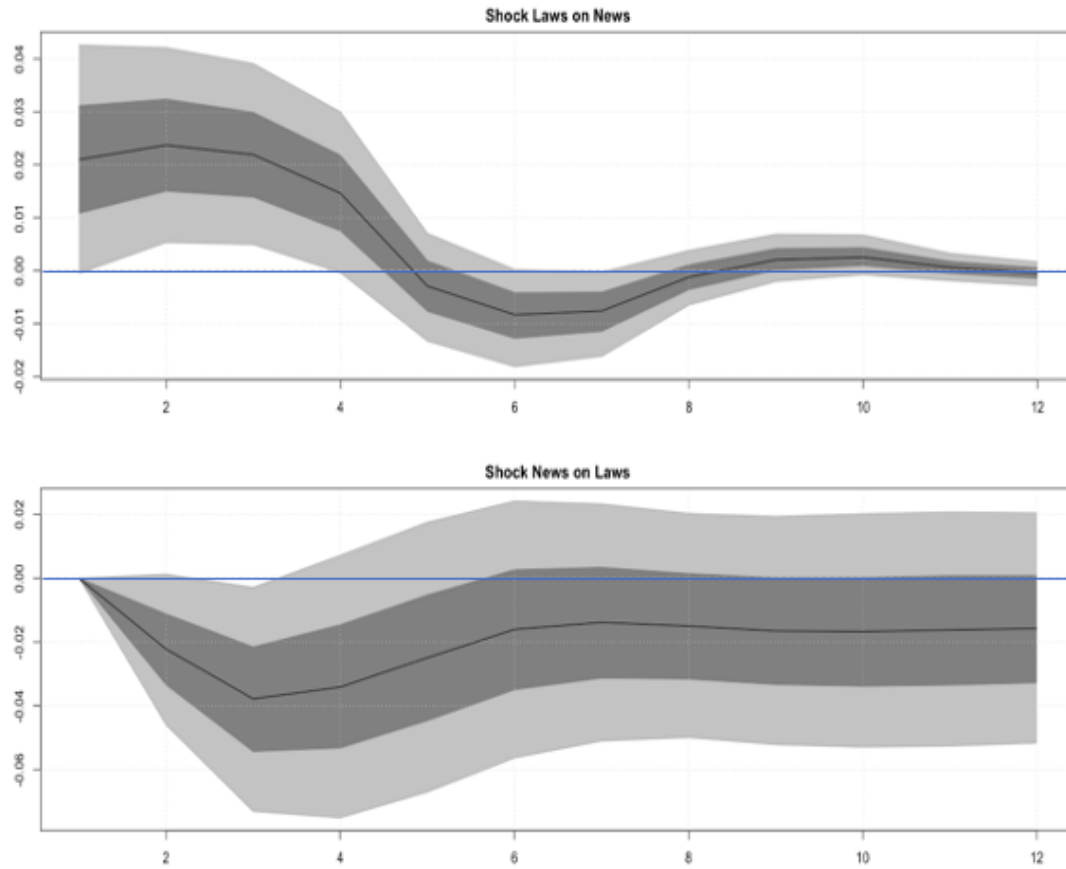


Notes: The figure depicts distributions of hyperparameters: ml (marginal likelihood), soc (sum-of-coefficients) prior, and sur (single-unit-root) prior.

Figure C.8: Convergence assessment of λ in the BVAR model.

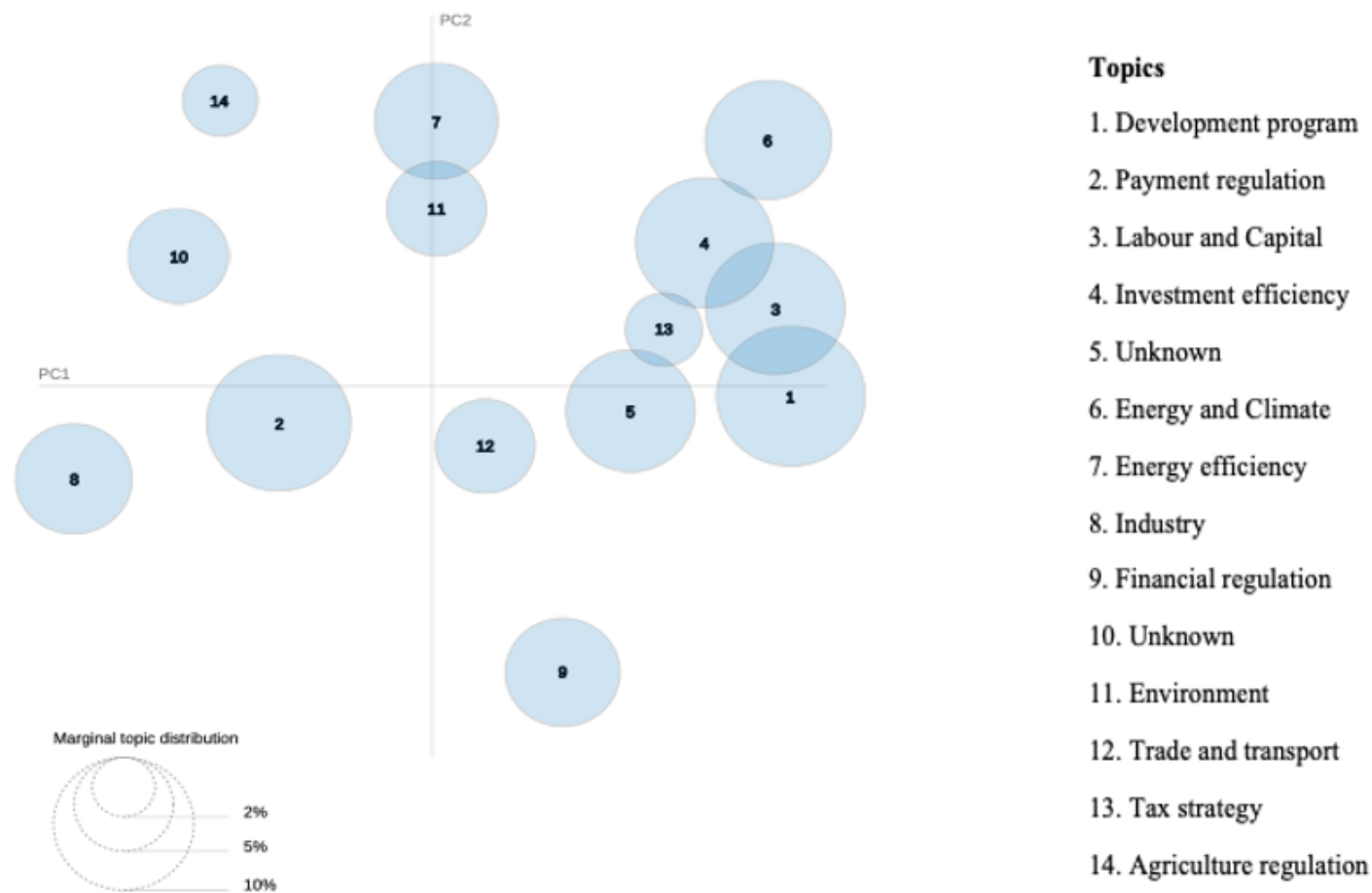
Notes: This figure reports the Geweke (1992) convergence diagnostic for Markov chains based on a test for equality of the means of the first and last part of a Markov chain (by default the first 10% and the last 50%). The test statistic is a standard Z -score (the difference between the two sample means divided by its estimated standard error). The standard error is estimated from the spectral density at zero and so takes into account any autocorrelation. The Z -score is calculated under the assumption that the two parts of the chain are asymptotically independent, which requires that the sum of both 10% and 50% parts of the chain is strictly less than 1. In our case, we choose by default the first 10% of your chain and we divide the final 50% into 25 segments and we perform a Z -test for each segment. The test is as follows: $H_0 : \lambda_{10\%} = \lambda_{50\%}^s$ vs $H_1 : \lambda_{10\%} \neq \lambda_{50\%}^s$. For each segment s , if the means are the same (i.e. we fail to reject H_0), then we have strong evidence of chain convergence. The dotted horizontal lines represent the 95% confidence interval.

Figure C.9: The reverse effects of law and news-based indices



Note: This figure presents the dynamic inference of the reciprocal effects between law and news-based indices as stressed in the subsection 4.3.

Figure C.10: The law-based indicator's intertopic distance map produced using the library LDAvis developed by Sievert and Shirley (2014)



Note: This figure presents a global visualization of the topic model. In this view, topics are plotted as circles in the two-dimensional plane whose centers are determined by computing the distance between topics, and then by using multidimensional scaling to project the intertopic distances onto two dimensions, as is done in (Chuang et al., 2012). We encode each topic's overall prevalence using the areas of the circles, where we sort the topics in decreasing order of prevalence. Topics are projected on two factorial axes bringing out the proximity and the imbrication across them.

C.6 Tables

Table C.1: **Variables description.**

Sources	Labels	Description
European legislation	Laws	Law-based energy and environment policy.
European press	News	News-based energy and environment policy.
Oil market	Oil price uncertainty	one-month oil price uncertainty.
Gas market	Gas price uncertainty	one-month gas price uncertainty.
Coal market	Coal price uncertainty	one-month coal price uncertainty.

Table C.2: **Descriptive statistics of variables.**

Variables	Mean	Std.Dev	Max	Min	Skewness	Kurtosis	Jarque-Berra
Laws	100.002	0.637	102.486	98.485	0.761	4.443	53.369***
News	99.959	0.775	102.019	98.120	-0.198	2.522	4.680***
Oil price uncertainty	0.086	0.030	0.247	0.038	1.893	9.516	688.719***
Gas price uncertainty	0.052	0.019	0.164	0.027	2.294	10.485	934.672***
Coal price uncertainty	0.056	0.023	0.156	0.020	1.313	5.476	158.056***

Note: The Jarque-Bera (1980) statistic tests for the null hypothesis of Gaussian distribution. *, **, *** denote the rejection of the standard null hypothesis at 10%, 5% and 1% significance levels.

Table C.3: Unit root tests.

	ADF		PP		KPSS		ZA
	level	first diff	level	first diff	level	first diff	level
Laws	-3.826***	-12.171***	-6.635***	-29.142***	1.258***	0.205	-5.180**
News	-3.511***	-7.608	-4.150***	-22.283	0.164	0.148	-3.810
Oil price uncertainty	-3.741***	-9.666***	-3.323**	-6.156***	0.116	0.037	-4.318
Gas price uncertainty	-3.080**	-10.977***	-1.419	-11.330***	0.275	0.276	-0.661
Coal price uncertainty	-2.519	-10.252***	-1.124	-10.030***	0.610**	0.150	-3.825

Note: The ADF, PP, KPSS, and ZA denote the statistics of Augmented Dickey-Fuller (1979), Phillips and Perron (1988), Kwiatkowski et al. (1992), and Zivot-Andrews (1992) unit root test, respectively. The optimal lag length of the ADF and the Perron test is chosen based on Schwarz information criterion (SIC) (Schwarz, 1978) and the bandwidth of the PP unit root test and KPSS stationarity test are determined based on Newey-West criterion (Newey-West, 1994). Noteworthy that ZA tests accounts for significant structural break dates in both intercept and trend. The null hypothesis of ADF, PP and ZA tests is a unit root and that of the KPSS test is stationarity. *, **, *** denote the rejection of the null hypothesis at 10%, 5% and 1% significance levels, respectively.

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APPENDIX C

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General Conclusion

Overview

This thesis starts with the disentanglement of commodity price fluctuations in terms of volatility shocks and uncertainty shocks. Over the past decade, several empirical studies (Jurado et al., 2015, Ludvigson et al., 2015, Joëts et al., 2017, 2018) highlight that unraveling price fluctuations is essential when assessing macroeconomic effects. Building on these studies, throughout this thesis we have explored drivers of commodity price uncertainty along three new lines of inquiry.

Chapter 1 investigates mechanisms of uncertainty transfer across commodity markets. To do so, we first identify four groups of commodities: agriculture (cocoa, maize, lumber, coffee, cotton, soybeans, sugar, and wheat), energy (oil, gas, coal), industry (aluminum, lead, tin, copper, nickel, zinc, and iron), and precious metals (gold, silver, platinum). For each group, we construct an aggregate price uncertainty index at a given horizon arising from the monthly prices of its individual components and their corresponding weights provided by the World Bank website. The development of uncertainty indices relies on the predictability-based approach of Jurado et al. (2015) and uses the moving average stochastic volatility approach of Chan and Jeliaskov (2009), Chan and Hsiao (2013). In particular, these predictability-based uncertainty measures are reliable in times of crisis since they outperform other volatility-based uncertainty measures such as the GARCH (generalized autoregressive heteroskedasticity) and the VIX (implied volatility index). Once these indices are constructed, we analyze the interconnections among markets using an econometric framework specifying a vector autoregressive (VAR) model.

Our main results indicate that there are bi-causal relationships between uncertainty in the agriculture, energy, and industry markets. In other words, price uncertainty is transmitted at various degrees within a pairwise of the aforementioned

markets. In contrast, precious metals markets are immune to other markets' uncertainty shocks and reinforce their safe haven nature. This chapter also unveils that industry uncertainty is a proxy for macro-financial uncertainty and as such acts as a key channel for transmitting uncertainty in heterogeneous markets. As a result, at an aggregate level, the analysis of the links between commodity markets shows evidence of the underlying role of the macro-financial factor in price uncertainty diffusion across commodity markets.

Chapter 2 examines, at a disaggregated level, economic policy uncertainty (EPU) as another factor of commodity price uncertainty in the oil and copper markets. In their seminal empirical work, Baker et al. (2016) set out the EPU as reflecting unexpected changes in economic and non-economic policies that keep the future unclear. The authors propose a measure of EPU using a tedious methodology of textual analysis on narratives embedded in 10 leading US newspapers. In this chapter, our research question is to determine how the EPU influences the dynamics of oil and copper price uncertainty using the pioneering supply-demand shock identification model initiated by Kilian (2009). We rely on the structural vector autoregressive (SVAR) model to perform the empirical strategy on the impacts of the EPU on oil and copper price uncertainties.

Our main finding indicates that the EPU shocks contribute, in the short run, to increasing oil and copper price uncertainties. Unlike the copper market, the upward effect appears stronger and more protracted in the oil market. We notice that the effects of traditional supply and demand factors remain economic-intuitive and are not altered with the introduction of the EPU to the model. In addition, we find out that while supply, demand and the EPU have quite similar contributions to oil price uncertainty shocks, copper price uncertainty shocks are highly dominated by aggregate demand.

Chapter 3 studies a particular aspect of economic policy, namely energy-related environmental policy and its consequences on the dynamics of prices in fossil energy markets. This chapter departs from a context characterized by efforts of the European Commission to engage state members to be aware of climate change, which is of interest when addressing global warming concerns. In 2008, the EU set a major turning point in its proactive legislative cycle by introducing a climate-energy program to promote an environmentally friendly energy system. This program emphasized three overarching targets: the cost-effective reduction of greenhouse gas emissions by 20%, the increase by 20% of the share of renewable energy in final consumption,

and the improvement in energy efficiency by 20%. This 3x20 program is part of low-carbon policies undertaken by the EU Commission to reach carbon neutrality by 2050 and is recorded in laws voted on and implemented at the European level. Since our interest is to assess the impact of the energy-related environmental policy on fossil energy markets, we need to quantify such a policy by constructing news and law-based indices of energy and environmental policy using textual analysis. To do so, we use state-of-the-art text mining techniques that allow for the extraction of relevant information from European newspaper articles and legal acts. We rely on a hands-off Latent Dirichlet Allocation (LDA) algorithm to cluster text into different themes or topics. It does so in an unsupervised manner, meaning that the algorithm infers the thematic information of any text without the need for pre-labeled data. Furthermore, in order to validate the usefulness of this algorithm in an economic context, we match indices derived from it with salient events that have occurred in the history of energy and environmental policy. Building economic policy indices with unsupervised machine learning models allows the researcher to endogenously extract the themes of any set of documents, and then select the relevant topics. Topics of interest are those which describe any issue regarding economic policies (energy, environment, climate, fiscal, trade, monetary, etc). Relying on both news and law-based indices helps disentangle two aspects of energy and environmental policy. While news covers both global uncertainty and energy and environmental policy-related regulatory aspects as reported by the European newspapers, laws describe structural changes in European energy and environment policy. According to this distinction, our news-based index differs from the EPU index. Thereby, we conduct an empirical investigation on the effects on fossil energy markets, and more specifically on fossil energy price uncertainty which is a standard measure in the literature to appreciate unpredictable price fluctuations. Following empirical studies examining the effects of text-as-data economic policy indicators on economic variables, we use a vector autoregressive (VAR) model to infer the dynamics.

Our results show that news-based index shocks lead to particular patterns of price uncertainty in markets that are worth highlighting. Especially, price dynamics in the oil and coal markets depict a two-way evolution implied by a short-run upsurge effect and a long-lasting bearish effect. We argue that each of these effects is the result of a news-based index component. Meanwhile, the downward impact starts earlier and is permanent in the gas market. Thus, we can deduce that the low-carbon policy appears to be beneficial to stabilize price uncertainty dynamics. Similarly,

the analysis of the effects of the law-based index shocks shows heterogeneous market responses in terms of maturity. We observe that the law-based index has a short-run and a persistent negative impact on oil and coal price uncertainty, respectively. Regarding the gas market, the evolution of price uncertainty highly depends on specific shocks in environmental regulations. Regarding the evolution of gas price uncertainty under news and law-based index shocks, there is a markedly similar momentum inducing a high sensitivity to regulations. In a further analysis dedicated to the incidence of the developed indices on market prices, our outcomes specify a downward adjustment of prices after an increase in the news-based index. This finding supposes that markets anticipate the regulations and adapt accordingly.

Some policy implications

Several policy challenges and responses can be drawn from this thesis. In particular, policy tools should be tailored to the developed drivers of commodity price uncertainty. It is commonly admitted that robust macroeconomic policy frameworks are critical to build buffers and allow authorities to better manage the negative economic effects of commodity price swings (Borensztein and Reinhart, 1994). More specifically, on the one hand, countercyclical policies are a way forward to mitigate macro-financial uncertainty-induced commodity price uncertainty, in particular, building a fiscal policy space that supports spending during slumps (Gill et al., 2014), and exchange rate flexibility linked to a monetary policy with credible low-inflation objectives (Broda, 2004, Céspedes and Velasco, 2012, Berg et al., 2016). On the other hand, the stringent management of structural policies in climate change could reinforce the resilience of emerging markets and developing economies (EMDEs) when facing unexpected shifts in commodity prices. According to the foregoing, chapters 1 and 2 show evidence that interdependencies across markets and uncertainty about economic policy fuel uncertainty in commodity prices. The underlying vulnerability of the commodity price cycle constitutes a permanent concern that could be addressed via longer-term sustainable policies. For instance, chapter 3 underscores a low-carbon policy as a structural policy to manage commodity price uncertainty. This chapter highlights that the efficacy of the European low-carbon policy is mainly due to its ability to stem unexpected price fluctuations in fossil energy markets. Besides, given the energy market and other markets nexus as described in chapter 1,

one might argue that such a policy affecting energy price uncertainty could spill over into other markets. Hence, the potential domino effect is beneficial for market price stability.

Research perspectives

Some lines of research have already been undertaken to extend the overall contribution presented in the thesis.

In this contemporary era, tackling climate concerns has become a vital energy-related environmental policy agenda, especially for realizing a temperature below 2°C. Relatedly, a key ingredient is promoting renewable energy to decarbonize the energy mix. Therefore, public incentives for companies to invest in renewable technologies range from feed-in tariffs, investment subsidies, tax credits, portfolio requirements, and certificate systems. A recent work of He et al. (2023) investigates the efficacy of scaling public investments to counter the causes and effects of climate change. The finding identifies natural resources and urbanization as the main factors responsible for piling up climate change concerns. In this regard, such investments exert moderating effects to partially neutralize the adverse effects of climate change. However, in 2020, the overwhelming bulk of fuel supply investment went into fossil fuels, namely 84% to oil and gas, 14.5% to coal (which is a much less capital-intensive sector), and only around 1.3% spent on low-carbon fuels. Therefore, investment spending appears caught between two worlds: neither strong enough to satisfy current fossil fuel consumption trends nor diversified enough to meet clean energy goals. Meanwhile, the World Energy Investment (2021) reports that clean energy investments by the oil and gas industry accounted for 1% of total capital expenditure and were expected to rise to more than 4% in 2021. Moreover, the financing of projects for offshore wind closely aligned with industry strengths was considerably higher in the first quarter of 2021 than in the whole of 2020. Apart from the pandemic, which caused diverging trends between government and private spending on research and development to support innovation on net-zero emissions plans, the signals for investment in low-carbon energy technologies are broadly positive.

In principle, as many countries agree on the strategy described above, our closing chapter can be extended in various respects. Notably, our law-based low-carbon

policy composite indicator could be explored as an alternative measure to appreciate environmental policy stringency at the European level. Furthermore, we can consider subsequent long-run perspectives through impacts on investments in energy utilities. This insight is all the more important since the new geopolitical and energy market realities require a drastic acceleration of the clean energy transition and an increase in Europe's energy independence from unreliable suppliers and volatile fossil fuels. The Renewable Energy Power of the EU (REPowerEU) is the European Commission's plan to make Europe independent from Russian fossil fuels well before 2030, in light of Russia's invasion of Ukraine. This plan sets out a series of measures to increase the resilience of the EU-wide energy system. Short-term measures include the following: common purchases of gas, liquefied natural gas, and hydrogen via the EU Energy Platform; new energy partnerships with reliable suppliers, including future cooperation on renewable and low-carbon gases; rapid rollout of solar and wind energy projects combined with renewable hydrogen deployment to save around 50 billion cubic meters (bcm) in gas imports; and an increase in the production of biomethane to save 17 bcm in gas imports. As medium-term measures to be completed before 2027, numerous actions are being undertaken, namely: new national REPowerEU Plans under the modified recovery and resilience fund to support investment and reforms worth €300 billion; boosting industrial decarbonization with €3 billion of frontloaded projects under the innovation fund; new legislation and recommendations for faster authorization of renewables, especially in dedicated 'go-to areas' with low environmental risk; investments in an integrated and adapted gas and electricity infrastructure network; increased ambition regarding energy savings by raising the EU-wide efficiency target for 2030 from 9% to 13%; increase of the European renewable target for 2030 from 40% to 45%; new EU proposals to ensure industry access to critical raw materials; and a modern regulatory framework for hydrogen to build 17.5 Gigawatt of electrolyzers by 2025 to fuel EU industry with a homegrown production of 10 million tonnes of renewable hydrogen.

Finally, given the interdependences between commodity markets, the implications of the European low-carbon policy on the new energy investment paradigm could also be great of interest for agricultural and industrial markets.

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GENERAL CONCLUSION

Jurado, K., Ludvigson, S. C., and Ng, S. (2015). Measuring uncertainty. *American Economic Review*, 105(3):1177–1216.

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Titre: Incertitude sur les prix des matières premières: diffusion et politique économique comme déterminants

Mots clés: Commodités; Incertitude du prix; Incertitude macro-financière; Incertitude de politique économique; Politiques à faibles émissions carbone.

Résumé: Une meilleure analyse des marchés des matières premières est plus que jamais essentielle au regard de l'épidémie de COVID-19, de la guerre en Ukraine et de la transition des énergies fossiles vers les énergies renouvelables. Les fluctuations des prix sont généralement attribuées à des chocs de volatilité. Cependant, les crises économiques récentes ont montré que ces fluctuations des prix révèlent une importante composante d'incertitude, questionnant ainsi l'hétérogénéité de ces marchés et les différents facteurs économiques qui les régissent. Cette thèse met en lumière trois principaux facteurs d'incertitude sur les prix des matières premières. Le chapitre 1 met en évidence l'incertitude macro-financière comme le premier facteur d'incertitude sur les prix, en analysant la diffusion de l'incertitude en-

tre les marchés. Le chapitre 2 analyse, à un niveau désagrégé, l'incertitude liée à la politique économique comme deuxième facteur d'incertitude sur les marchés du pétrole et du cuivre. Enfin, le chapitre 3 examine l'influence des politiques européennes à faibles émissions de carbone sur l'incertitude des prix des énergies fossiles. Nous identifions les différents aspects des politiques à faibles émissions de carbone à travers deux indicateurs : un indicateur basé sur la presse et un indicateur structurel basé sur les textes de lois. Notre principal résultat suggère que les politiques à faibles émissions de carbone contribuent à réduire l'incertitude des prix sur les marchés des énergies fossiles. Ce résultat demeure cohérent lorsqu'on considère l'incertitude liée à l'environnement international.

Title: Commodity Price Uncertainty: Diffusion and Policy Drivers

Keywords: Commodity markets; Price uncertainty; Macro-financial uncertainty; Economic policy uncertainty; Low-carbon policies.

Summary: A thorough understanding of commodity markets is now more crucial than ever, given the impact of the COVID-19 outbreak, the war in Ukraine, and the ongoing transition from fossil fuels to renewable energy commodities. These price movements are typically attributed to volatility shocks. However, economic disruptions reveal evidence that commodity price fluctuations can also stem from a significant element of uncertainty, highlighting the heterogeneity of commodity markets and the diverse economic forces that influence them. This thesis sheds light on three primary drivers of commodity price uncertainty. Chapter 1 emphasizes macro-financial uncertainty as the primary driver of commodity price uncer-

tainty, analyzing the diffusion of uncertainty across markets. In a similar vein, Chapter 2 examines economic policy uncertainty as the second driver of uncertainty in oil and copper markets, analyzing it at a disaggregated level. Finally, Chapter 3 explores how European low-carbon policies influence uncertainty in fossil energy prices. We disentangle aspects of low-carbon policies using two indicators: a news-based indicator and a structural laws-based indicator. Our main finding suggests that low-carbon policies contribute to reducing price uncertainty in fossil energy markets. This result holds true even when considering uncertainty related to the international environment.