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# Green Connections : A Network Economics Approach to the Energy Transition

Côme Billard

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**THÈSE DE DOCTORAT**

**DE L'UNIVERSITÉ PSL**

Préparée à l'Université Paris-Dauphine

## ***Green Connections : A Network Economics Approach to the Energy Transition***

Soutenue par Côme Billard

Le 3 Décembre 2020

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### Composition du jury :

Mme Mirabelle MUÛLS  
Assistant Professor, *Imperial College London*  
Rapporteure

Mme Katheline SCHUBERT  
Professeure, *Paris School of Economics*  
Rapporteure

M. Arnaud MAGNIER  
Docteur, *Institut d'Etudes Politiques de Paris*  
Membre du jury

Mme Stéphanie MONJON  
Maître de Conférence HDR, *Université Paris-Dauphine*  
Présidente du jury

Mme Anna CRET  
Professeure, *Université Paris-Dauphine*  
Directrice de Thèse



*Patience.*

*Persévérance.*

*Ainsi va la vie, à bord du Redoutable.*

*Le Redoutable, M. Hazanavicius, 2017.*



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# General Introduction

## Preamble

To limit global warming to less than 2°C by the end of the century, economies worldwide must reach carbon neutrality by 2050 (IPCC, 2018). Large scale diffusion of low carbon technologies represents an important component of international strategies to achieve such a target and is largely driven by the implementation of environmental policies (Grantham Research Institute, 2018; OECD, 2018). This thesis builds upon concepts from network theory to investigate both theoretically and empirically diffusion dynamics on the path toward a low carbon society. We provide analysis for three different diffusion perspectives : clean technologies, environmental policy and the effects of economic shocks on (imported/generated) emissions. This dissertation complements different strands of the academic literature (network economics, environmental economics) and proposes implications for policy-makers willing to meet objectives set in the Paris Agreement (2015). First, it highlights how the structure of networks plays a critical role in diffusion dynamics, whether these networks are social connections, policy flows across states or sectoral economic interactions. The latter is particularly relevant for clean technology spreading (*Chapter 1*), for which underlying social structures affect diffusion in many respects (i.e. adoption, variance, time). Governments willing to maximize the deployment of low carbon products could take advantage of such dimensions when designing public interventions. Regarding environmental policy (*Chapter 2*), the analysis of diffusion across American states strongly emphasizes how

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positions of states in the network of policy flows are critical to understand dynamics of spreading. This work provides critical insights on states likely to foster diffusion across the U.S. as well as the determinants of such observations. Finally, the last two contributions of the present manuscript settle in the context of resurgent calls to limit imported emissions at the EU scale (*Chapter 3*) and the implementation of COVID-19 recovery plans within states of the region (*Chapter 4*). In both cases, we provide insights regarding the potential benefits of phasing out/not bailing out<sup>2</sup> carbon-intensive sectors in terms of (imported) emission reductions in the whole system. Although results emphasize the key role of some industries, the network perspective suggests policy-makers should take into account sectoral dependence of downstream sectors (i.e. strength of interactions) when implementing economic instruments targeting GHG intensive sectors.

In conclusion, this thesis illustrates how network structures, the positions of embedded agents and the strength of neighborhood connections are critical dimensions to take into account when designing policies aiming at accelerating the green transition.

The remainder of the introduction is structured as follows : we first put in perspective the notion of interconnectedness into perspective by discussing the advent of the COVID-19 crisis to justify the relevance of a network approach when addressing topics of diffusion. We then explore how network theory has slowly become a relevant tool in the economic literature addressing diffusion dynamics. We conclude by presenting the contributions of this thesis and their implications in the field of environmental policy. Overall, this dissertation paves the way to future research at the interface between network economics and climate economics.

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<sup>2</sup>Without clearly defined environmental counterparts.

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## Facing Climate Change in an Interconnected World : Short Lessons from the COVID-19 crisis

The advent of the multifaceted COVID-19 crisis (2019) coincides with the critical emergency to tackle climate change ([European Central Bank, July 2020](#); [World Economic Forum, September 2020](#)). Last year, cumulative worldwide emission levels put the environmental system on track for a 3°C temperature rise by the end of the century ([United Nations, 2019](#)). Limiting this rise to 1.5°C requires governments to meet the net zero climate target by 2050 ([IPCC, 2018](#)).<sup>3</sup> Although causing severe economic and social damages ([United Nations, 2020](#); [International Monetary Fund, 2020](#)), the unexpected COVID-19 pandemic could act as a milestone in the reduction of greenhouse gas emissions over the next decades. In the short run, GHG emissions are expected to fall by around 7% in 2020, representing the annual rate at which our economies should decarbonize to reach carbon neutrality in 2050 ([Liu et al., 2020](#)). In the long run, GHG emission trajectories will depend on forthcoming recovery plans (both domestic and/or regional) and their ability to decouple growth and emissions by deploying clean energy sources as well as enlarging and strengthening the corpus of environmental policies ([Allan et al., 2020](#); [Hepburn et al., 2020](#)). While the standard environmental policy toolkit provides well-established instruments to pursue such objectives (i.e. command and control measures and market-based incentives, see [Kolstad, 2010](#)), policy-makers aiming to match economic recovery objectives with climate targets set in the [Paris Agreement \(2015\)](#) could take advantage of a less investigated nonetheless ubiquitous dimension emphasized by the ongoing pandemic crisis : the increasing interconnectedness of our social and economic activities ([Bazilian and Gross, 2020](#); [OECD, 2020](#)).

Years after the 2008 global financial crisis (GFC) dramatically revealed the interconnection of banks in the financial system ([International Monetary Fund, 2010](#); [Battiston et al., 2012](#)), the COVID-19 pandemic (2020) has highlighted how both our

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<sup>3</sup>'Net zero' means that any emissions are balanced by absorbing an equivalent amount from the atmosphere.

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social and economic activities are interconnected. People are connected to each other by social interactions, business and geographic ties along which the virus has been propagating. Firms use each other's inputs and outputs, engage in joint ventures and compete on markets. Lockdown measures have severely impacted both sides of demand and supply, creating activity contractions from upstream to downstream sectors and vice-versa (eg. from airlines to hospitality sectors and further to local companies), thus leading to numerous bankruptcies ([The Economist, March 2020](#); [International Monetary Fund, 2020](#)). At the international scale, governments are tied by alliances, by geographical borders, by trade and by cross-border capital/human flows. The latter dimension has played a critical role in the spreading of the virus, leading to mobility restriction measures ([Chinazzi et al., 2020](#); [Zhou et al., 2020](#)).

From a broader perspective, modern societies are continuously undergoing overlapping social and economic diffusion processes. Epidemics, information ([Centola, 2010](#); [Thörnberg, 2018](#)), ideas ([Haggit et al., 2003](#); [Jackson and Yariv, 2010](#)), innovations ([Rogers, 1995](#)), and more recently economic shocks (e.g. surge in energy commodity prices, financial risks) are all examples of spreading phenomena. Whatever the mechanism driving diffusion ([Young, 2009](#)), such processes propagate on underlying structures, either social (groups of individuals) or economic (industrial value chains, banking system) and the resulting final outcome largely depends on the strength and the pattern of ties. For instance, whether an agent adopts an innovation or not depends on choices made by nearby agents, i.e. our neighbours. However, the (unpriced) effects of these neighbours on our behaviour - externalities - depend on the strength and the pattern of ties between us and our neighbours, on our neighbours' ties with their neighbours, and so on. From another perspective, research on the propagation of the financial shock during the GFC has demonstrated that the structure of connections within the banking system has driven risk diffusion ([Paltalidis et al., 2015](#); [Hale et al., 2016](#)). To capture how these patterns affect diffusion, we should not only consider the direct contacts but also the more general structure of connections in which all

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agents are embedded (be they individuals, states or industrial sectors). Economists have been using the term *networks* to describe the overall structure of connections (Elliott et al., 2019).

## **Networks in Economics : Some perspectives from the Literature**

### **The Theoretical Advent of Networks in Economics**

The analysis of *networks* in economics started in the 1990s, adding up to game theoretical approaches and general equilibrium models (GEM). While the former examine the behaviour of agents in small exclusive groups, the latter provide tools to study large economic systems. At that time, theoretical frameworks in economics were largely built upon concepts derived from either game theory or GEM, thus failing to account for events and phenomena arising between these two extremes. As an illustration, models of diffusion in the 1980s had weaknesses in terms of introspection and failed to match empirical findings (Goyal, 2015). Such observations paved the way for initial attempts to model individuals' decision-making embedded in a social network. Hereafter, I review the design of these first set of settings and show how they depart from received models. I discuss the main insights and relate them to subsequent empirical developments in the field.

Diffusion of ideas, practices or technologies are fundamental for understanding social changes and growth. For decades, economists have investigated diffusion dynamics through the lens of individual characteristics (heterogeneity) and profitability (cf. the seminal work of Griliches (1957)). At the beginning of the 1970s, emerging concepts of asymmetries and imperfect informations gained a prominent interest in the field with a burgeoning literature on the economic value of information (Rothschild and Stiglitz, 1976; Grossman and Stiglitz, 1980; Stiglitz, 1985). Starting with imperfect information, key questions were whether individuals would “acquire” information

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and “learn” the “optimal” action. The work of [Rothschild \(1974\)](#) demonstrated that a patient and dynamic optimizing agent will stop learning, ending up locked in sub-optimal action with positive probability. This study marked the beginning of a large current of sophisticated works on single agent learning until the 1990s. Interestingly, a multi-agent literature also developed in parallel. It focused on learning rational expectations and Nash equilibrium. Studies by [Fudenberg and Levine \(1998\)](#) and [Evans and Honkapohja \(2001\)](#) fall in this category. In broad terms, this economic literature mainly concentrated on single individuals or groups where interactions were uniform and homogeneous.

However, previous research from various fields of social sciences (e.g. sociology, economic geography, communications) suggested that real world interactions are at the interface between these two situations ([Katz and Lazarsfeld, 1955](#); [Coleman, 1966](#); [Granovetter, 1973, 1974](#); [Ryan and Gross, 1943](#); [Hagerstrand, 1967](#); and [Rogers, 1995](#)). Indeed, agents tend to have interactions with a limited subset of the group. These direct connections, their neighbours, are stable and overlap with others’ neighborhoods. For [Coleman \(1966\)](#) and [Hagerstrand \(1967\)](#), these neighbors are the conduit through which information and influence circulate, shaping the diffusion dynamics of ideas, innovations and practices. Such settings of multiple agents interacting in complex networks make strategic reasoning models (i.e. game theoretical approach) difficult to implement while local interaction in social networks makes anonymous competitive equilibrium analysis implausible. The appearance of this methodological gap to capture behaviour challenged economic theory in the 1980s and motivated new advances. A critical development to cope with this issue was the introduction of multiple agents making repeated choice, located in a table social network. Seminal works of [Bala and Goyal \(1998, 2001\)](#) embody such a new strand. Authors developed a framework including models of networks with individual choices and learning dynamics. The original innovation was to locate rational individuals in a directed network in which individual are not aware of the true value of different actions. In addition to experiences from the

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past, agents rely on the experience of their neighbors to make their decisions. In such a setting, information percolates across the network. This work marks the first attempt to evaluate how the structure of underlying social networks affects individual choices and diffusion of actions. From another point of view, a salient point of their work is the introduction of a wide range of concepts from graph theory (e.g. connectedness, hubs). This combination of individual choice and graphs is central to subsequent works on networks in economics.

Overall, the work of [Bala and Goyal \(1998, 2001\)](#) marks a significant break from the diffusion models implemented in the 1980s. As previously mentioned, economists in the 1980s mainly tried to capture dynamics of single-agent or groups of agents learning. Research in the 1990s provides novel frameworks with the introduction of graphs and related concepts of network analysis, thus allowing academics to examine large interacting social groups with overlapping neighborhoods. This approach appears as a new way of understanding diffusion patterns, for which small-group analysis (game theory) and large-group theoretical approaches were not in adequacy. In other words, networks fall between the “small” and the “large”. So far, this tension has been continuously driving new theoretical research in this field ([Goyal, 2015](#)).

Before moving to empirical contributions of network economics on diffusion, it is important to mention that a branch of theoretical and empirical researches has been investigating the issue of network formation<sup>4</sup> following the prominent contribution of [Jackson and Wolinsky \(1996\)](#). This contribution has generated an extensive set of economic applications. Examples include formation and coordination in networks ([Goyal and Vega-Redondo, 2005](#); [Jackson and Watts, 2002](#)), research collaboration networks formation ([Goyal and Joshi, 2003](#)), collusion networks ([Belleflamme and Bloch, 2004](#)), information networks ([Galeotti and Goyal, 2010](#)), labor market networks ([Calvo-Armengol, 2004](#); [Calvo-Armengol and Jackson, 2004](#)), financial networks ([Cabrales et al., 2012](#); [Farboodi, 2014](#)), free-trade agreement networks ([Goyal](#)

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<sup>4</sup>Although not studied in this manuscript.

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and Joshi, 2006), peer networks (Cabrales, Calvo-Armengol, and Zenou, 2011), and cyberattack and network design (Goyal and Vigier, 2014; Acemoglu, Malekian, and Ozdaglar, 2014). For a general review of advances and applications in network economics, Jackson (2008) and Bramoullé et al. (2016) provide insightful elements.

## **Diffusion in Networks : Evidence from the field**

Following the increasing body of theoretical literature in network economics, an empirical strand of the literature addressing questions related to the role of social interactions on diffusion patterns has flourished. Major contributions came from economists in the field of development economics that investigated the impact of peer effects and social networks on learning and diffusion of new products, practices and technologies. Prominent examples include Bandiera and Rasul (2006), Munshi (2004), Kremer and Miguel (2007) and Duflo et al. (2011). More recently, empirical research covered specific questions about underlying social networks (e.g. the impact of neighbors' behaviour on individual decision (Conley and Udry; 2010), optimal seeding strategy to maximise diffusion (Banerjee et al., 2013)). Moreover, very recent works have emphasized the contagious feature of technology adoption in social networks (Baranzini et al., 2017; Beaman et al.; 2018). In the following, I specifically review these original findings as they critically embody how network theory applied in the field - and thus acting as a ground-breaking approach - could guide policy interventions.

In the literature of economic development, a common issue to investigate is the diffusion of new products, be they crop technologies, insurances, with the objective of enhancing productivity and alleviating poverty. Conley and Udry (2010) focused on the diffusion of a new agricultural technology among farmers in Ghana. They innovated by investigating the role of social learning in the adoption of a crop innovation. To do so, they collected a description of farmers' information neighborhood to reconstruct underlying social networks and assess the impact of neighbours' behaviour on the de-

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cision to adopt. They found that farmers tend to adapt their inputs with those of their neighbors who were successful in the past. To confirm such a result, they introduced another but known technology crop for which they observe no learning. [Conley and Udry](#) conclude that information has value in these villages, as do network connections through which information about the innovation flows. From another perspective, [Banerjee et al. \(2013\)](#) evaluated the diffusion of micro-finance practices in 43 Indian villages, with information on underlying social networks. They were interested in assessing the role of initial seeded individuals in the network (i.e. injection point) on diffusion dynamics. After varying such injection points of information across different villages, they found that diffusion of micro-finance practice is larger when seeded agent displays high eigenvector centrality in the village. In other words, targeting individuals that are in contact with well-connected individuals in the village (e.g. village leaders) increases diffusion of the practice. These two major contributions empirically show that underlying social networks have a prominent role in the diffusion of innovations while, depending on their positions in such networks, individuals targeted in the first period to introduce a new behaviour (e.g. injection point for micro-finance) define the future dynamics of diffusion. Overall, such works mark the departure of studies on the explicit treatment of network architecture.

More recently, [Beaman et al. \(2018\)](#) focused on inducing farmers to adopt a productive new agricultural technology by implementing contagion models on rich social network data from 200 villages in Malawi. The main objective was to identify seed farmers to target in order to reach high levels of diffusion. To do so, they carried out a randomized controlled trial to compare theory-driven network targeting approaches and simpler strategies that either rely on a government extension worker or an easily measurable proxy for the social network (geographic distance between households). Interestingly, results are consistent with a complex contagion model in which many farmers need to learn from multiple people before they adopt the technology themselves. This means that without proper targeting of information, the diffusion process can stall and tech-

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nology adoption remains perpetually low. Both reduced form and structural estimates suggest a learning environment in which most farmers need to learn about the technology from multiple people before they adopt it themselves. As a result, innovation in social networks tends to be diffused following an epidemiological pattern of transmission. The latter dimension is developed in the next section, lying at the core of this thesis' contribution.

As a summary, the emergence of network theory in economics started in the 1990s with the first set of models incorporating individual choice and network structures within a common framework. By implementing concepts and insights from graph theory, it marks a major advance in the theoretical framework of diffusion analysis and brings concepts of graph theory into the mainstream of economics. In the wake of these theoretical works, an empirical literature has developed investigating the role of social networks on diffusion patterns of practices, information and innovations. The research discussed above emphasizes several elements : how structures of social networks affect diffusion patterns; the role of initial seeds to launch a diffusion process; and the contagious feature of technology diffusion in networks. In the following section, we center our approach on the potential benefits network economics could bring to increase the understanding of spreading phenomena aiming at combating climate change. We present our contributions for clean technologies (*Chapter 1*), environmental policies (*Chapter 2*) and economic shock impacts on emissions (*Chapter 3*; *Chapter 4*).

## **Network Economics and Diffusion : On the Path towards a Net Zero Society**

The four contributions of this thesis complement each other in the objective of offering a global picture on how network theory could enhance the understanding of diffusion processes on the path toward a low-carbon society. By investigating the case green

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technologies, environmental policies and economic shocks (affecting GHG emissions), research in this manuscript highlights how the structure of underlying networks (be they social, policy flows or economic interactions), the location of embedded agents and the strength of connections affect diffusion processes. Such findings provide key elements to pro-environmental policy-makers willing to implement effective interventions related to diffusion issues.

## **Low Carbon Technologies and the role of underlying social structures**

In 2018, a special report from the Intergovernmental Panel on Climate Change (IPCC) revealed that there is still a window to reduce GHG and limit climate change to manageable levels. Among other elements, accelerating the deployment of low carbon technologies to decarbonize energy systems is a key dimension of the strategy. Numerous technological products are already available on the market (Hötte, 2019). So far, we have pointed to the fact that both behaviours and technologies are diffused via social interactions. In the academic literature, many papers have theoretically and empirically investigated the situation in which reinforcing choices lead to accelerating diffusion of a behavioural pattern or technology once a critical threshold in the population has been reached (Currarini et al., 2014). In marketing and fashion, such a process is referred to as "bandwagon effects" (Leibenstein, 1950), "positive feedback trading" in finance (Barberis and Shleifer, 2003), while in the literature of contagious diffusion, individuals' adoption thresholds (Granovetter, 1978), "network externalities", "social reinforcement", and "cascades" (Watts, 2002; Lim et al., 2016) are most commonly used. The common ground of such approaches is the deeply rooted opinion that diffusion of behaviours and technologies follows the same pattern as epidemics. In other words, there exists a contagious feature in technology and behaviour spreading and agents have an adoption threshold that is a positive function of the number of other adopters (cf. Bass model (1969) for seminal work).

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The literature on diffusion in networks through contagion models provides very interesting insights on how network structures influence diffusion. Two main diffusion processes are frequently identified : "simple contagion" and "complex contagion" dynamics ([Centola and Macy, 2007](#)). While the former requires only one contact for transmission (e.g. information, disease), the latter calls for multiple sources of reinforcement to induce adoption (e.g. behavior, technology). On this issue, [Centola and Macy \(2007\)](#) demonstrated that the impact of the underlying network structure changes according to the diffusion process operating. While direct connections between agents (i.e. a short path) allow for simple contagion phenomena to spread faster, clustering (i.e. the tendency for nodes to form small groups) is a determinant of diffusion under complex contagion scenarios ([Centola, 2018](#); [Beaman et al., 2018](#)). Then, whether the goal is to reduce the risk of contagion or to maximize the adoption of a technology, understanding how network structures affect diffusion cascades (i.e. propagation) is relevant for effective policy design.

In the context of global warming, investigating contagion of clean technologies in social networks is relevant. The latter are subject to effects of learning (i.e. costs tend to drop exponentially, at different rates that depend on the technology ([Farmer and Lafond, 2016](#))), making the analysis original in terms of diffusion. Moreover, technologies such as solar PV and wind turbines must be deployed at a large scale to limit global warming "well-below" 2°C by the end of the 21st century ([OECD, 2016](#)). If the existing literature on green technology diffusion is large, little attention has been paid to network perspectives ([Halleck-Vega and Mandel, 2018](#)). Moreover, questions related to the spreading of a costly technology in social networks (i.e. network of individuals) and the associated impacts of a network's structure on diffusion remain unstudied. In the case of low-carbon technologies, these aspects are relevant as public policies are used to support their deployment (e.g. economic instruments supporting solar PV, biogas technology, see [Blazquez, 2018](#) for a review). Understanding how these innovations spread in networks could bring new insights for designing efficient and cost saving

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policies. From another perspective, addressing these issues is important to achieve a faster deployment of these low-carbon goods.

As such, this thesis' first contribution is to theoretically evaluate the contagion pattern of clean technologies in social networks. We propose a generalization of the [Watts model \(2002\)](#), a well-established contagion model implemented in the literature, to investigate how underlying social networks influence diffusion dynamics. Our main innovation is the introduction of a technology cost function which is subject to learning effects. Based on this, an agent will adopt the product if a certain amount of his neighbors has adopted it and if he can afford the technology. Regarding our main results, aggregate diffusion reaches higher levels in highly clustered networks. The latter confirms the critical role of clustering in favouring propagation in networks. Interestingly, we also find that adoption cascades in clustered networks are subject to greater variability (variance) with respect to final outcomes (i.e. adopters). The latter result has strong implications for public policy implementation. For governments interested in maximising diffusion of green technologies, there exists a real tension between achieving a large spreading and uncertainty in results. We argue that implementing economic instruments to increase affordability of the technology for agents less able to afford the product would limit such uncertainty. In less clustered social structures, although propagation reaches lower levels, it occurs at an equivalent speed as in clustered networks with a lower variability in final outcomes.

As regards policy takeaways, the use of data from social platforms would allow governments to design actions while being aware of underlying social structures. As these platforms grow, there is a new potential to construct tools to design more effective policies in a wide range of topic (e.g. epidemic transmission, information and technology flows). With respect to the technology, whatever the underlying structure, higher learning rates lead to larger adoption. Such findings emphasize the critical role of governments in supporting the "good" product. We further discuss key policy im-

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plications, ranging from the potential to map technology spreading and predict cost trajectories to favouring clustered organisations such as cooperatives of farmers to facilitate diffusion. Overall, this chapter theoretically shows how the shape of underlying social structures impact the contagion of a costly clean technology. The second contribution proposes an analysis of environmental policy spreading, emphasizing another critical dimension : the position of heterogeneous agents in networks.

## **Diffusion of Green Policies in the U.S. : A matter of Location in Networks**

The worldwide deployment of environmental technologies is largely driven by the diffusion of environmental policies ([International Renewable Energy Agency, 2018](#)). With respect to past research on policy adoption, the case of American states has attracted a lot of interests. Indeed, federalism is a peculiar political environment as it provides a certain amount of legislative autonomy to member states, encouraging them to compete with or learn from one another (see [Berry and Berry, 1990](#) for description). The states are connected in many ways, including history, culture, the exchange of goods, citizens' migration, and overlapping media markets ([Gray, 1973](#); [Shipan and Volden, 2012](#)). A key result of these features is that states tend to "look to each other" when making policy ([Desmarais et al., 2015](#)).

For the specific case of environmental and climate policies, political scientists as well as sociologists have classified the drivers of adoption as either internal (e.g. extreme climate events, pro-climate groups) or external (e.g. states' bilateral/international agreements). As a result, many previous works have investigated the factors that influence policy adoption from a state-based perspective. A limit to this approach is to fall short on capturing national dynamics of diffusion, thus leaving unclear how environmental policies spread. For instance, is there any existing diffusion pattern across American states ? (e.g. once California has enacted a set of policies, do we observe

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regular patterns in terms of following states/adopters). And if yes, which states act as facilitators of the diffusion ? (i.e. those maximising the diffusion likelihood across the whole country). In the context of global warming, answering these questions is relevant for at least two reasons. First, it would enhance the understanding of how diffusion behaves in the U.S. by observing a national scale process (i.e. diffusion patterns). Secondly, identifying states facilitating the spread of environmental policies across the U.S. would bring multiple benefits. Among these, targeting such states (i.e. governor, representatives) to maximize the likelihood of diffusion at a larger scale would be a relevant strategy for various types of actors (e.g. NGOs, citizens, companies' representatives), especially those interested in passing pro-environmental laws in "big emitter" states. From another perspective, it would also bring insights to private firms on the possible pattern of environmental regulation diffusion. As differences in legislation across states drive day-to-day business decisions of private actors (e.g. investments, market strategy etc.), addressing this issue is critical in that respect too ([Bradbury et al., 1997](#)).

Based on these observations, the second contribution is to propose a methodology based on an epidemic-like model to estimate the network of environmental policy diffusion across American states and evaluate the determinants from adoption data. By doing so, we enhance the body of knowledge of environmental policy diffusion and give policy-makers insights to maximize the spreading of green policies in the U.S.. We infer environmental policy diffusion patterns from a constructed dataset of 74 green policies (e.g. energy, climate, waste recycling) from 1974 to 2018. After constructing a second database of economic, political as well as environmental features for each considered state, we have combined both of them in order to estimate the determinants of the network (of environmental policy flows). Precisely, we estimate, via maximum likelihood, the parameters that best explain the observed patterns of environmental policy diffusion at the U.S. scale. Findings emphasize the central role of Minnesota, California and Florida in the diffusion process while Alaska, South Carolina and South Dakota

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are among the less integrated states. Aforementioned central states are among the most ambitious to tackle climate change as reported in recent studies (e.g. [Statista, 2019](#)). Results also suggest a disconnected dynamic of policy transmission between states belonging to the Northeastern region and the rest of the country. Mainly, Eastern states tend to influence each other and are not sensitive to legislative actions occurring outside their region. With respect to the determinants of the network, we find that contiguity, GDP per capita and Genuine Progress Indicator are key drivers of environmental policy diffusion. It is also found that the level of expected cost of climate change has a negative impact on the diffusion likelihood among considered states. Overall, this contribution offers an in-depth analysis of the environmental policy diffusion network in the U.S., calling for regular updates to capture new emerging dynamics. It also highlights how positions of states within the network of policy flows drive the diffusion of green policies. To go on exploring other features of diffusion in networks, the last two contributions offer a network approach of economic interactions across industrial systems. They highlight how the strength of connections could act as a conduit to reduce emissions following a contraction of activity in a specific sector.

## **Economic shocks and Emissions**

*Chapter 3* and *Chapter 4* propose a similar methodology - combining network theory and input output analysis - to provide novel insights on the topic of reducing industrial imported emissions and emissions rebound following the implementation of COVID-19 recovery packages.

### **Triggering reductions of imported emissions in connected sectors**

In December 2019, the presentation of the [EU Green Deal project](#) has brought back the issue of imported emissions in the E.U. political debate. The resurgent European interest in designing border adjustment mechanisms to limit such dynamics has been widely commented, especially by European trade partners. Such an economic instru-

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ment would target carbon-intensive imports, affecting their competitiveness on the market with the objective to limit carbon leakage. The latter comes as a prerequisite to reach the climate objectives set in the [Paris Agreement \(2015\)](#) ([Görlach and Zelljadt, 2019](#)).

In academia, the topic of imported emissions has gained particular attention over the last decade as several studies point out a critical disconnection between territorial and consumption-based emissions ([Barrett et al., 2013](#); [Karstensen et al., 2018](#)). Regarding E.U. countries, France provides a good example of such dynamics : consumption-based emissions per capita have remained stable over the last two decades (11.5 Mt of CO<sub>2</sub>) while territorial emissions have fallen, suggesting an increase in imported emissions ([Haut Conseil pour le Climat, October 2020](#)). These figures highlight the responsibility of such states in driving foreign countries' territorial emissions, therefore challenging the success of domestic environmental policies addressing carbon leakage. While an expanding literature has been investigating both the economic repercussions of instruments targeting imported emissions and possible legislative designs, less attention has been devoted to understanding the potential reduction of imported emissions resulting from a loss of activity in a sector, and how this would cascade within a network of economic sectors' interdependencies.

The third contribution of this thesis provides a framework to quantify, in the short run, the amount of emission reductions in a sector that could be the result of a reduction in primary inputs flowing into another sector (i.e. a contraction of activity). Based on OECD data available for five European countries (France, Germany, Italy, Poland and the United Kingdom), this chapter shows that industries exhibiting the largest “emission reduction coefficients” are mining activities, basic metals and computer and electronics. Such results were expected as these activities exhibit high imported emission intensities, leading to significant amounts of internal emission reductions. When focusing on external coefficients to examine sectors likely to have

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the strongest emission reduction impacts on the rest of the industrial system, results suggest that mining and quarrying sectors, basic metals and chemicals products are particularly relevant. As these sectors provide large amounts of essential inputs to other sectors with high imported emission intensity, these findings are consistent too. Using network theory, this contribution also identifies the cascading process of imported emission reductions due to a contraction of activity in mining. Results suggest that moving away from fossil fuels would have a particularly strong effect on sectors linked to coke and refined petroleum products, basic metals and electricity and gas. Those sectors display the strongest economic connections with mining (i.e. proximate neighbors). The latter acts as a proxy approach of sectoral exposure to phasing-out dirty industries. For exposed sectors, it emphasizes the importance of future shifts in their input consumption toward cleaner products to avoid stranded assets. Finally, this chapter examines the impact of a \$25 carbon tax on imported basic metals. It highlights that exposed industries are identical across countries, with basic metals and fabricated metal products taking the first ranks. However, the strength of the sectoral exposure is unequal across economies (e.g. fabricated metal activity is more affected in Poland compare to those in France or the U.K). In the short run, the latter suggests different cost on economies following the implementation of such a uniform tax. This outcome gives insights to understand the position of E.U. countries with respect to the implementation of such policies.

Finally, the last contribution follows the methodology of *Chapter 3* to identify industries that should not be targeted by governments' recovery packages (without environmental counterparts) in order to avoid a GHG emission rebound. Again, a critical dimension pointed by the following research is the need for industrial sectors heavily relying on dirty sectors (i.e. strong connections with dirty sectors) to clean their inputs in the coming years.

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## Covid-19 Recovery Packages

From the end of 2020 to 2024, COVID-19 economic recovery packages will be introduced by governments in the EU. These packages will shape EU's future prosperity and determine if targets recently set in the Green Deal (European Commission, 2019) will be met on time. In this last contribution, we apply the approach developed in *Chapter 3* to identify industrial sectors that, if governments wish to decouple growth and emissions in the coming decades, should not benefit from forthcoming economic stimuli. If mining activities play a significant role (by providing inputs to other sectors), other GHG intensive industries will have a particular contribution to meet the Paris Agreement targets. For those sectors, forthcoming economic stimuli (e.g. public investments) should be conditional on these industries developing a measurable plan to limit GHG emissions in the future. Coke and refined petroleum products, chemicals, other non-metallic mineral products, basic metals and electricity and gas are the most GHG intensive sectors of our sample (France, Germany, Italy, Poland and Spain). A decrease in their inputs (supplied by mining) generates large amounts of avoided emissions. In those activities, the key challenge for forthcoming recovery plans is to ensure a shift from dirty to low carbon inputs.

The contribution also discusses some policy recommendations to decarbonize inputs of such sectors (e.g. storage capacity, R&D in electricity and gas activities). At the EU regional scale, a major issue to come is the allocation of such recovery funds across states - and further, sectors to benefit from such funds within national economies. In this chapter, we show that economies display differences in terms of industrial structures and GHG emission levels. The latter calls for different national approaches to tackle GHG emissions. If some countries have a large share of mining inputs in the energy mix (e.g. Germany and Poland), a uniform implementation of tools to meet the EU targets would cause heterogeneous impacts across economies, likely reinforcing economic and political divisions within the Union. In the coming months, the European Commission will have to be aware of such differences when evaluating the effectiveness

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of recovery plan allocation funds by national states. Whether the supervision of such funds is centralised or decentralised (i.e. EU Institutions or national states), it will have a strong impact on the EU's ability to meet its legally mandated environmental targets.

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# Chapter 1

## Network Structures, Environmental Technology and Social Contagion

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We represent a social system as a network of agents and model the process of technology diffusion as a contagion propagating in such a network. By setting the necessary conditions for an agent to switch (i.e. to adopt the technology), we address the question of how to maximize the contagion of a technology subject to learning effects (e.g. solar PV) in a network of agents. We focus the analysis on the influence of the network structure and technological learning on diffusion. Our numerical results show that clusters of agents are critical in the process of technology contagion although they generate high levels of variance in aggregate diffusion. Whatever the network structure, learning effects ease the technology contagion in social networks.

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*This chapter is an adaptation of a research paper currently "Revised and Resubmitted" in Climate Policy.*

## 1.1 Introduction

Research on diffusion in social and economic networks has focused on a wide range of topics such as diseases (Klovdhal, 1985), rumors (Moreno, 2004), systemic risks of bank failures (Elliott et al., 2014; Eboli, 2019), platform adoption (David, 1985) and patenting (Aghion, 2015). These phenomena are, at least temporarily, irreversible and share common features. First, diffusion is a social process and an individual's adoption behavior is highly correlated with the behavior of her contacts (i.e. network externalities). Second, the structure of the network plays a critical role in the propagation dynamics. While some processes remain contained in isolated clusters, others spread to the whole network. Overall, these phenomena are path-dependent : their irreversibility means that early history matters for the final outcome (Lim et al., 2016).

With respect to dynamics of propagation in networks, two main diffusion processes are frequently identified : "simple contagion" and "complex contagion" dynamics (Centola and Macy, 2007). If the former requires only one contact for transmission (e.g. information, disease), the latter calls for multiple sources of reinforcement to induce adoption (e.g. behavior, technology). On this issue, Centola and Macy (2007) demonstrated that the impact of the underlying network structure changes according to the diffusion process operating. While direct connections between agents (i.e. a short path) allow for simple contagion phenomena to spread faster, clustering (i.e. the tendency for nodes to form small groups) is a determinant of diffusion under complex contagion scenarios (Beaman et al., 2018; Centola, 2018). Then, whether the goal is to reduce contagion risk or to maximize adoption of a technology, understanding how

network structures affect diffusion cascades (i.e. propagation)<sup>1</sup> is relevant for effective policy design.

A critical issue to explore for network studies is the case of technology diffusion (Halleck Vega et al., 2018). Particularly, technologies subject to effects of learning (i.e. costs tend to drop exponentially, at different rates that depend on the technology)<sup>2</sup> are of great interest as they are operating in different sectors (Farmer and Lafond, 2016). For instance, this is the case for renewables (e.g. solar PV, wind turbines, see IRENA, 2016) that must be deployed at a large scale to limit global warming "well-below" 2°C by the end of the 21st century (OECD, 2016). If the existing literature on technology diffusion is large, little attention has been paid to network perspectives (Halleck-Vega and Mandel, 2018). In particular, questions related to the spreading of a costly technology in social networks (i.e. network of individuals) and the associated impacts of network structures on diffusion remain unstudied. For the case of clean technologies, these aspects are critical as public policies support the deployment by implementing economic instruments (e.g. solar PV, biogas technology, see Blazquez, 2018). Understanding how these costly innovations spread in networks could bring new insights for designing efficient and cost saving policies. From another perspective, addressing these issues provide new perspectives on how to achieve a faster deployment of low carbon goods. In the context of climate change, increasing this body of knowledge is of great importance too.

In order to evaluate technological propagation in social networks, we build upon the Linear Threshold Model (LTM) exposed by Granovetter (1978). Our main theoretical innovation is the introduction of a technology cost function subject to learning effects. The latter gives to our approach a large scope of applications (e.g. renewables). In our agent-based model, we call "a switch" an irreversible transition to new state, such as adoption of the technology (Jackson, 2008). All agents in the network

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<sup>1</sup>In this paper, we call "cascade" the dynamics of diffusion.

<sup>2</sup>See Farmer and Lafond (2016).

are initially switched off. Then, some agents are randomly switched, i.e., seeded. Every heterogeneous agent in the network is endowed with two individual thresholds. We assume that agents' thresholds are randomly and independently drawn from a uniform distribution at the start of the cascade (Kempe et al., 2003). In the following periods, if the cost of the technology falls below his first threshold and if the proportion of neighbors that switches exceeds his second threshold, the agent also switches (Granovetter, 1978; Schelling, 1978). This process propagates through the network. In our approach, one can consider neighbors as agents with shared proximity (e.g. geographic, relationship, regular contacts). Moreover, once an agent has switched, he remains switched forever. This assumption matches clean technologies investments (e.g. solar PV, biogas installation in agriculture) for which buyers cannot easily step away.

Our model assumes that agents react to stimuli both from the local and global environments (i.e. neighborhood and cost dynamics). If the social threshold is widely documented in the literature on complex contagion and threshold models (Granovetter, 1978; Watts, 2002; Dodds and Watts, 2004), we assume agents' ability to afford the technology to differ. To capture this feature, we introduce a cost threshold as a proxy measure. By doing so, we can investigate the diffusion of a costly product in social networks of heterogeneous agents. Our setting, a generalization of the Watts model (2002), is relevant as recent studies shed lights on the contagious feature of renewable technology adoption (see Baranzini et al., 2017). We consider technology spreading as an epidemic dynamics processing among agents in a network (Collantes, 2007). Then, our framework is intertwined with the "complex contagion" modelling approach as the distribution of neighborhood thresholds will require, in most cases, multiple neighbors having switched to make the considered agent switch.

With respect to underlying social structures, we apply our contagion model to three different classes of networks : lattice, small-world and random networks - as

constructed by [Watts and Strogatz \(1998\)](#).<sup>3</sup> By doing so, we can investigate at a macroscopic level how diffusion spreads according to network clustering, path length and technological learning. If the notion of path length is obvious (average distance between any pair of two random agents), clustering refers to the share of peers of each node being peers among themselves ([Acemoglu et al., 2011](#)). In the literature on diffusion in networks, clustering has been extensively considered to capture the impact of network structures on diffusion ([Centola and Macy, 2007](#); [Centola, 2010](#); [Acemoglu, 2011](#); [Beaman et al., 2018](#)). For our purpose, this approach is relevant as social networks tend to exhibit high levels of clustering ([Watts and Strogatz, 1998](#); [Levine and Kurzban, 2006](#)). Therefrom, our comparative approach allows us to evaluate aggregate levels of diffusion, associated cascades' lengths and adoption speed of convergence from low to highly clustered networks.

Our main results suggest that aggregate diffusion reaches higher levels in lattice and small-world networks compared to random networks. The latter confirms the critical role of clustering in favouring propagation in networks. Interestingly, we also find that adoption cascades in clustered networks are subject to greater variability (variance) with respect to final outcomes (i.e. adopters). The latter has strong implications for public policy implementation. Indeed, for governments interested in maximising diffusion of, for instance, green technologies, there exists a real tension between maximising spreading and uncertainty in results. We argue that implementing economic instruments aiming at increasing affordability of the technology would limit such uncertainty. In random networks, although propagation reaches lower levels, it processes at an equivalent speed - compared to clustered networks - with a lower variability in final outcomes. In practice, the use of data from social platforms would allow governments to design policies while being aware of underlying social structures. As these platforms grow, there is a new potential to construct tools to design more effective

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<sup>3</sup>Remember that lattice networks exhibit high levels of clustering and (comparatively) very long path length; small-world structures demonstrate high level of clustering but with lower average path length; random networks are subject to low clustering and low average path length.

policies to increase the exposure of agents to clean products. For instance, governments could match data from social platforms and technology buyers to target groups in which the product has not percolated yet. With respect to the technology, whatever the underlying structure, higher learning rates lead to larger adoption. Such findings emphasize the critical role of governments in supporting the "good" product. Further policy implications of our results are developed in the conclusion part (Section 4) of this chapter.

The theoretical literature on cascades and diffusion in networks is vast. Irreversibility of our cascade dynamics (i.e. diffusion) sets the present paper apart as a considerable part of research supposes that agents can switch multiple times (Ellison, 1993; Blume, 1995; Young, 2006; Montanari and Saberi, 2010; Adam et al., 2012). Moreover, the double diffusion-reinforcing feedback that we introduce has, to our knowledge, never been implemented so far. Indeed, diffusion itself makes it easier for others to adopt because of the social threshold, and learning makes it easier to adopt because of the cost threshold. In contrast to some of the previous work (Acemoglu et al., 2011; Yildiz et al., 2011; Singh et al., 2013), we do not look at a particular instance of a distribution of thresholds. Instead, we assume that agents' thresholds are randomly and independently drawn from uniform probability distributions at the start of the cascade (Kempe et al., 2003). This is a reasonable assumption if the social planner has no reason to believe that some thresholds are more likely than others (Lim et al., 2016). Moreover, papers mentioned earlier (e.g. Blume, 1993; Ellison, 1993; Blume, 1995; Young, 2006; Montanari and Saberi, 2010; Adam et al., 2012) usually assume that agents play a coordination game with their neighbors and analyze the dynamics using tools from game theory. For certain problems, such as the possibility of contagion, the models are equivalent (Morris, 2000; Watts, 2002; Lelarge, 2012; Adam et al., 2012).

On the issue of technology diffusion, a recent survey on the diffusion of green technology pointed out the fundamental role of networks (Allan et al., 2014). In some of the

previous works mentioned, models of innovation and technology diffusion (e.g. Centola et al., 2007; Montanari and Saberi, 2010; Acemoglu et al., 2011) provide insights on the influence of the network topology on propagation dynamics. These models consider a wide range of diffusion processes ranging from epidemic-like contagion to strategic adoption and linear threshold models. Under complex contagion, research suggests that innovations spread further across networks with a higher degree of clustering. Clusters can promote diffusion where a seed node exists inside them, but are more difficult to permeate when not targeted during the initial seeding phase (Halleck-Vega and Mandel, 2018).

By implementing the linear threshold model and introducing a technology cost function, we complement the literature and contribute to a better understanding of technology diffusion dynamics. We are dealing with large complex networks of agents interacting and switching over time (Centola et al., 2007; Centola, 2010; Acemoglu et al., 2011). As carried out in the literature, we implement our agent-based model and provide numerical analysis to capture cascades' features and build our comparative evaluation.

We proceed as follows. Section 2 describes the Watts-Strogatz algorithm (1998) to create selected networks and expose the linear threshold model. Section 3 shows and analyses numerical outcomes in terms of average aggregate adoption, speed of diffusion and time of convergence for the three classes of networks. The relevant government seeding strategy with respect to the amount of initial seeds is presented too. Finally, Section 4 discusses the main findings as well as relevant policy implications and lays out some directions for future research.

## 1.2 Model of Cascades in Networks

In this section, we present the [Watts-Strogatz](#) algorithm to generate lattice, small-world and random network. We then expose our two-threshold model of contagion in networks.

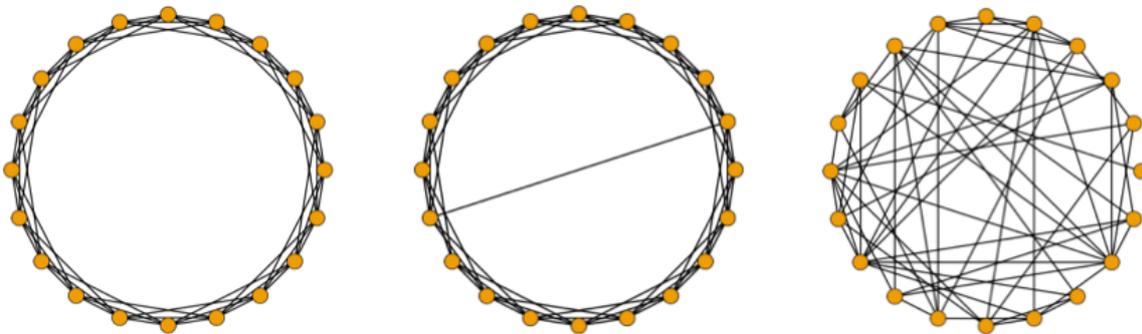
### 1.2.1 The Network

The algorithm of [Watts and Strogatz \(1998\)](#) is a powerful tool to create constant network density graphs ranging from nearest-neighbor networks (lattice) to uniform degree random networks. As exposed in [Cowan and Jonard \(2004\)](#), we assume that  $I = \{1, \dots, N\}$  represent a set of agents and for any  $i, j \in I$ , we define the binary variable  $\chi(i, j)$  such that  $\chi(i, j)=1$  if a connection exists between  $i$  and  $j$ , and  $\chi(i, j)=0$ , if there is no connection. Therefrom, the resulting network  $G = \{\chi(i, j); i, j \in I\}$  represents all pairwise connections between agents. The neighborhood of an agent  $i$  is the total amount of her connections  $\Gamma i = \{j \in I : \chi(i, j)=1\}$  while a path in  $G$  connecting  $i$  and  $j$  is a set of pairwise relationships  $\{(i, i_1), \dots, (i_k, j)\}$  such that  $\chi(i, i_1) = \dots = \chi(i_k, j)=1$ . Finally, the distance  $d(i, j)$  between  $i$  and  $j$  is captured by the shortest path between them.

To generate the lattice with  $n$  nearest neighbors, we consider each edge of the graph and allocate a probability  $p$  to disconnect one of its edges, and connect it to a node selected uniformly at random (with no self-connection (loop) and only one connection between two agents). By setting  $p$ , we vary the graph structure from completely regular (lattice networks with  $p=0$ ), through intermediate states ( $0 < p < 1$ ), to totally disordered (random networks with  $p=1$ ). By doing so, we change the number of edges per agent, keeping constant an average of  $n$  connections per agent and a total of  $Nn/2$  edges,  $\forall p$ . We denote the final network produced to be  $G(n;p)$ . Figure 1.1 below shows three configurations with increasing disorder as  $p$  is increased, for  $N=20$  and  $n=6$ .

For the sake of neutrality in visualisation, networks are represented as circular layouts. This is a common procedure in social network analysis. By placing all nodes at equal distances from each other and from the center of the drawing, none is given a privileged position (Huang et al., 2007).

Figure 1.1: Transition from a locally ordered network (lattice) to a disordered one (random) via a small-world state. From left to right :  $p=0$  (Lattice),  $p=0.1$  (Small-World),  $p=1$  (Random).



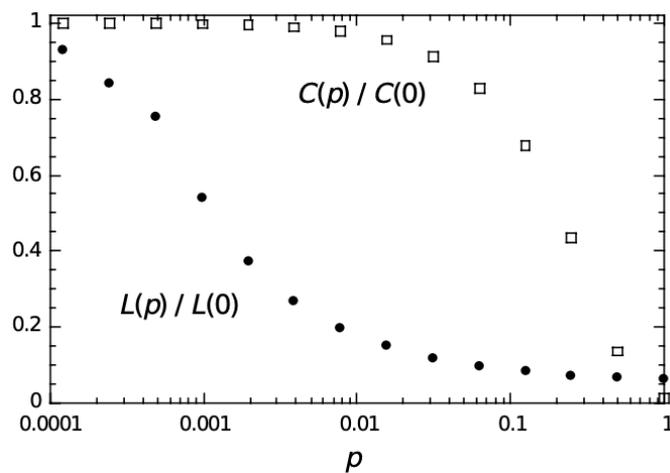
Based on the algorithm output, Watts and Strogatz suggest that the properties of such networks are captured by two complementary parameters : average clustering and average path length. Precisely, the clustering of a set  $S \subseteq I$  is the proportion of pairwise relationships in  $S$  over the total possible number of relationships, that is :

$$cl(S) = \frac{\sum_{i,j \in S} \chi(i,j)}{\#S(\#S - 1)/2}$$

In network science, clustering is commonly define as the share of friends of on individual who are also friends of each other. This parameter is used to measure local coherence or redundancy by taking  $S$  to be the neighborhood of an agent. Then, the local structure in the network is measured by the average neighborhood clustering  $C(p) = \sum_{i \in I} cl(\Gamma_i)/N$ . With respect to average path length, this measure captures the average number of edges separating two random agents (i.e.  $L(p) = \sum_{i,j \in I} d(i,j)/(N(N-1)/2)$ ).

Although clustering and path length are strongly dependent, Watts and Strogatz expose the existence of an interval for  $p$  over which  $L(p) \simeq L(1)$  yet  $C(p) \gg C(1)$ . The small-world network arises in such interval. The latter is due to the following : with a small amount of long distance links, their marginal effect on average path length is large because introducing a long-range link provides a shortcut between the two nodes that this edge connects, and for immediate neighbors as well, and so on. On the opposite, removing one link affects the clustering of only a small number of neighborhoods and has little effect on the population average. The evolution of path length and clustering with  $p$  is shown in Figure 1.2, where the averaged normalized values of  $L(p) = L(0)$  and  $C(p) = C(0)$  are plotted over a sample of 500 different graphs.

Figure 1.2: Average clustering and average path length as a function of  $p$



We note that normalized average clustering remains almost constant when  $p$  is reasonably small and falls slowly for large values of  $p$ . By contrast, average path length decreases quickly for very small  $p$  values. Hence, for  $p \in [0.01, 0.1]$ , clustering and path length diverge, creating a small-world region in the space of network structures. Therefrom, working on these three network structures allows us to investigate the role of clustering and path length on technology diffusion. Hereafter, we expose our two-threshold model of technology contagion in networks.

## 1.2.2 Technology Adoption

### Preliminaries

We assume that technology propagates in these three classes of networks. Suppose that  $G(V, E)$  is an unweighted and undirected connected graph representing a set of  $n$  agents  $V := \{1, \dots, n\}$  and  $m$  links  $E$ . Neighbors of  $i \in V$  are denoted as  $N_i(G) := \{j | (j, i) \in E\}$  and the degree of each agent  $i$  is defined as  $d_i := |N_i(G)|$ . Two thresholds are allocated to each agent  $i \in V$  :

- A cost threshold is a random variable  $\mu_i$  drawn independently from a probability distribution with support  $[0, 1]$ . The associated multivariate probability density function for all the nodes in the graph is  $f_1(\mu)$ . The cost threshold profile of agents is  $\mu := (\mu_i)_{i \in V}$ .
- A social threshold for agent  $i$  is a random variable  $\theta_i$  drawn independently from a probability distribution with support  $[0, 1]$ . The multivariate probability density function for all the nodes in the graph is  $f_2(\theta)$ . We define the social threshold profile of agents as  $\theta := (\theta_i)_{i \in V}$ .

As mentioned, we assume that agents' thresholds are randomly and independently drawn from uniform probability distributions as the government has no reason to believe that some thresholds are more likely than others (Kempe et al., 2003; Lim et al., 2016). Then, a network  $G_{\mu, \theta}$  is a graph endowed with the two profiles of thresholds.

Let  $C_t$  be the cost function of the technology at time  $t$ , bounded between  $[0, 1]$ . This property ensures the matching between the cost function and corresponding agents' thresholds  $\mu_i$ . To introduce the learning characteristics, we assume  $\alpha$  to be a technological learning effect on the cost function. As a result, shapes of the cost curve will follow a decreasing and convex trend (matching cost trajectories observed for some renewables (e.g. solar PV)). We then evaluate the effect of learning on diffusion by

discretizing  $\alpha$  over different constant rates (i.e. [0.1; 0.3; 0.5; 0.7]).<sup>4</sup> This allows us to capture the relationship between technological learning and diffusion. In our setting,  $\alpha$  is bounded between [0, 1] - meaning that the cost of the technology decreases from 1 to 0 with respect to the number of adopters  $S$ . That is :

$$C_t = C_0 \times (|\cup_{\tau=0}^{t-1} S_\tau|)^{-\alpha}$$

### Conditions for switching

We now consider dynamics of diffusion cascades in a network  $G_{\mu,\theta}$ . The binary state of agent  $i$  at time  $t$  is denoted  $x_i(t) = \{0, 1\}$ , referring to off and switched. The set of additional switches in network  $G$  at time  $t$  is defined as  $S_t(G_{\mu,\theta})$ . To launch the process of diffusion, we assume the government to seed a random set of agents with the technology at time  $t = 0$ . This subset of agents is denoted as  $S_0 \subseteq V$ , at  $t_0$ . Then, at  $t = 1$ , any agent  $i \in V \setminus S_0(G_{\mu,\theta})$  will switch, i.e.,  $i \in S_1(G_{\mu,\theta})$  if

$$|C_t(S_0(G_{\mu,\theta}))| \leq \mu_i, \quad \text{and} \quad \frac{|S_0(G_{\mu,\theta}) \cap N_i(G_{\mu,\theta})|}{|N_i(G_{\mu,\theta})|} \geq \theta_i.$$

This means that at  $t = 1$ , agents switch only if the cost of the technology is lower than their respective threshold  $\mu_i$  and if the proportion of their neighbors having adopted exceeds their threshold  $\theta_i$ . This hypothesis matches the literature on innovation diffusion and complex contagion in networks (Delre et al., 2007; Beaman et al., 2018). Then, for a given period  $t \geq 0$ , node  $i \in V \setminus \cup_{\tau=0}^{t-1} S_\tau$  will switch at  $t$ , i.e.,  $i \in S_t(G_{\mu,\theta})$  if

$$(1) \quad |C_t(\cup_{\tau=0}^{t-1} S_\tau(G_{\mu,\theta}))| \leq \mu_i, \quad \text{and} \quad (2) \quad \frac{|(\cup_{\tau=0}^{t-1} S_\tau(G_{\mu,\theta})) \cap N_i(G_{\mu,\theta})|}{|N_i(G_{\mu,\theta})|} \geq \theta_i.$$

Eq.(1) and Eq.(2) represent the necessary conditions for switching. This means that any agent who has not switched by some period  $t$ , switches in time period  $t + 1$  if the cost of the technology falls below his threshold  $\mu_i$  and if the proportion of his

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<sup>4</sup>We relegate extreme scenarios  $\alpha=\{0;1\}$  to the [Appendix, Section 1.1](#).

neighbors who switched is greater or equal to his threshold  $\theta_i$ . In other words, there is a reinforcing feedback : the more agents adopt, the more the cost decreases leading to more agents to adopt in the subsequent period. This pattern has been observed for clean technologies such as solar PV (Farmer et al., 2019). For a given  $G_{\mu,\theta}$ , define the fixed point of the process such that :

$$S_0(X) = S(G_{\mu,\theta}, S_0) \longrightarrow S_t(G_{\mu,\theta}) = \emptyset \text{ for all } t > 0.$$

### Expected size of switches

Although not implemented in the following sections, we can estimate the expected average size of the resulting cascade of switches from  $f(\mu, \theta)$ , separable into two independent and non-correlated probability density functions  $f_1(\mu)$ ,  $f_2(\theta)$  (cf. Lim et al., 2016). For a given graph  $G$  and  $S_0$ , we can map the realization of  $f(\mu, \theta)$  to a set of switches  $S(G_{\mu,\theta}, S_0)$  and treat  $S(G_{\mu,\theta}, S_0)$  as a random variable with a probability distribution  $f(\mu, \theta)$ , keeping into account the cost rule.

Therefrom, we compute the expected probability of any particular agent  $i$  switching, given a seeded subset of agents  $S_0$ , by taking the expectation with respect to  $f(\mu, \theta)$  :

$$P_i(G, S_0) = \int_{\mathbb{R}^n} \int_{\mathbb{R}^n} |S(G_{\mu,\theta}) \cap \{i\}| f(\mu, \theta) d\mu d\theta$$

Then, the expected number of switches in graph  $G$  when  $S_0$  is defined is :

$$E[S(G, S_0)] := \int_{\mathbb{R}^n} \int_{\mathbb{R}^n} |S(G_{\mu,\theta}, S_0)| f(\mu, \theta) d\mu d\theta = \sum_1^n P_i(G, S_0)$$

## 1.3 General results and Analysis

### 1.3.1 Preliminaries : Numerical Setting

We consider a population of  $N=100$  agents with  $n=10$  connections per agent.<sup>5</sup> Agents are placed on three distinctive graphs created according to the [Watts Strogatz algorithm \(1998\)](#).<sup>6</sup> The network is fixed throughout a simulation run. Each agent is endowed with two thresholds profiles  $\mu_i$  and  $\theta_i$ , drawn independently from a uniform probability distribution with support  $[0, 1]$ . At  $t_0$ , we set the number of initial seeds  $S_0 \in [0, \dots, 100]$ , randomly selected, to launch the cascade process. We test this approach on four learning effects scenarios where  $\alpha$  takes the respective values  $[0.1; 0.3; 0.5; 0.7]$ .<sup>7</sup> In each single history, we randomized the agents in the seed set and the associated thresholds allocation. Resulting cascade follows the dynamics exposed in [Section 2](#). This framework guarantees that the process eventually stops. To examine the considered graphs, we set for every edge - following the [Watts Strogatz algorithm](#) described above - the rewiring probability  $p$  to  $[0; 0.1; 1]$ . For each  $p$  value, 1000 different graphs are created and on each graph a single history is run. For lattice networks ( $p=0$ ), note that the structure of the network remains unchanged between simulation runs (i.e. only thresholds and seeds vary).

We are interested in evaluating how diffusion processes in lattice, small-world and random networks, where clustering ranges from high to low levels. To this end, we examine the average number of aggregate adopters, length of cascades as well as speed of adoption convergences. Such a macroscopic perspective brings insights on the role of clustering, path length and learning in diffusion propagation. In the remainder of the paper, the curves provided are averages over 1000 replications and presented for each class of networks. We expose the number of aggregate final adopters, associated

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<sup>5</sup>Although social networks are sparse, meaning they exhibit fewer links than the possible maximum number of links within that network ([Hu and Wang, 2009](#)), such framework is common in the literature on complex social networks ([Cowan and Jonard, 2004](#); [Zhaoyang et al., 2018](#); [Snellman et al., 2019](#)).

<sup>6</sup>cf. [Section 2.1](#) for description.

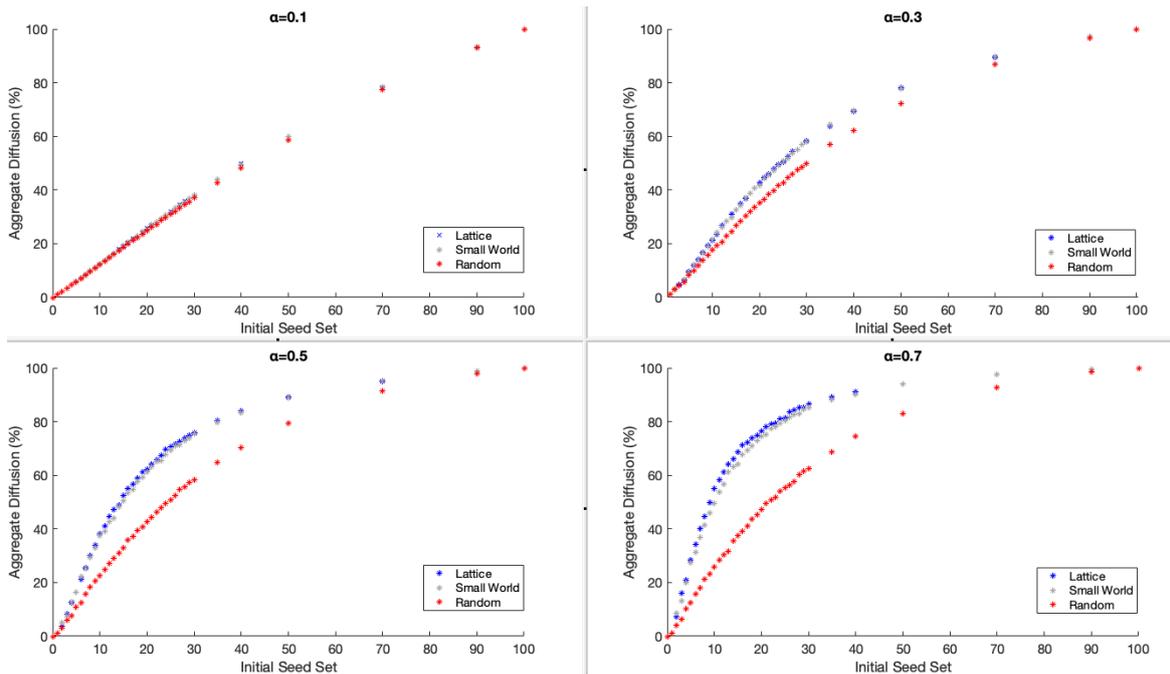
<sup>7</sup>cf. [Appendix, Section 1.1](#) for  $\alpha=\{0;1\}$ .

times of convergence as well as resulting cascades process per period. With respect to times of convergence and per period cascading processes, we only show relevant results ( $S_0=[5; 35]$ ) for clarity of presentation.

### 1.3.2 Understanding diffusion (I) : Seed set and Learning effects

For lattice, small-world and random networks, Figure 1.3 and Figure 1.4 hereafter exhibit the relationship between initial seed set  $S_0$  and average aggregate diffusion under four scenarios of learning (i.e.  $\alpha=[0.1; 0.3; 0.5; 0.7]$ ).

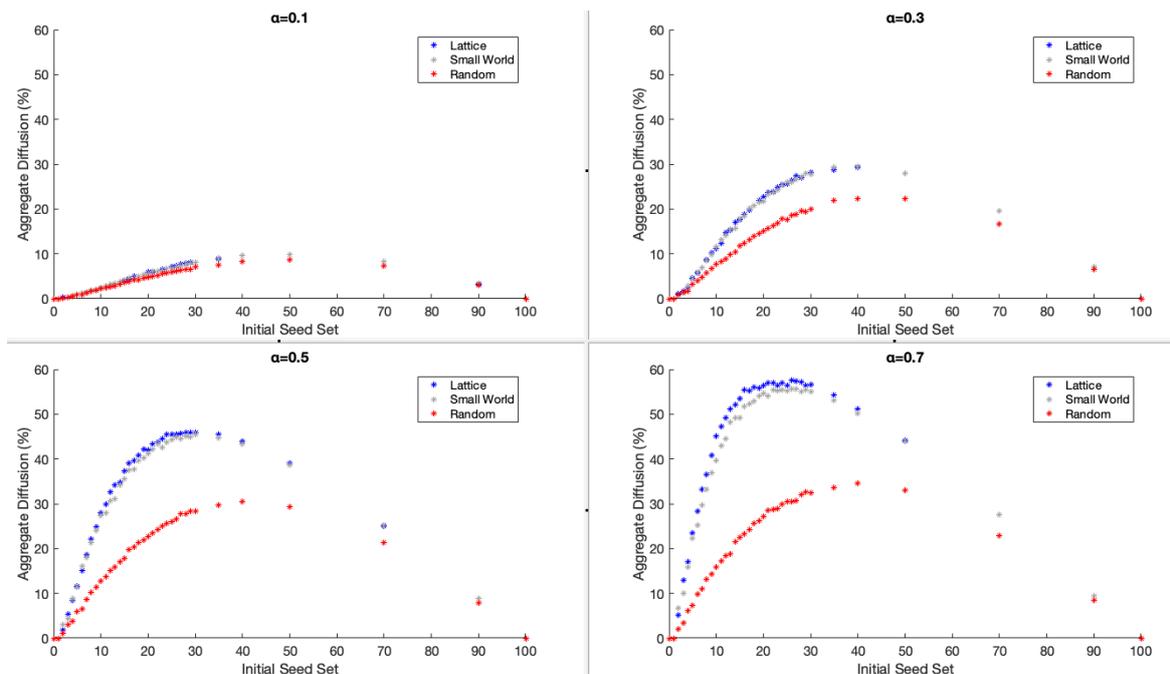
Figure 1.3: Aggregate diffusion as a function of initial seed sets



Overall, aggregate diffusion in the non-seed population (cf. Figure 1.4) is a non-monotonic function of  $S_0$ , concave where the function equals zero at extremes  $[0; 100]$  (i.e. when  $S_0=[0; 100]$ , the diffusion is either null or full). A peak in resulting diffusion (i.e. after seeding) is observed when  $S_0$  lies somewhere between 24% and 50% (cf. Fig.1.b.). Precisely, for each network configuration, minimum diffusion peaks occur

when  $\alpha=0.1$  (e.g. when  $S_0=50$ , diffusion reaches 9% of adopters in random networks) while maximum peaks are observed when  $\alpha=0.7$  (e.g. approximately 57% final adopters for 26% initial agents seeded in lattice and small-world networks).

Figure 1.4: Aggregate diffusion as a function of initial seed sets (non-seed population)



With respect to clustered structures, results suggest that the more learning rate increases, the larger the cascade is, and the lower the amount of the initial seed set needs to be to reach high levels of spreading. This feature is captured by the following : increasing the learning effect fosters the impact of one agent adopting on the technology cost function. In other words, with higher rates of learning, fewer new adopters are required to reach an equivalent decrease in the cost function. Therefrom, a faster drop in technology cost leads to a larger scope of agents whose thresholds  $\mu_i$  is crossed (for the same amount of initial seeds). The latter suggests that aggregate diffusion and learning rates are intertwined with one another. To better investigate this feature, we map in the Appendix (Section 2.4) aggregate diffusion in a one threshold scenario (social effect). Interestingly, results reinforce our findings. In a model only based on neighborhood influence, diffusion reaches higher levels in the non-seed popu-

lation (e.g. for 20 initial seeds, diffusion in the non-seed population reaches 67 agents in clustered networks and 33 in random networks). Then, adding a cost threshold contains the dynamics of adoption and increasing the learning parameter allows the technology to percolate as the cost condition (1) is more easily met in the set of agents (cf. [Section 2.2](#)). Overall, the higher the learning parameter is, the closer to a one threshold scenario diffusion levels stand. This observation is particularly relevant for policy-makers as the choice of the technology to support and its associated learning dimension have a great influence on diffusion dynamics.

From a network approach, the aggregate amount of final adopters differs in every scenario. Indeed, lattice and small-world networks, both exhibiting high levels of clustering, perform better than random networks, whatever the levels of learning and initial seeds - except extremes (i.e.  $S_0=[0; 100]$ ). Moreover, as the learning parameter grows, the diffusion gap<sup>8</sup> between clustered and random networks gets larger, embodying the strong influence of learning and the critical role of clustering in diffusion. As an example, for  $S_0=24$  and  $\alpha=0.7$ , diffusion levels achieve nearly 81% in clustered networks while in random networks, technology propagates to less than 54% of agents. This result matches previous research on complex contagion diffusion in networks, suggesting that clustering is critical for innovation spreading ([Centola and Macy, 2007](#)). Following the recent work of [Centola](#) on complex contagion ([2018](#)), we assume the process of technology diffusion to start out locally, then spilling over to nearby neighborhoods, and ultimately percolating through the population of agents. Overall, our results suggest that clustered structures and learning effects favour the adoption of a technology subject to learning. These networks exhibit higher diffusion levels compared to dynamics examined in random networks.

Considering small-world networks, technology tends to diffuse a bit lower than in lattice structures (cf.  $\alpha=[0.5; 0.7]$ ). Here, one can assume that differences between small-world and lattice networks explain this observation. Although exhibiting high

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<sup>8</sup>cf. [Appendix, Section 2.1](#).

level of clustering, small-worlds are less clustered than lattice structures - due to some short paths crossing the whole network (cf. [Section 2.1](#)). Hence, we can treat small-worlds as halfway structures between lattice and random networks. In this case, a lower clustering coefficient explains the relative underperformance of small-worlds compared to lattice networks. Again, note that the largest diffusion gap between clustered and random networks is observed when the learning effect is the highest ( $\alpha=0.7$ ) for an initial seed set fixed at 13%. We conclude that parameter  $\alpha$  drives the diffusion and associated adoption gaps between considered networks.

### 1.3.3 Understanding diffusion (II) : Cascades' spreading

We are now interested in evaluating the heterogeneity of diffusion with respect to networks. We base our analysis on the variance of diffusion rate between models run as it represents a natural measure of dispersion ([Cowan and Jonard, 2004](#)). Remember, our results are averages over 1000 numerical replications. Moreover, studying how cascades spread is relevant for questions related to policy design and associated outcomes' uncertainty. Figure 1.5 reports the variance of aggregate diffusion as a proxy for heterogeneity. Interestingly, heterogeneity and diffusion behave in a similar manner. In every scenario, a peak in heterogeneity is observed for both examples of clustered networks, displaying highest levels of disparity in cascades outcomes. Heterogeneity increases as a function of learning with larger ranges for clustered networks (e.g. for  $S_0=7$  and  $\alpha=0.7$ , aggregate diffusion variance in lattice, small-world and random equal 567, 522 and 92 respectively). Moreover, in lattice and small-world networks, an increase in learning leads to fewer initial seeds required to reach highest levels of variance (as observed for aggregate diffusion).

To gain more qualitative insights on this issue, we also map heterogeneity in the case of a one threshold scenario ( $\theta_i$ ).<sup>9</sup> We observe that in the absence of a cost threshold, heterogeneity decreases as a function of initial seeds in clustered networks. In

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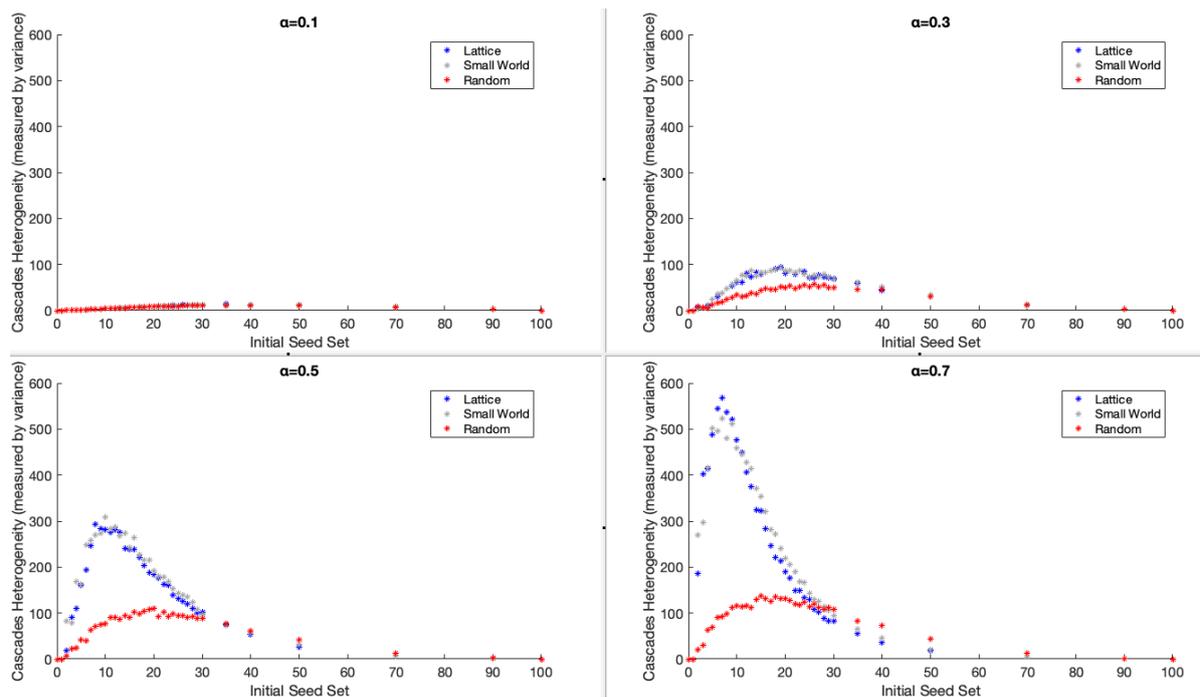
<sup>9</sup>cf. [Appendix, Section 2.4](#).

our scenarios, as noticed for aggregate diffusion, an increase in learning brings levels of variance and diffusion closer to the ones observed in a one threshold setting ( $\theta_i$ ) - highlighting again the critical effect of learning parameters. Moreover, in a two-threshold setting, variance increases to reach highest peaks associated with highest levels of diffusion while in a one threshold model, variance decreases as a function of initial seeds. We conclude that adding a second condition to adoption (i.e. cost threshold) also has a strong impact on heterogeneity in clustered networks compared to a one threshold configuration. For random networks, diffusion and heterogeneity follow the same pattern in the two designs.

To provide some perspectives to our results, levels of heterogeneity observed in clustered networks refer to the percolating process. As exposed, the diffusion starts out locally, then spreads to nearby neighbors, and ultimately percolates through the network. This process tends to be subject to a clear "rigidity" in terms of diffusion dynamics. On the one hand, if diffusion percolates, it reaches high levels of global spread; on the other hand, if it does not propagate in the initial clusters (i.e. where the initial agents are seeded), diffusion is capped to a low number of adopters. In random networks, the process is smoother as short path lengths do not contain or exacerbate diffusion. These observations complement papers on seeding strategy and percolation in networks. As [Acemoglu \(2011\)](#) developed, diffusion in clustered networks requires at least one initial seed among clustered groups to make percolation in the whole neighborhood possible. Here, heterogeneity of our aggregate diffusion results reinforces this view - that technology only "diffuses" in random networks while in clustered networks, diffusion is exacerbated to one extreme or another (i.e. low or high level). From a policy perspective, this observation is critical. Indeed, it suggests a possible trade-off between maximising adoption and uncertainty in results. Namely, where aggregate diffusion levels are the highest, dispersion is the largest. If there is a strong connection between diffusion and network structures, this may indicate a policy tension : targeting diffusion levels with lower expected variability or favouring maxi-

imum adoption with more uncertainty in terms of final results. Because uncertainty is critical for public policy design, this observation calls for a different policy approach with respect to the objective targeted. In the context of climate change, this dimension is critical as public policies tend to implement strategies dealing with peer effects and social influence. Designing policies aiming at targeting clustered network (e.g. cooperatives of farmers) does not imply that diffusion will be successful. Then, to limit variability in results, economic instruments targeting a specific class of agents could be implemented to allow the technology to percolate within groups. Such perspectives are discussed in conclusion of this work (Section 4).

Figure 1.5: Diffusion heterogeneity measured by variance



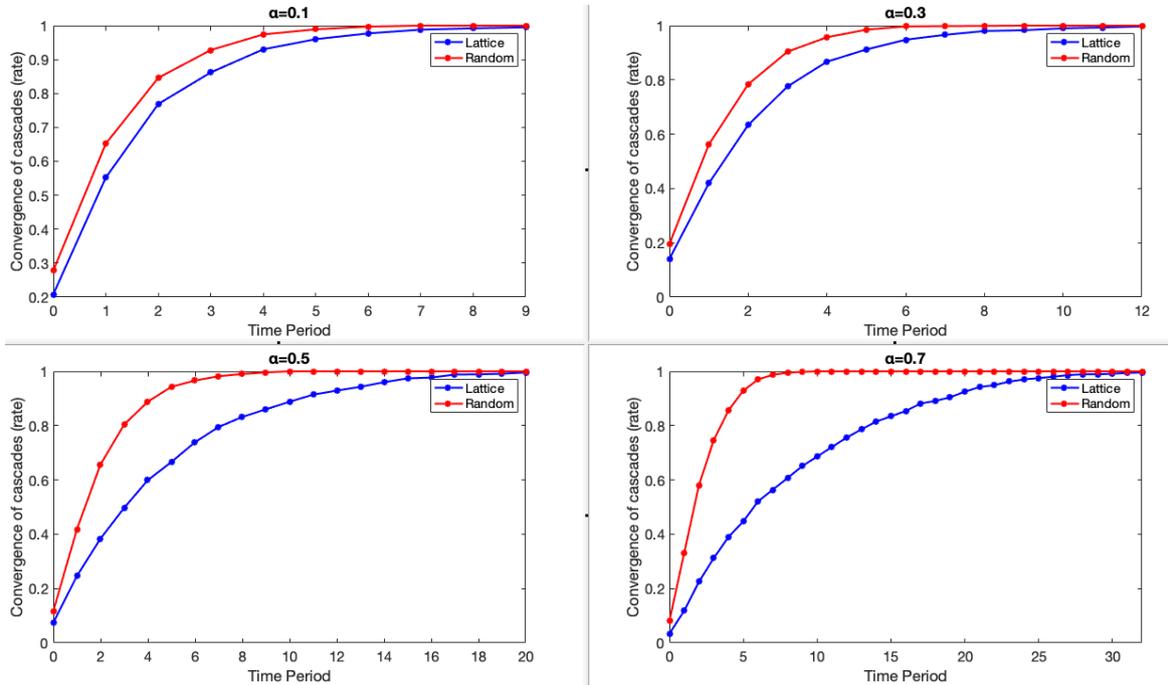
### 1.3.4 On Cascades' lengths and Adoption dynamics

To this point, our evaluation has focused on aggregate diffusion properties. We now turn to the transitory analysis of the model. The speed at which the technology diffuses is a major policy concern, especially for technologies aiming at reducing greenhouse

gases emissions (International Energy Agency, 2018). Here, we address this issue and examine how spreading dynamics is affected by network structures. We name "time of convergence" the number of time periods required for a cascade process (i.e. a simulation) to stop. For ease of presentation, we only consider lattice and random networks as small-world configurations mimic lattice curves in our results. Indeed, in our two-threshold model, clustering tends to overcome path length dimension in diffusion dynamics in the small-world configuration. This outcome was expected as high levels of clustering favour diffusion (see Centola (2018) for a review). In addition, we focus on scenarios where  $S_0=[5; 35]$ <sup>10</sup> as they exhibit the main interesting outcomes.

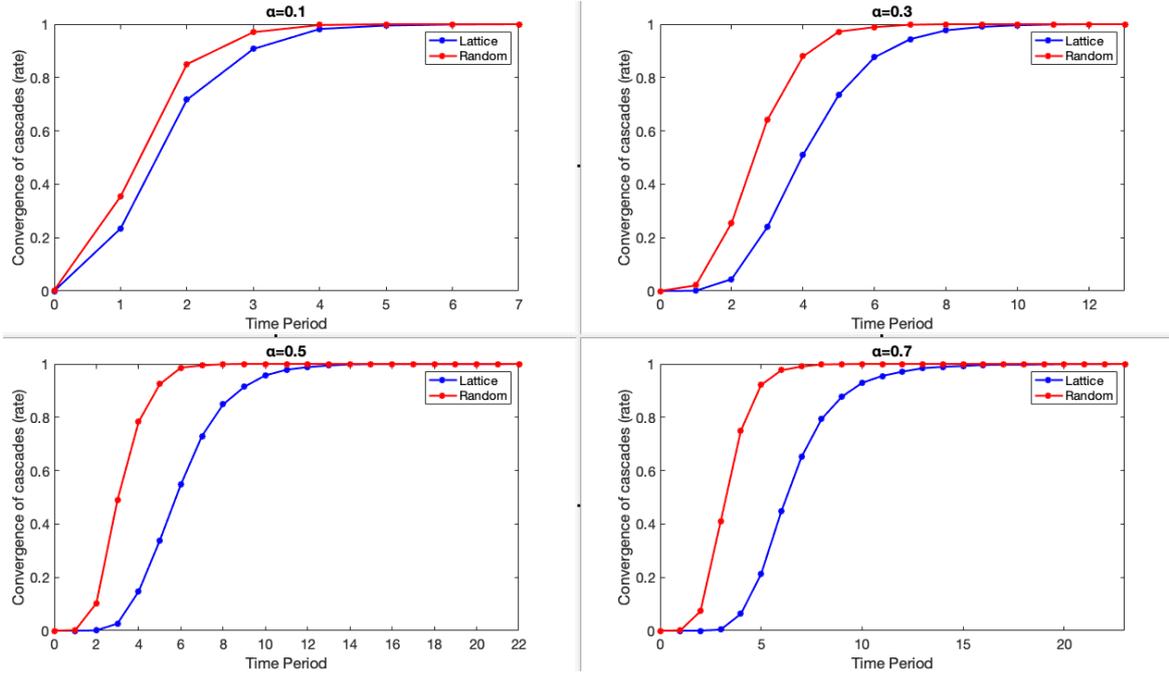
Then, Figure 1.6 and Figure 1.7 show the relationship between the total amount of simulations (i.e. 1000) in percentage and the associated speed of convergence, reported up to 32 time periods.

Figure 1.6: Rate of Cascades convergences as a function of time,  $S_0=5$



<sup>10</sup>cf. Appendix, Section 2.3 for other scenarios.

Figure 1.7: Rate of Cascades convergences as a function of time,  $S_0=35$



As a reminder, random networks have little local structure and short paths connecting agents. In this case, simulations converge faster after the launch of the process. Precisely, at least 70% of simulations have converged at  $t \leq 4$  in most scenarios, reaching relatively low levels of aggregate diffusion. For lattice networks, early diffusion tends to spread slower than in random networks (e.g. at  $t \leq 4$ , some scenarios exhibit rates of convergence lower than 5%, cf.  $\alpha=0.7$ ,  $S_0=35$ ). But the process continues longer, and reaches higher levels of aggregate diffusion.

Again, note that the learning parameter  $\alpha$  influences cascades' lengths. Indeed, increasing its effect leads to, in most cases, additional periods to converge, whatever the level of initial seeds. When  $\alpha=0.7$ , speeds of convergence in lattice networks are the slowest observed for each period, in every scenario. By matching this observation with aggregate number of adopters, we suggest that lower times of convergence stem from a larger scope of agents whose thresholds  $\theta_i$  are crossed. The latter induces a longer and higher adoption dynamics in clustered networks.

We also observe that a larger initial seed set combined with high values of learning

leads to S-shaped curves for cascades' convergences. In other words, once a period threshold is crossed, cascades tend to stop processing (cf.  $\alpha=0.7$ ,  $S_0=35$ ). In order to strengthen our claim, we map in Figure 1.8 and Figure 1.9 (at the end of this section) the associated times of convergence with respect to aggregate amount of adopters at each period for  $S_0=[5; 35]$ . This approach sheds light on two key aspects. First, diffusion dynamics in lattice and random networks share common features as regards speed and aggregate diffusion. For  $S_0 \leq 35$ , in early periods ( $t \leq 3$ ), they perform equivalently regarding final aggregate diffusion. Second, when the process converges in random networks, diffusion in clustered structures propagates to reach higher levels, increasing the length of the cascade. This observation confirms our previous expectations.

Overall, if our results suggest that high diffusion is coupled with clustering, we found out more heterogeneity (i.e. variance) in cascades propagating in these networks. Following our findings on cascades lengths, it might not be relevant for policy-makers to favour clustered structures if the amount of diffusion targeted is low. The latter confirms previous research suggesting that for low levels of seeds and small values of  $t$ , networks exhibiting a low degree of clustering might diffuse the innovation further (Acemoglu et al., 2011). However, when it comes to large spread of technologies subject to learning, clustering performs better. Adding up to these results, the next section evaluates the relevant government strategy in terms of initial seeds to efficiently maximize diffusion in networks examined.

Figure 1.8: Adoption dynamics as a function of time,  $S_0=5$

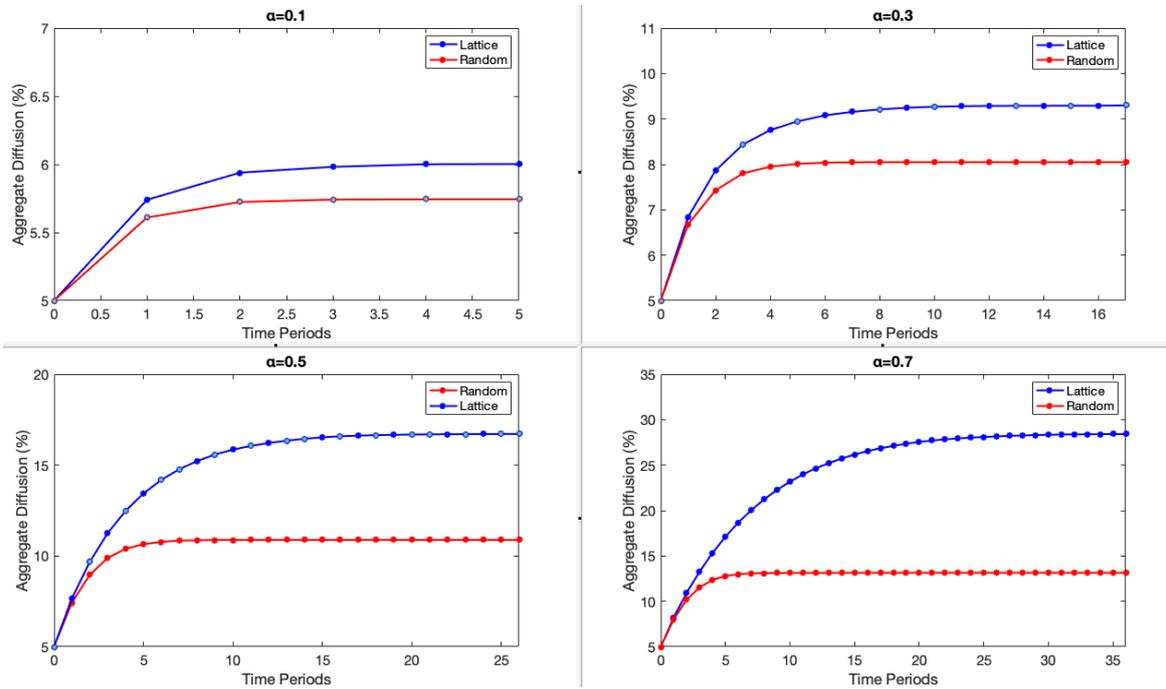
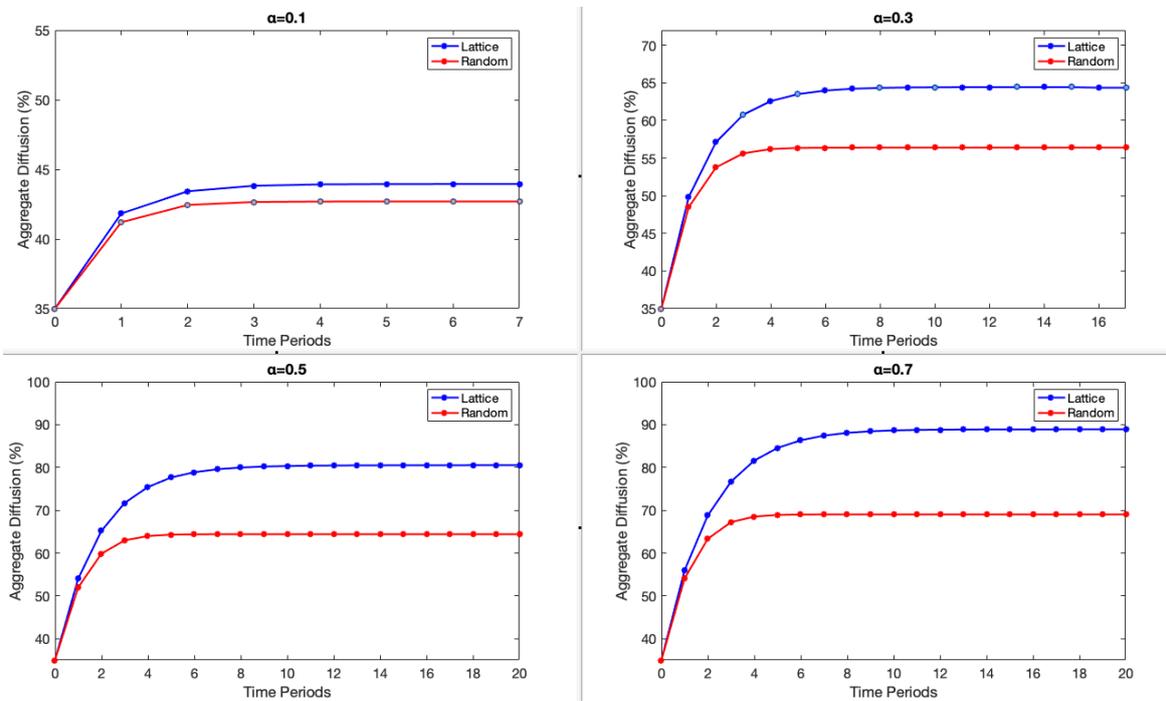


Figure 1.9: Adoption dynamics as a function of time,  $S_0=35$



### 1.3.5 Efficient Strategy : Tipping Points in Seeding

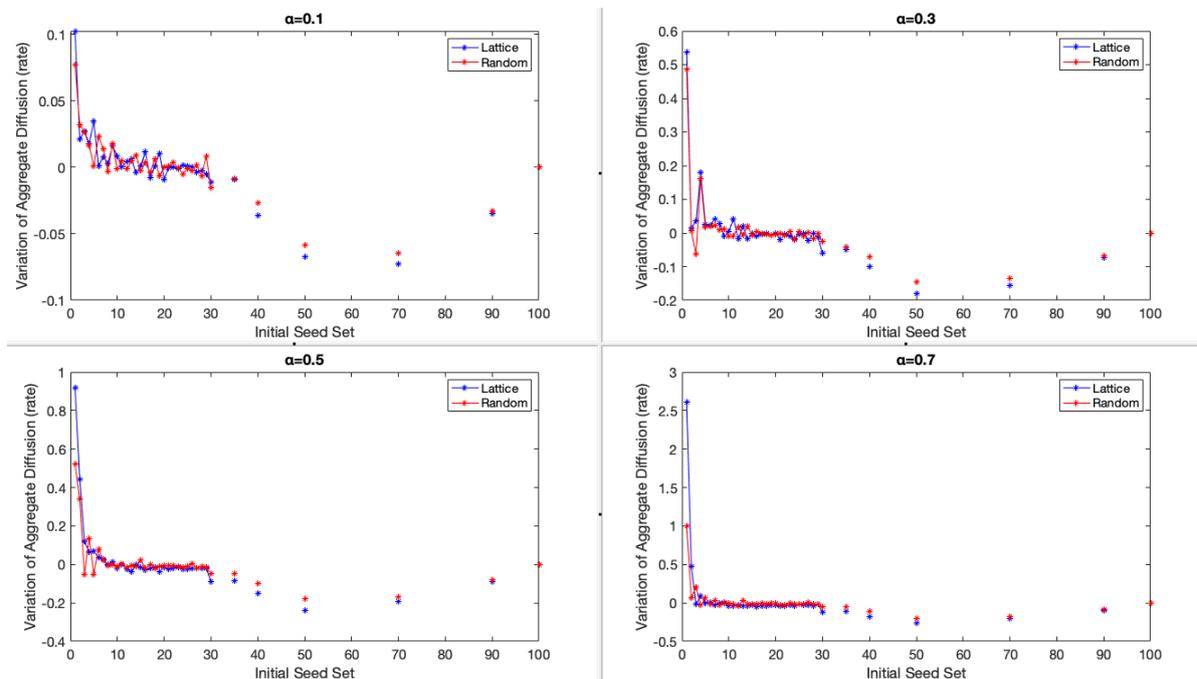
From a government perspective, maximizing or limiting the spread of diffusion comes with a cost of action (e.g. number of seeds in our case). These issues have been largely documented in the literature (Kempe et al., 2003; Akbarpour et al., 2018). In the context of climate change, deploying environmental-friendly technologies at least cost is a key objective for governments - already subject to public debt. In our framework, a cost efficient strategy for a public intervention would be to set the level of initial seeds (i.e. cost) such that it maximizes final aggregate adoption. In other words, maximizing the ratio between aggregate diffusion and initial seed set, in which seeding one supplementary agent leads to a larger effect on aggregate diffusion. By investigating the issue of marginal seeding, we complement our previous policy outcomes on the role of learning and network structures in diffusion. Indeed, an increase in the learning parameter leads to larger diffusion and to lower associated amounts of seeds required (i.e. in clustered networks). From a government perspective, this suggests that it could be inefficient to target high amounts of initial seeds to reach high levels of adoption. If this result is critical, it fails to precisely evaluate the impact of seeding one supplementary agent (i.e. cost) on aggregate diffusion.

To address this question, we map in Figure 1.10 below the marginal change of aggregate diffusion divided by the number of seeds in lattice and random networks (i.e. high and low clustered structures). If the corresponding value is positive, seeding the associated amount of agents is beneficial for diffusion. In other words, an additional seed leads to more than one additional adopter. On the contrary, a negative value suggests that the size of the seed set outweighs the final diffusion benefits (i.e. adopters), even if diffusion still increases (note here that it remains optimal to seed at a rate indicated by the peak observed in Figure 1.4). Here again, we focus our analysis on lattice and random structures as small-world mimic lattice structures).

From Figure 1.10, we note that the learning parameter has two main effects :

first, moving from low to high levels of learning decreases the angular variation pattern observed. Second, higher learning parameters lead to a smaller amount of initial seeds subject to positive ratio values.<sup>11</sup> Overall, the level of initial seeds having positive values is always lower in clustered networks compared to random networks which makes a government intervention (i.e. seeding) less costly in these configurations. The latter matches previous observations on the impact of the learning parameter on diffusion in clustered networks - namely, higher learning effects lead to larger diffusion with lower amount of initial seeds required to reach maximums.

Figure 1.10: Marginal change of aggregate diffusion divided by the number of seeds



## 1.4 Conclusion

For some types of technologies, the cost of a unit decreases exponentially over time. As for hardware technologies, green technologies like solar PV follow this trend ([Farmer](#)

<sup>11</sup>Note : here we report associated seeds above which we observe no more positive values : when  $\alpha = 0.1$ , negative values arise when  $S_0=25$  (lattice),  $S_0=29$  (random); when  $\alpha=0.3$ , negative values appear when  $S_0=14$  (lattice) ,  $S_0=25$  (random); when  $\alpha=0.5$ , negative values arise when  $S_0=10$  (lattice),  $S_0=15$  (random); when  $\alpha=0.7$ , negative values arise when  $S_0=7$  (lattice),  $S_0=14$  (random).

and Lafond, 2016). We have shown that under a complex contagion approach, the spreading of these technologies is clearly affected by the structure of the social network over which it takes place. In the context of global warming, these findings are critical as public policies aim at maximising their deployments by implementing economic incentives (e.g. subsidies). In this paper, we provide clear evidences that under a particular diffusion process (i.e. contagion), clustered organizations are critical to spread a technology. By adding a cost dimension, we innovate with respect to previous research on epidemic diffusion in networks and gives practical insights to policy-makers. Among those, targeting clustered organisations (e.g. favouring cooperatives of farmers in agriculture (Viardot, 2013)) comes at a cost : greater uncertainty in global adoption outcomes. This is the very old efficiency versus uncertainty trade-off. When network structures result in a high average aggregate diffusion rate, they also generate higher variances. That is, the distribution of cascade results is relatively variable. To the extent that efficiency in policy implementation remains a governmental concern and if diffusion of technologies is considered as a key input to develop regions - and ease global warming-, policies aimed at inducing efficient diffusion will have to address the consequent uncertainty in results. But whether or not this concern is real depends on the measure used — if variance is the appropriate measure of distribution, there is a real problem. As exposed, the impact of learning rates - on associated cost function - remains critical for spreading. In this context, the choice of the technology to promote is of great importance for the design of effective policies (e.g. case of renewables).

Practically, to target clustered structured, government should be aware of underlying social networks in the selected population. On this issue, the growth of social platforms and the associated increasing amount of data (e.g. social, geographic, consumption) could help capturing underlying social structures and would provide powerful informations for policy-makers. For instance, one objective could be to increase the social exposure of an agent to clean products by targeting agents in her social neighborhood. On this issue, a recent study based on PV adoption data demonstrated

the contagious feature of such a technology (Baranzini et al., 2017) while the use of facebook data has already been explored to capture the diffusion of epidemics across agents (Kuchler et al., 2020). For the specific case of agriculture, the role of cooperatives to diffuse knowledge and technology has been pointed out over the last decade (Joffre et al., 2019). In this field, governments could design adoption incentives relying on membership data of cooperatives to increase likelihood of adoption. Overall, our model paves the way to applications using such data.

From another perspective, if the underlying network is estimated, mapping the contagion of a technology in a network of agents could give an estimate of the potential future cost of the technology. By doing so, policy-makers could evaluate the learning parameter of the technology as it is a key determinant for diffusion. However, reaching this objective depends on first periods of diffusion (i.e. launch of the process). Then, governments should promote key technologies able to reach a certain amount of adoption. The learning dimension is a critical aspect to deploy green technologies (e.g. PV, wind turbine) and tackle climate change.

Finally, policy-makers could limit uncertainty in results in cluster structures by giving access to the technology to agents less able to afford such a product. Indeed, those agents, exhibiting a low cost threshold (i.e. they cannot afford the technology if the latter does not diffuse massively), are hampering the diffusion as they are not adopting the product. By implementing economic mechanisms to support such population to adopt, diffusion would be less subject to heterogeneity and could reach higher levels. Such policies would allow a large share of the population to adopt the technology, creating feedback effects for the rest of the whole group.

With respect to our model, it could be extended in several obvious ways. We have taken the network structure as given, and have examined its effect on the diffusion process. Apart from paving the way to applications in the field of technology adoption and diffusion, our model could be extended by investigating relevant economic questions. Indeed, we exposed the impact of learning on diffusion and the associated cost

function but we did not investigate the optimal decreasing path of the cost function with respect to threshold distribution. This approach would bring insights on how should a cost decrease behave. In the wake of network science analysis, some studies would be valuable to apprehend the impact of degree distribution on general diffusion under a two-threshold approach. The latter would fill the gap in the literature and would allow some comparisons with other complex contagion problems. In terms of modelling, other models of diffusion could also be implemented such as the Independent Cascade Model (ICM). This could bring some relevant comparisons in terms of outcomes. Finally, in the model in this paper, there is no innovation, only diffusion after a government random seeding action (which is proven to not be the most effective (Singh et al., 2013)). Questions related to the centrality of agents in networks and their potential cascading powers are relevant to explore, especially if some are to be characterized as innovators. Overall, our model could be implemented to real cases of technology diffusion (e.g. energy technologies exhibiting experience curve patterns).

## Appendices of Chapter 1

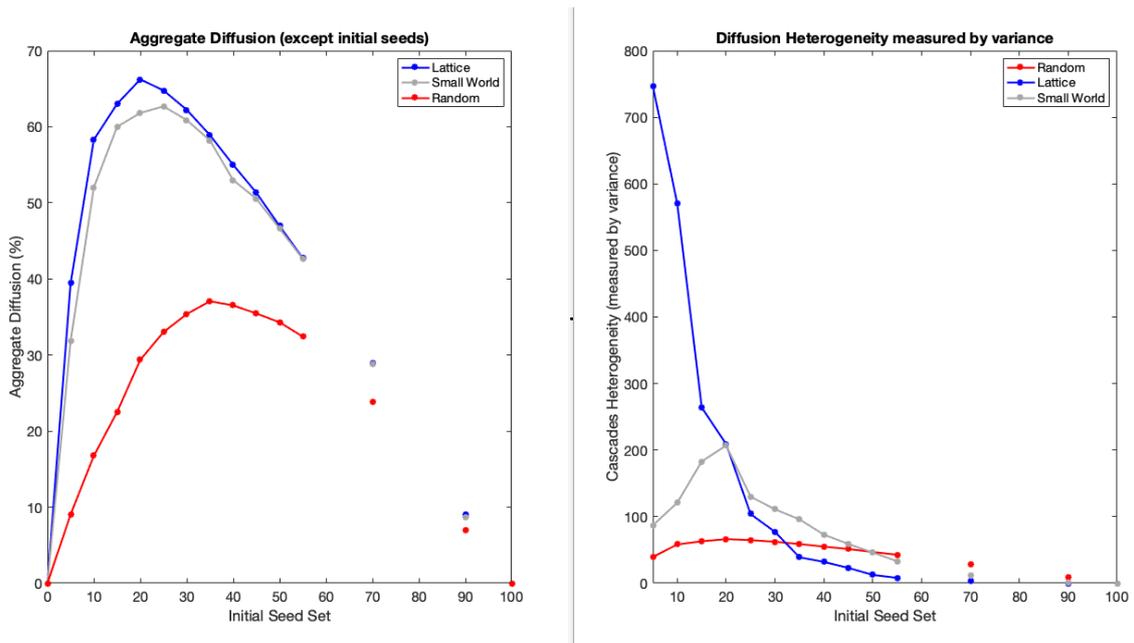
### 1.1 Aggregate diffusion and variance, $\alpha=[0;1]$

1) For  $\alpha=0$ , the cost function is :

$$C_t = C_0 \times (|U_{\tau=0}^{t-1} S_\tau|)^{-0} = 1$$

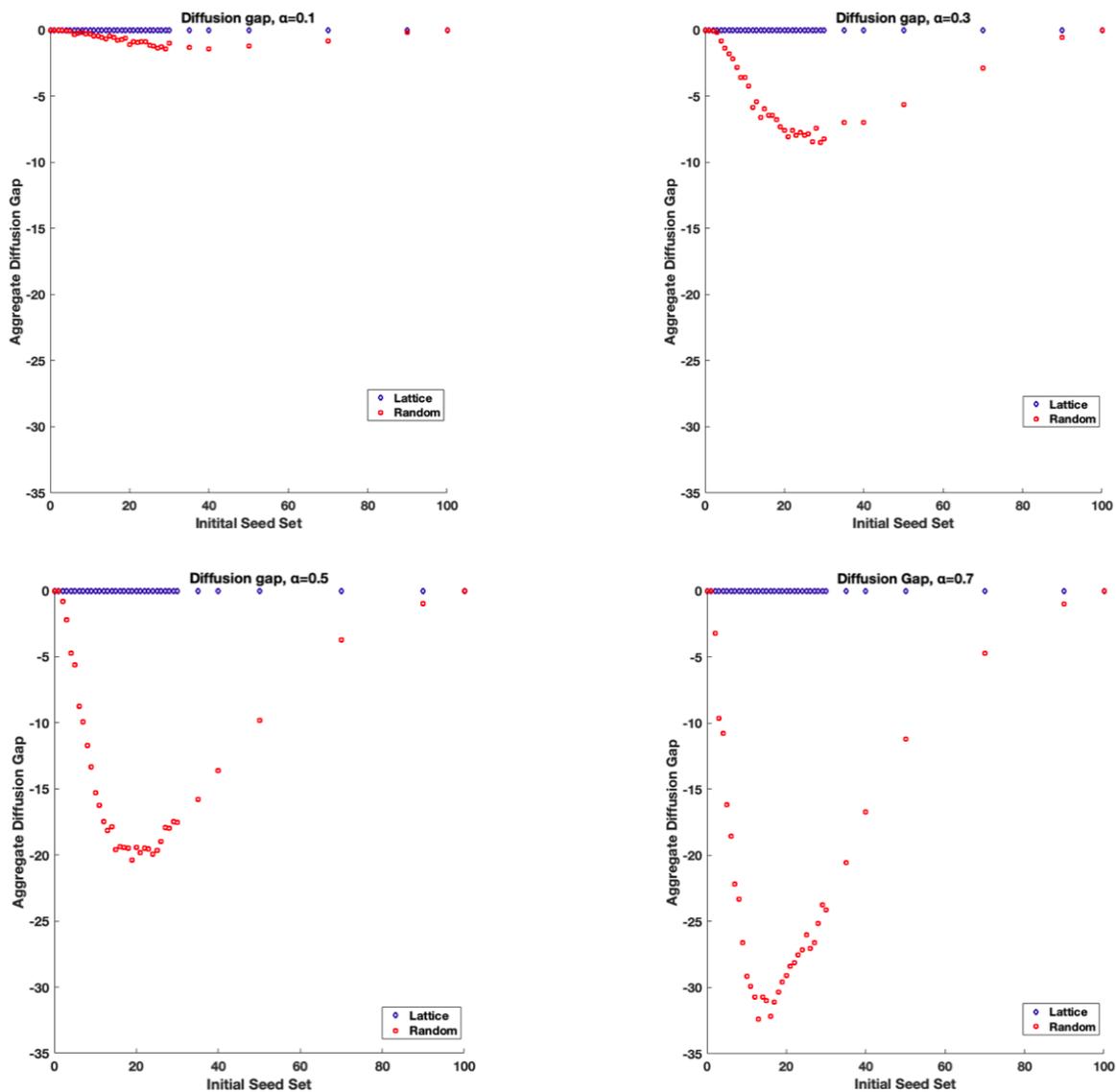
whatever the initial seed set. Then, we observe no diffusion in networks at all as the cost remains too high.

2) For  $\alpha=1$ , we have (for steps of 5 seeds):



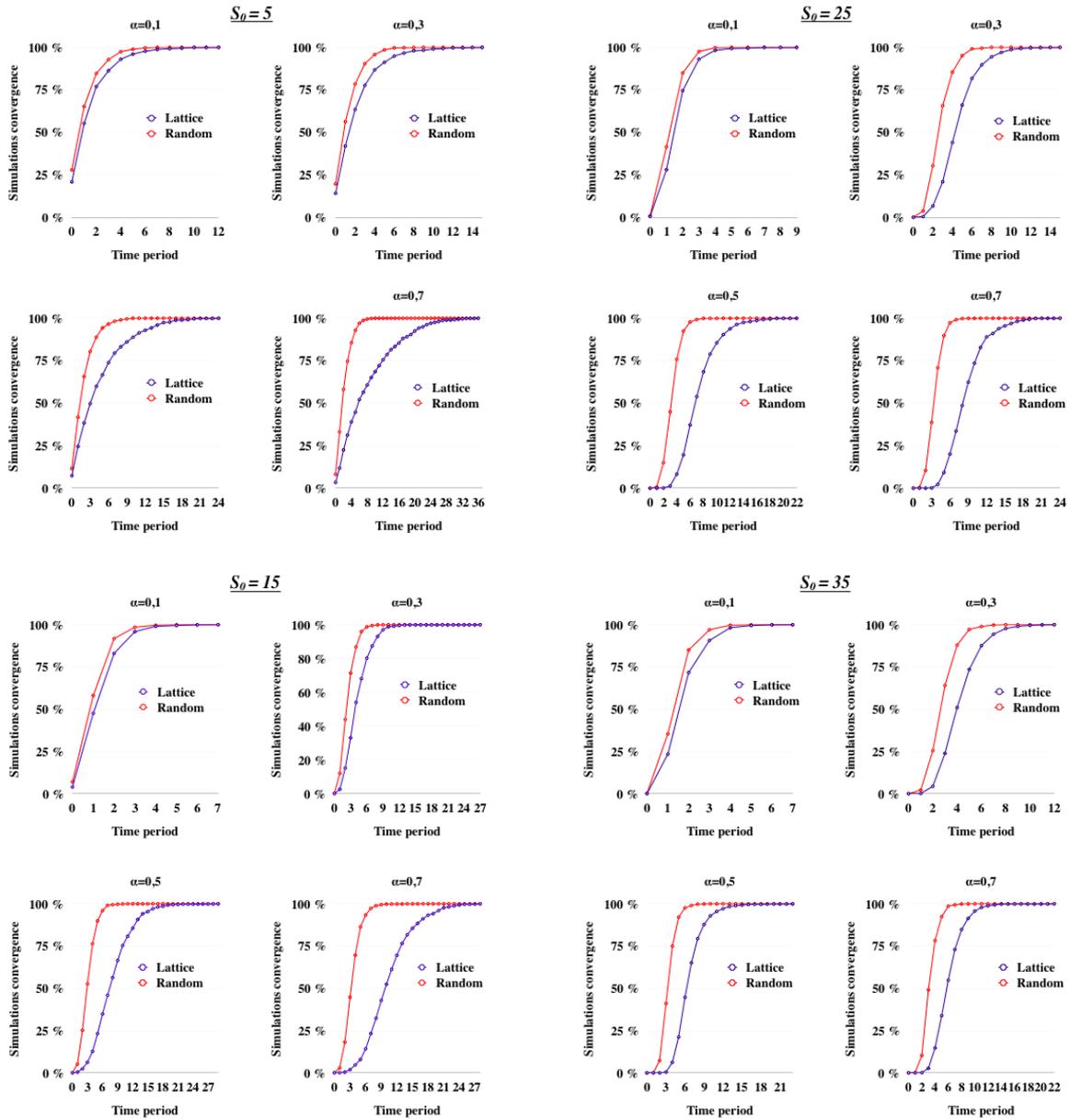
## 2.1 Diffusion gaps

Figure 1.11: Diffusion gaps, baseline lattice



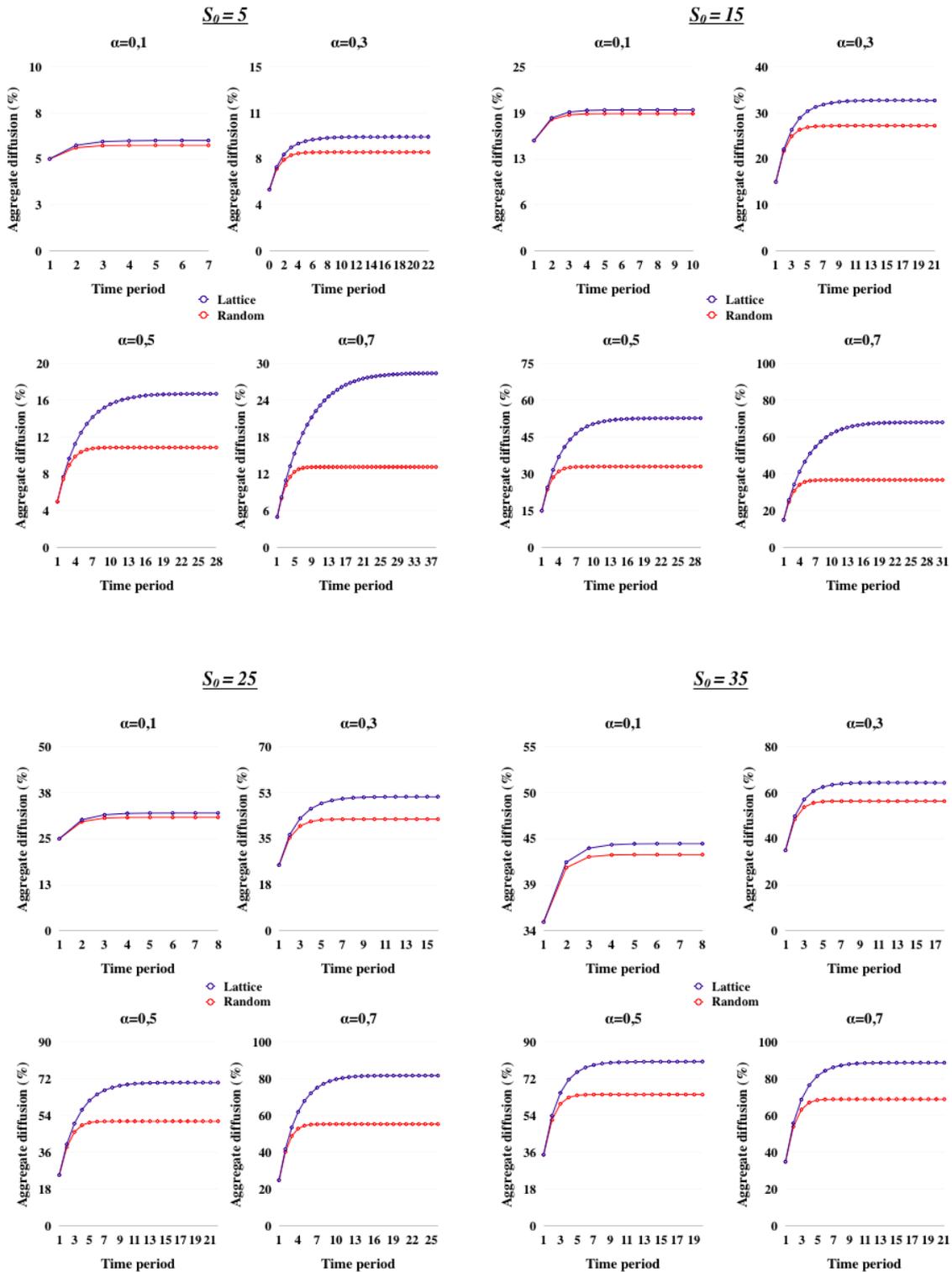
## 2.2 Cascades convergences

Figure 1.12: Cascades convergences,  $S_0=[5; 15; 25; 35]$



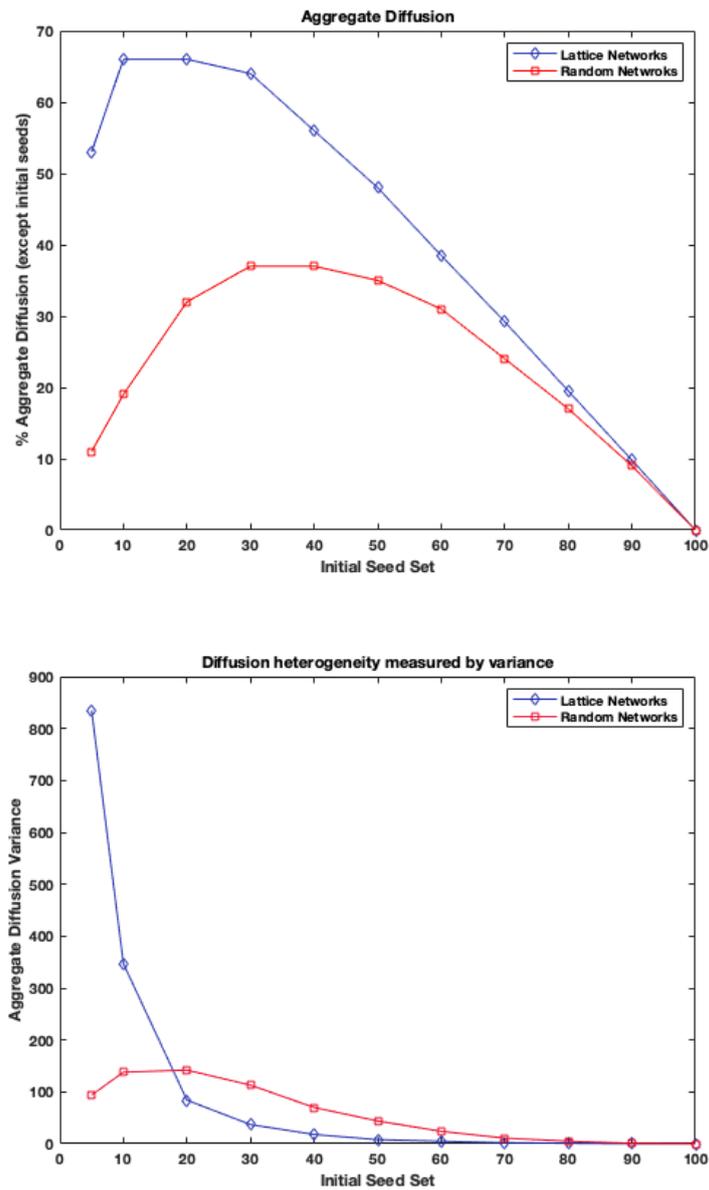
## 2.3 Adoption convergence

Figure 1.13: Adoption dynamics with respect to time,  $S_0 = [5; 15; 25; 35]$



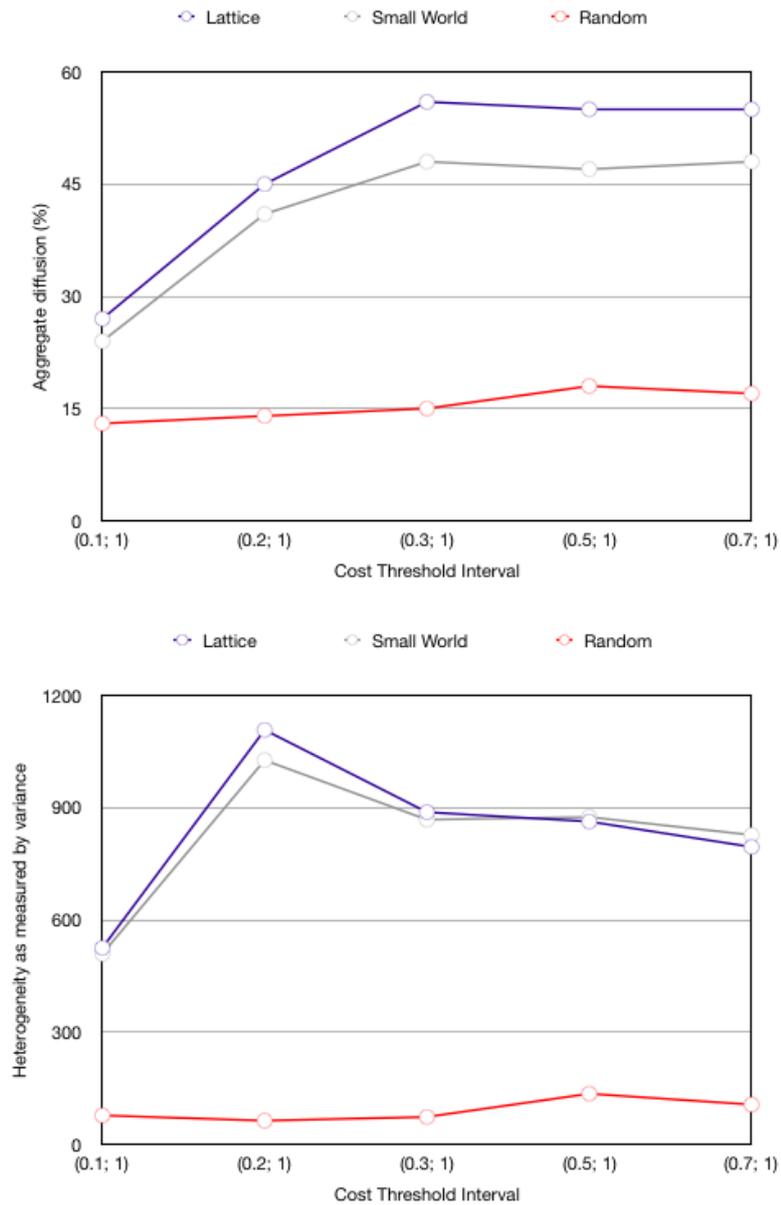
## 2.4 One threshold scenario $\theta_i$

Figure 1.14: Aggregate diffusion (except initial seeds) and heterogeneity in a one threshold scenario (neighborhood effect without cost dimension)



## 2.5 Variation in cost threshold distribution

Figure 1.15: Aggregate adoption and heterogeneity for different scenarios of cost threshold distribution over specific intervals (0,1;1); (0,2;1); (0,3;1); (0,5;1); (0,7;1), with  $S_0=[5]$



## 2.6 Robustness check : Number of connections per agent & Aggregate diffusion

### 2.6.1. For $S_0=[5]$

Table 1.1:  $n=5$

Learning effects $\alpha$	Lattice	Small-World	Random
0.1	6	6	6
0.3	10	9	7
0.5	18	15	9
0.7	36	26	10

Table 1.2:  $n=20$

Learning effects $\alpha$	Lattice	Small-World	Random
0.1	6	6	6
0.3	9	9	8
0.5	15	13	11
0.7	26	23	12

Table 1.3:  $n=30$

Learning effects $\alpha$	Lattice	Small-World	Random
0.1	6	6	6
0.3	9	9	7
0.5	15	14	10
0.7	23	22	16

Table 1.4:  $n=40$

Learning effects $\alpha$	Lattice	Small-World	Random
0.1	6	6	6
0.3	9	9	9
0.5	15	16	14
0.7	21	22	19

**2.6.2. For  $S_0=[35]$**

Table 1.5:  $n=5$

Learning effects $\alpha$	Lattice	Small-World	Random
0.1	44	43	42
0.3	65	64	61
0.5	81	81	58
0.7	92	89	59

Table 1.6:  $n=20$

Learning effects $\alpha$	Lattice	Small-World	Random
0.1	44	44	43
0.3	63	63	60
0.5	80	79	69
0.7	87	87	76

Table 1.7:  $n=30$

Learning effects $\alpha$	Lattice	Small-World	Random
0.1	44	44	44
0.3	62	63	61
0.5	78	79	72
0.7	86	86	79

Table 1.8:  $n=40$

Learning effects $\alpha$	Lattice	Small-World	Random
0.1	44	44	43
0.3	62	62	60
0.5	79	77	73
0.7	86	85	79

\* \* \*



## Chapter 2

# How Environmental Policies Spread ? A Network Approach to Diffusion in the U.S.

\* \* \*

We reconstruct the network of environmental policies diffusion across American states from 1974 to 2018. Our results highlight an inefficient structure, suggesting lags in policy spreading. We identify Minnesota, California and Florida to be the main "facilitators" of the dynamics. Targeting them ensures the maximum likelihood of policy diffusion across the country. We then evaluate the determinants of the inferred network. Our results emphasize the role of contiguity and wealth in policy transmission. We also find sustainable economic systems as well as state's expected economic losses due to climate change as critical factors of environmental policy flows.

\* \* \*

*This chapter is an adaptation of a joint work with Pr. Anna Creti and Pr. Antoine Mandel.*

## 2.1 Introduction

The withdrawal of the American federal government from the [Paris Agreement \(2015\)](#) has been largely debated and documented worldwide ([Zhang et al., 2017](#); [Pickering et al., 2018](#)). Although defined as "a major disappointment for global efforts to reduce greenhouse gas emissions and promote global security" ([United Nations, 2017](#)), it created unexpected new dynamics across the country. Namely, some American governors publicly expressed their willingness to take the political lead against global warming by setting domestic environmental policies. For example, states such as California, Massachusetts and Minnesota are at the forefront while Wyoming, North Dakota and Arkansas appear more reluctant to push forward pro-environmental laws ([New York Times, June 2019](#)). If implemented at a larger scale, states' policies could significantly mitigate the federal decision (i.e. Paris Agreement withdrawal) and keep the country on track with respect to its COP21 contribution (i.e. reducing U.S. emissions to at least 26% under 2005 levels by 2025 ([UNFCCC, 2016](#))). However, this comes with a challenging requirement : a widely spread adoption of environmental policies across American states.

With respect to past research on policy adoption, the case of American states has attracted many interests. Indeed, federalism provides a peculiar political environment by encouraging member governments to compete with or learn from one another. U.S. states represent a salient example of such a system (e.g. [Berry and Berry, 1990](#)). The states are connected in many ways, including history, culture, the exchange of goods, citizens' migration, and overlapping media markets ([Gray, 1973](#); [Shipan and Volden, 2012](#)). A key result of these features is that states tend to "look

to each other" when making policy (Desmarais et al., 2015). For the specific case of environmental and climate policies, political scientists as well as sociologists have classified the drivers of adoption as either internal (e.g. extreme climate events, pro-climate groups) or external (e.g. states bilateral/international agreements).<sup>1</sup> These are important results as they add up to the literature on environmental and climate policy shaping (Bromley-Trujillo et al., 2016). In sum, much of the previous works have investigated the factors that influence policy adoption from a state-based perspective. A critical limit of this approach is to fall short on observing national dynamics of diffusion, thus leaving unclear how environmental policies spread. For instance, is there any existing diffusion pattern across American states ? (e.g. once California has enacted a set of policies, do we observe regular patterns in terms of following states/adopters). And if yes, which states act as facilitators of the diffusion ? (i.e. those maximising the diffusion likelihood across the whole country). In the context of global warming, answering these questions is relevant for at least two reasons. First, it would enhance the understanding of how diffusion behaves in the U.S. by capturing a national scale process (i.e. diffusion patterns). Secondly, identifying states facilitating the spreading across the U.S. would bring multiple benefits. Among those, targeting such states (i.e. governor, representatives) to maximize the likelihood of diffusion at a larger scale would be a relevant strategy for various types of actors (e.g. NGOs, citizens, companies' representatives), especially those interested in passing pro-environmental laws in "big emitter" states. From another perspective, it would also bring insights to private firms on the possible pattern of environmental regulation diffusion. As differences in legislation across states drive day-to-day business decisions of private actors (e.g. investments, market strategy etc.), answering this question is critical in that respect (Bradbury et al., 1997).

Therefrom, a second intertwined issue to address is about the determinants of the observed patterns of diffusion. Namely, what are the underlying factors driving policy

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<sup>1</sup>See Massey et al. (2014) for a review.

transmission between states-pairs ? As suggested in the aforementioned literature, do we observe higher likelihood of transmission between states sharing common characteristics ? (e.g. economic, political, climate change risks etc.). Investigating the latter would enlarge the understanding of determinants driving diffusion and provide an in-depth approach to pro-environmental policy diffusion across U.S. states.

In order to address these questions, this paper proposes a methodology to infer, from adoption data (i.e. laws enacted), the network structure of environmental policy transmission likelihood between American states. Precisely, environmental and climate policies being a powerful tool to drive changes toward a cleaner economic system (IPCC, 2019), we apply our methodology using a comprehensive dataset of 74 policies - that have spread - from 1974 to 2018. We consider environmental legislations that were not enacted at the federal scale. This allows us to map the legislative diffusion from state to state. For each policy, data (i.e. date of the enacted law in the state) were collected from the Database of State Incentives for Renewables & Efficiency (DSIRE),<sup>2</sup> the Center for Climate and Energy Solutions (C2ES) and the United States Congress platform. As a result, our compiled database encompasses both environmental and climate legislations, covering a large scope of policies that tackle environmental as well as climate-related issues (e.g. renewables support, carbon pricing, greenhouse gases reduction targets, recycling, biodiversity etc.). We assume this approach to be relevant as climate and the environment are intertwined concepts, impacting each other in sophisticated ways (e.g. physical, chemical, see IPCC 1.5 Report, 2019 for more description). Following Halleck Vega, Mandel and Millock (2018), we provide an empirical contribution by identifying existing influences in the environmental policy diffusion network (i.e. states-pairs) and by assessing the impacts of different attributes (e.g. economic and political proximity, environmental features) on the formation of the existing structure over time. Importantly, we implement an

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<sup>2</sup>This database is provided by the U.S. Department of Energy and NC Clean energy Technology Center.

ex-post analysis of environmental policies diffusion based on enacted laws. The latter sets our paper apart as previous research has mainly focused on the rationale of policy adoption (e.g. emulation, competition, coercion, and learning).<sup>3</sup>

Our main conceptual innovation is to adopt a network-based approach. By doing so, we provide a systemic perspective that accounts for the impact of each state not only on its direct connections, but also on the global diffusion process. Indeed, a state might be quantitatively neither the most important source nor the most important adopter of a policy, but still play an important role as a hub in the diffusion. The fundamental role of such network effects has been identified in a wide range of contexts such as epidemics and contagion processes (e.g. [Pastor-Satorras and Vespignani, 2001](#)), social dynamics ([Watts and Strogatz, 1998](#); [Castellano et al., 2009](#)), spatial econometrics ([Lesage and Pace, 2009](#); [Elhorst, 2014](#)), or the diffusion of innovations ([Rogers, 1995](#); [Centola and Massy, 2007](#); [Beaman et al., 2018](#)).

From a methodological point of view, an important difficulty is that policy diffusion networks are generally not directly observed. To address this issue, we build upon the independent cascade model of [Gomez-Rodriguez et al. \(2010, 2011, 2014\)](#) and infer the structure of the network by maximizing the likelihood of the observed patterns of policies adoption using a parametric model of diffusion. This allows us to reconstruct the national policy diffusion network over time. We then perform a statistical analysis of the network. It highlights a relatively inefficient organization, characterized in particular by a great heterogeneity between states in terms of centrality in the network. The latter leads to inefficiencies and induces relatively long lags in the diffusion process. We identify Minnesota, California and Florida as the central states in the diffusion process (i.e. facilitators), against Alaska, South Carolina and South Dakota. Targeting the facilitators would maximize the diffusion likelihood across the country as they are the main hubs in the network. We also find out a relative disconnection between Northeastern states and the rest of the country. The latter suggests that in this re-

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<sup>3</sup>See [Dobbin et al., \(2007\)](#) for a review.

gion, transmission activity is concentrated between neighborhood states. From these observations, we then estimate the impact of several attributes - covering economic and political scopes as well as environmental features (e.g. environmental-friendly economic system, expected cost of climate change (% GDP)) - on observed diffusion patterns. Our results suggest that contiguity and GDP per capita are among the key drivers of policy flows. We also identify Genuine Progress Indicator, a proxy for economic sustainability, to have significant effects (i.e. positive impacts) while states being subject to high expected economic losses due to climate change do not favour policy diffusion. The latter informs us on how spreading occurs across sustainable states and those vulnerable to future climate impacts.

The remainder of the paper is organized as follows. [Section 2](#) reviews the related literature. [Section 3](#) outlines the methodology and [Section 4](#) applies it to the diffusion of environmental policies. It is then followed by an in-depth analysis of the network. [Section 5](#) aims at evaluating the role of several economic, political and environmental attributes in the formation process of the network. [Section 6](#) gives some elements of conclusion.

## 2.2 Related Literature : Policy adoption, Diffusion and Network perspectives

Our work is at the interface between different strands of the academic literature. By considering environmental policies, our paper fits in the wide literature of environmental policy while our singular network approach matches previous research on diffusion in networks.

When considering the case of environmental policy adoption in American states, studies have examined the role of determinants ([Huang et al., 2007](#); [Lyon and Yin, 2010](#)) as well as features of policy diffusion ([Carley and Miller, 2012](#); [Chandler, 2009](#); [Mati-](#)

soff, 2008; Stoutenborough and Beverlin, 2008). Overall, conclusions provide disparate results for the determinants of environmental and climate change policy adoption. With respect to internal drivers, papers often indicate a relationship between climate change policy adoption and political factors. In a cross-sectional study of a large set of climate change policies, Matisoff (2008) finds citizen ideology to be the primary driver. Similarly, Matisoff and Edwards (2014) identify a strong positive relationship between liberalism and policy adoption. In their examination of Renewable Portfolio Standards adoption, Huang et al. (2007) find out a significant effect through partisan control of the state legislature. In addition, higher membership levels in environmental organizations tend to increase environmental policy activity (Newmark and Witko, 2007). This leads Bromley-Trujillo et al. (2016) to conclude that states with political environments that are more favorable to climate change policy, will adopt at a higher rate (e.g. more liberal states, democratically controlled states, and states with a greater level of environmental interest group activism).

The literature also indicates that states' economic factors influence decision to implement environmental policy. State economies that depend on manufacturing and mining may be less likely to pass policies that could potentially harm these industries. In addition, less developed states tend to favour economic policies targeting growth as a priority, resulting in the increase of adoptions among wealthy states (Ringquist, 1994; Matisoff and Edwards, 2014). The latter suggests that states with economic environments that are particularly sensitive to climate policy will adopt at a lower rate (e.g. states with high levels of mining or manufacturing and poorer states).

With respect to external drivers of policy adoption, research has been abundant since the pioneering work of Berry and Berry (1990). Through the use of event history analysis, scholars have determined that a number of policies are spreading across states based on geographic proximity (Berry and Berry, 1990, 1992; Mooney and Lee, 1995; Wong and Shen, 2002). Policy learning is argued to drive this process (Walker, 1969; Boehmke and Witmer, 2004; Karch, 2007). Despite this rich literature on "horizontal"

diffusion, [Mooney \(2001\)](#) asserts that the learning process moves beyond simple geographic proximity. For instance, states may be more likely to learn from states that share basic characteristics (i.e. budgets, politics, and demographic ([Volden, 2006](#))). Recent research points to the importance of ideological distance between states ([Chandler, 2009](#)). [Grossback et al. \(2004\)](#) develop a measure of ideological distance between previous and potential adopters. Their results indicate that states use information concerning the ideology of previous adopters when deciding to adopt. This measure moves the literature forward in understanding the information used by states when looking to others for guidance on policy action. Overall, determinants of environmental policy adoption are often categorized as internal and external. From another perspective, some of the previous works have also investigated the rationale of policy diffusion across states. As exposed by [Dobbin et al., \(2007\)](#), it could stem from different underlying forces operating across states (e.g. coercion, learning, emulation). On this issue, [Boehmke \(2009\)](#) demonstrated that observing multiple policy adoptions is not necessarily evidence of an influence or a flow of ideas, it could be independent responses to the same issue.

As exposed in the introduction, the previous literature has not explored the role of networks in the context of policy diffusion. To the best of our knowledge, the work of [Desmarais et al. \(2015\)](#) and [Boehmke et al. \(2018\)](#) are the only attempts so far. In their papers, they infer the national policy diffusion network. Focusing on the U.S., [Desmarais et al. \(2015\)](#) evaluate the redundancy of a policy transmission between states to generate a global diffusion network based on 187 policies. Their results suggest that diffusion ties connect states that are not geographic neighbors (contradicting the literature) and the existence of leadership, with larger and wealthier states more often acting as sources of diffusion. More recently, [Boehmke et al. \(2018\)](#) provided a methodological contribution with respect to static and dynamic policy innovativeness for U.S. states. Based on a database of 728 policies covering numerous areas (e.g. health, agriculture, transportation, domestic commerce etc.), they propose dif-

ferent sets of comparisons with respect to latent diffusion policy pathways, using the algorithm NetInf (Gomez Rodriguez et al., 2010). Their results suggest that New York, California, and Minnesota are among the most redundant states in the policies diffusion network.

More generally, studies on diffusion in networks have focused on innovations and technologies (Beaman et al., 2018). Recently, a network approach to the diffusion of wind technologies (Clean Development Mechanism projects) at the world scale has been implemented by Halleck Vega, Mandel and Millock (2018). Their conclusions indicate a relatively inefficient organization of the network with a lack of South-South diffusion links, leading to longer lags in technology spreading. Although the literature has mainly apply network approaches to innovation diffusion, we assume our paper to fall apart as we focus on the adoption of environmental policies. As a result, we expect the drivers of policy diffusion to be different compared to private products and innovations. Our peculiar focus on environmental policies is relevant as previous research has not considered environmental policies per se but as a part of a larger set of policies (e.g. in Boehmke et al. (2018), only 2% of policies deal with the environment). In addition, over the past decades we have observed an increasing amount of environmental policy adoption in the U.S. (CCCEP, 2018). The latter gives robustness (i.e. number of observations) to evaluate underlying diffusion dynamics and the rationale behind it, allowing for comparisons with previous findings.

Overall, there are two main approaches. The first covers non-network studies such as descriptive and econometric analyses of factors driving environmental policy adoption, through internal or external intermediaries. The second focuses on understanding how the topology of the network affects diffusion. The present paper is at the interface of these two research areas.

## 2.3 Methodology : Inferring the network

Following Halleck Vega and Mandel (2018), the cornerstone of our approach is to use the independent cascade model of Gomez-Rodriguez et al. (2011) to infer a network of environmental policy diffusion from time-series of observations of the enacted date of subsequent legislations of environmental policy within American states. The weights of the resulting network are interpreted as the rates at which a subsequent environmental legislation is likely to be transferred between states. These weights summarize the effects of a number of latent variables that govern the bilateral diffusion between states (e.g. geographic proximity, political closeness), and the systemic role that certain states can play by serving as intermediaries in the national diffusion process.

More formally, we consider that we are given series of observations of the diffusion of subsequent types of an environmental policy legislation. Each type  $c$  is characterized by a cascade of adoptions<sup>4</sup>  $\mathbf{t}^c = (t_1^c, \dots, t_N^c)$ , which is an  $N$ -dimensional vector of observed activation times. More precisely, for each node  $i$ ,  $t_i^c$  is an element in  $[t_0^c, t_0^c + T] \cup \{\infty\}$ , which is equal to the time at which state  $i$  enacted the legislation  $c$  if finite and is infinite if the state did not enact during a time interval of length  $T$  starting with the first adoption at time  $t_0^c$ . Note that the fact that a node is assigned  $+\infty$  as activation time does not mean stricto-sensu that the node did not get activated, but rather that his activation was discarded given the time-window considered as relevant. The data can then be represented by a set  $C$  of cascades, one cascade for every legislation, and denoted as  $C := \{\mathbf{t}^1, \dots, \mathbf{t}^{|C|}\}$ .

Our aim then is to infer from this data a diffusion network consisting in a pair  $(G, A)$  where  $G = (V, E)$  is a graph (i.e. a set of nodes  $V$  and a set of edges  $E$  representing the potential diffusion paths of the environmental legislation) and  $A = [\alpha_{j,i}]$  is a matrix of transmission rates, i.e.  $\alpha_{j,i} > 0$  quantifies how likely it is that a policy spreads from node  $j$  to node  $i$  if  $(j, i) \in E$  (and  $\alpha_{j,i} = 0$  if  $(j, i) \notin E$ ). The principle of the independent

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<sup>4</sup>In this paper, we call "cascade" the diffusion of a policy.

cascade model is to infer the maximum likelihood network under the assumption that each cascade is an independent instance of a diffusion process drawn from a parametric model in which the probability of diffusion from node  $j$  to node  $i$  is parameterized by the transmission rate  $\alpha_{j,i}$  that is to be determined.

Precisely, the building block of our approach is the probability  $f(t_i|t_j; \alpha_{j,i})$  that node  $i$  gets activated by node  $j$  at time  $t_i$ , given node  $j$  was activated at time  $t_j$  and assuming a transmission rate  $\alpha_{j,i}$  between nodes  $j$  and  $i$ . One then says that node  $j$  is the parent of node  $i$ . The functional form of  $f$  conveys the structural assumptions about the diffusion process (see the discussion below). Now, given the conditional density  $f(t_i|t_j; \alpha_{j,i})$ , one can infer the likelihood of a set of cascades  $\{\mathbf{t}^1, \dots, \mathbf{t}^{|\mathcal{C}|}\}$  given a network  $A = [\alpha_{j,i}]$  as follows (see [Gomez-Rodriguez et al., 2011](#) for a comprehensive discussion).

First, given a cascade  $\mathbf{t}^c = (t_1^c, \dots, t_N^c)$ , the likelihood of node  $i$  being activated by node  $j$  is given by :

$$f(t_i|t_1, \dots, t_N \setminus t_i; A) = \sum_{j:t_j \leq t_i} f(t_i|t_j; \alpha_{j,i}) \times \prod_{j \neq k, t_k \leq t_i} S(t_i|t_k; \alpha_{k,i})$$

where  $S(t_i|t_j; \alpha_{j,i})$  is the survival (anti-cumulative distribution) function of edge  $j \rightarrow i$ , that is the probability that  $j$  does not cause  $i$  to activate by time  $t_i$ . Indeed, assuming a node gets activated only once, one shall consider it is activated by node  $j$  only if it has not been activated before by another node in the cascade.

One can then compute the likelihood of the activations in a cascade before time  $T$  :

$$f(\mathbf{t}_{\leq T}^c; A) = \prod_{t_i \leq T} \sum_{j:t_j \leq t_i} f(t_i|t_j; \alpha_{j,i}) \times \prod_{k:t_k < t_i, k \neq j} S(t_i|t_k; \alpha_{k,i})$$

Further, the likelihood of a cascade accounts for the fact that some nodes did not get activated (we consider that nodes not activated before time  $T$  never get activated). It is therefore given by :

$$f(\mathbf{t}^c; A) = \prod_{t_i \leq T} \prod_{t_m > T} S(T|t_i; \alpha_{i,m}) \prod_{t_i \leq T} \prod_{j: t_j \leq t_i} f(t_i|t_j; \alpha_{j,i}) \prod_{k: t_k < t_i, k \neq j} S(t_i|t_k; \alpha_{k,i})$$

Finally, the likelihood of a set of cascades  $C = \{\mathbf{t}^1, \dots, \mathbf{t}^{|C|}\}$ , assuming each cascade is independent, is the product of the likelihoods of the individual cascades given by :

$$f(\{\mathbf{t}^1, \dots, \mathbf{t}^{|C|}\}; A) = \prod_{\mathbf{t}^c \in C} f(\mathbf{t}^c; A)$$

The objective of the network inference problem then is to find  $A = [\alpha_{j,i}]$  such that the likelihood of the observed set of cascades  $C = \{\mathbf{t}^1, \dots, \mathbf{t}^{|C|}\}$  is maximized. More precisely, we aim at solving the following maximum likelihood (ML) optimization problem:

$$\begin{aligned} & \text{minimize}_A - \sum_{\mathbf{t}^c \in C} \log f(\mathbf{t}^c; A), \\ & \text{subject to } \alpha_{j,i} \geq 0, i, j = 1, \dots, N, i \neq j \end{aligned}$$

In practice, we solve this minimization problem using CVX, which is a general purpose package in MATLAB for specifying and solving convex programs ([Grant and Boyd, 2015](#)) and the algorithm NETRATE ([Gomez-Rodriguez et al., 2011](#)), which are publicly released open source implementations. As emphasized above, structural assumptions about the diffusion process are embedded in the functional form chosen for the function  $f$ . Our baseline assumption will be to consider that once a state has enacted a legislation, the probabilistic rate at which it diffuses it to one of its neighbor is constant over time (although it might depend on the neighbor under consideration). This amounts to considering the diffusion follows a Poisson process and therefore leads to an exponential model for the conditional density of diffusion over time ([Kingman, 1993](#)). That is  $f(t_i|t_j; \alpha_{j,i}) = \alpha_{j,i} e^{-\alpha_{j,i}(t_i - t_j)}$  (if  $t_j < t_i$  and zero otherwise) where  $\alpha_{j,i}$  is the diffusion rate. The Poisson assumption of a constant diffusion rate is a simple and natural benchmark in absence of specific information about the dynamic aspects of the diffusion. In particular, a Poisson process emerges if diffusion opportunities are distributed uniformly across time.

Independently of the underlying diffusion model, the network inferred by maximum likelihood provides two main types of information. First, the adjacency structure of the network indicates which routes environmental policies are likely to follow in their diffusion. Secondly, the weight of an edge gives an estimate of the speed at which diffusion is likely to occur between nodes.

## 2.4 The U.S. Environmental Policy Network

### 2.4.1 General Context and Data

In the United States, the Trump administration's decision to withdraw from the [Paris Agreement](#) (2017) has deeply changed the environmental legislation dynamics within the country ([Hejny, 2018](#)). In the wake of this announcement, some sub-national actors such as local states governors publicly expressed their ambition to take the political lead in the fight against global warming ([Georgetown Climate Center, 2017](#)). The launch of the U.S. Climate Alliance (June, 2017), a coalition of states and unincorporated self-governing territories in the United States that are committed to achieve the objectives of the [Paris Agreement](#) within their borders is a salient example. Other examples include California, Illinois, New York and Connecticut, currently creatively pushing their portions of the electric grid away from fossil fuels ([CCCEP, 2018](#)). By implementing aggressive environmental policies, states' action could "mitigate" negative impacts of the federal administration's decision ([Zhang et al., 2017](#)). However, keeping the U.S. on track with respect to the out-dated COP21 commitments calls these local policies to diffuse rapidly across states. This further emphasizes the need of efficient policy diffusion to ensure that newly enacted climate laws are spreading faster and as much as possible across the country. In this respect, very little observation data is available on the diffusion process of environmental and climate policies. Yet, understanding the structural properties of the diffusion network is a prerequisite to determine key states in the process. In this perspective, the methodology we have

introduced in [Section 3](#) allows to infer the structure of the diffusion network from enacted environmental and climate policies data, which is much easier to collect than diffusion data.

To do so, we build a dataset of 74 policies (i.e. cascades) upon three initial databases: the Database of State Incentives for Renewables & Efficiency (DSIRE), the Center for Climate and Energy Solution (C2ES) and the US Congress Platform. Already used in the literature ([Bromley-Trujillo et al., 2016](#)), DSIRE and C2ES are relevant databases to consider as they give details about states' legislative action and associated enacted time-windows. More precisely, DSIRE encompasses policies dealing with renewables support schemes (e.g. wind energy supports, solar rebate, sales tax incentives) and energy efficiency (e.g. smart meters policies, energy audit refrigerator/cooling, rebate program). These policies represent more than 40% of our dataset. C2ES refers to climate policies and related adaptation actions (e.g. climate adaptation plan, water plan, droughts plan). Finally, we collected policies from the Congress platform as it provides state by state laws description (enacted date, content). In this case, we built cascades based on the first occurrence of a word (e.g. GMO) in the laws of the corresponding state.<sup>5</sup> We gathered 27 policies targeting transportation (e.g. biofuel policies, LEV Californian standards), sustainability (e.g. composting, plastic bag, electronic recycling program) and environmental management (pesticides regulation, bees keeping policies, environmental cleanup, wildlife conservation).

As a result, for each cascade, we collected the enacted dates of the policy in each state wherein the policy has been implemented. It allows us to map the cascade diffusion across states as a function of time. Note that we do not look at the intensity of the policy, our focus is more on the extensive than the intensive margin of environmental policy diffusion. Overall, policies fit into seven categories exposed in [Table 2.1](#)<sup>6</sup> and cover the scope of environmental and climate state-based legislative actions from 1974

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<sup>5</sup>See [Appendix, Section 2](#) for keywords list.

<sup>6</sup>For full description, see [Appendix, Section 1](#).

to 2018.

We include policies related to climate action, the energy sector (mainly renewables), transportation, and buildings. Our primary goal was to gain as much variation in policies as possible, while still maintaining generalizability to other climate-related policies. In this framework, we consider states as our nodes and set the "activation" time of a given policy in a state as the enacted date of the policy (i.e. a state become active once the policy is enacted). By convention, the activation time of a state not enacting the policy is set to infinity. We hence constructed the cascades spanning 51 states over a period of 45 years (1974-2018).

Table 2.1: Environmental and Climate Change Policies collected in Brief.

<b>Scope (Number)</b>	<b>Policies Description</b>
Climate Policies (5)	Action Plans and reduction targets
Climate Change Adaptation (9)	Plans to cope with current climate damages
Renewable support (24)	Promoting the use of clean energy
Energy Efficiency (9)	Targeting emissions in the dwelling sector
Transportation (8)	Promoting the use of clean fuels/vehicles
Circular Economy (7)	Targeting recycling/products efficient use
Environmental Concerns (12)	Regulating environment management/health

We then proceed with the maximum likelihood estimation of the network following the procedure described in [Section 3](#).

## 2.4.2 Statistical Analysis of the Network

### Generalities

As illustrated in Figure 2.1, the inferred network<sup>7</sup> first provides a map of existing diffusion routes and hence a much broader view than obtained from the sole consideration of bilateral influences among states. For example, in our setting, it could be the case that California and Oklahoma are not linked by a direct link, but that there exists a very short path from California to Oklahoma through Minnesota, hence diffusion would nevertheless occur relatively rapidly from California to Oklahoma. On the contrary, the path from California to New Jersey could be relatively long (going through Wyoming, Florida, Maryland, Maine, Connecticut, New York, and so forth), which would suggest a relatively long lag in the diffusion from California to New Jersey.

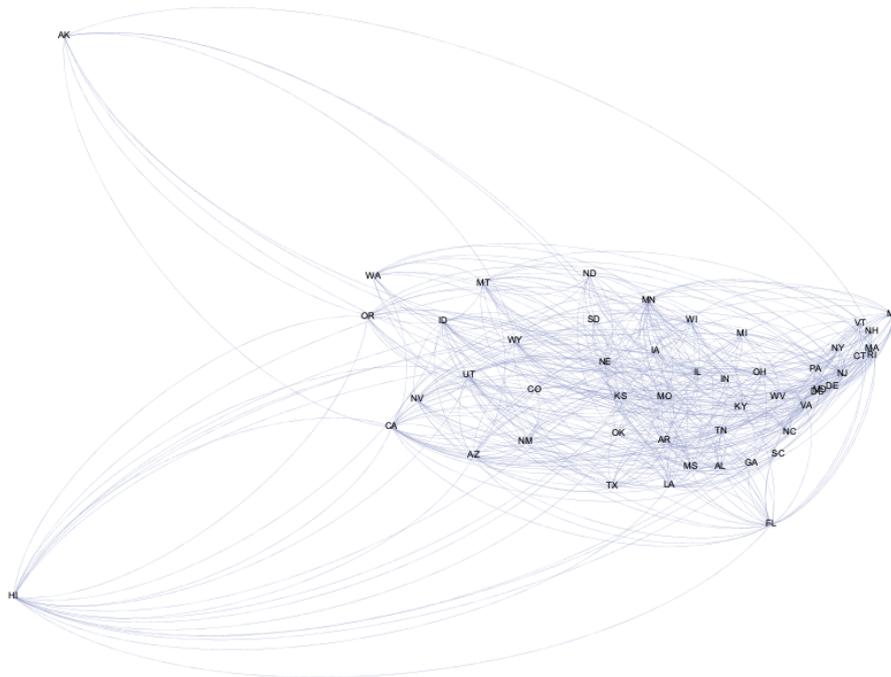


Figure 2.1: Reconstructed environmental policies diffusion network in the U.S. using geographical layout.

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<sup>7</sup>We relegate to the [Appendix, Section 9](#) supplementary inferred networks (i.e. Energy Network (Renewable Support + Energy Efficiency); Environmental and Climate Network (remaining policy categories)).

Overall, Figure 2.1 puts forward the existence of a strongly connected network formed by all American states. This observation suggests that every state belongs to the network. In other words, there is a path connecting each pair of states. The latter matches the literature on diffusion in a federal context as states tend to compete and mimic each other in terms of policy implementation (Desmarais et al., 2015). From a quantitative perspective, structural properties of the diffusion process can be characterized via a statistical analysis of the network (Halleck Vega and Mandel, 2018). In this respect, key features of the network are reported in Table 2.2.

Table 2.2: General properties of the network.

Overall Network Characteristics	Exponential Model
Number of Nodes	51
Number of Links	440
Network Density	0.173
Mean Degree	8.627
Mean Path Length	2.075
Network Diameter	4
Mean Clustering Coefficient	0.211

First, the basic measure of importance of a node is the degree, which measures its number of connections. In a directed network, one distinguishes the in-degree (number of incoming links) and the out-degree (number of outgoing links). As regards policy diffusion, they respectively measure the direct potential to adopt or spread a policy. Here, the inferred network has 440 edges, i.e. 440 links among the 51 states. In other words, the average degree is approximately 8.6 and the network density, i.e. the ratio between actual and total potential number of links, is 0.173. These values are in line with those generally observed in socio-economic networks (Albert and Barabási, 2002; Chandrasekhar, 2016). The basic measure of distance between two nodes is the shortest path, also known as the geodesic distance, which corresponds to the length of the

path that connects them with the smaller number of edges. The average path length of the network is then computed by summing up all the shortest paths and dividing by the total number of pairs. In the context of environmental policy diffusion, the average path length can be seen as a measure of the average policy distance between two states. In our setting, it has a value of 2. This is close with respect to the random graph benchmark<sup>8</sup> usually satisfied by socio-economic networks (Albert and Barabási, 2002) and for which the average path length corresponds to the log ratio between number of nodes and average degree (1.8 in our setting).

A common property of social and economic networks is to exhibit clustering, indicating the tendency for nodes to form small groups (Centola, 2010). The clustering coefficient in our setting has a value of 0.211 which is in line with previous findings in economic networks (Soramaki et al. 2006; Halleck Vega and Mandel, 2018) and greater than in random graph (0.169). This complements our observations, suggesting some local structural organizations. Furthermore, the diameter of the network (the shortest path between the two most distant nodes) has a value of 4 in our setting, which is relatively large with respect to the random graph benchmark (it ought to be close to the average path length following equation (16) in Albert and Barabási, 2002). These values (i.e. diameter and average path length) hint at the existence of lags in the diffusion process as well as heterogeneity in terms of nodes attributes (e.g. degree, centrality).

To gain more quantitative insights, we provide a systemic characterization of the network via its degree distribution, which is constructed by computing for each potential value of the degree, the number (or the share) of nodes assuming that particular value. The degree distribution hence summarizes the structure of the network. The out-degree and in-degree cumulative distributions of the environmental policy diffusion network are shown in Figure 2.2 in log-log scale.

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<sup>8</sup>Random graph is often used as benchmark in network analysis as some network properties could have emerged by chance. For this reason, we turn to the random network model as a guide: if the property is present in the model, it means that randomness can account for it. If the property is absent in random networks, it may represent some signature of order, requiring a deeper explanation (Albert and Barabási, 2014).

The distribution clearly has fatter tails than normal, consistently with the presence of highly connected nodes in the network. Indeed, we note that 70% of nodes have less than 10 out-degrees while 2% of nodes have more than 17 out-degrees. However, these nodes could play different roles, either by their abilities to spread the policy (out-degree), to contain it or both.

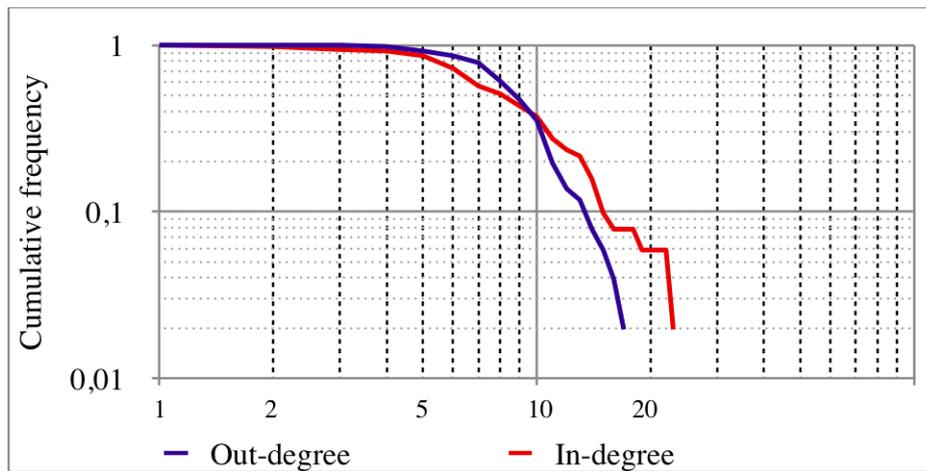


Figure 2.2: Cumulative distribution of states' out-degree and in-degree.

### 2.4.3 Centrality Analysis : Looking for Facilitators

In this section, we analyze how centrality measures are distributed among nodes to capture central nodes and peripheral nodes in the network. The former represents states facilitating diffusion (hubs) suggesting a strong ability to spread a policy in the network while the latter points out less integrated states. We base our centrality approach on several measures developed in the literature (see [Jackson, 2008](#) for an overview). For clarity of presentation, we relegate centrality measures' description and associated tables of results in the [Appendix](#).<sup>9</sup>

Overall, it is clear that Minnesota (Midwest), California (West) and Florida (South) are among the most prominent states. In fact, many overlap across the different cen-

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<sup>9</sup>See [Appendix, Section 4](#), Centrality measures description; Table 2.6 - 2.19.

trality measures. Maryland and Louisiana also appear in the top for some of the indicators. In addition, it can be observed that some other states including Hawaii, Idaho and Utah have a relative presence. These leading states are facilitating the diffusion across the network. Namely, once such states have enacted a policy, the likelihood for that policy to diffuse in the network is high (compared to other states). On the opposite, states such as Alaska, South Dakota as well as South Carolina are among the worst performers with respect to centrality indicators, suggesting a low integration in terms of connections and positions in the network.<sup>10</sup> As for centrality leaders, many overlap across measures.

Although out-degree can be seen as reflecting a spreader of policy, with a higher number implying greater coverage, in-degree can also be a key indicator of the receptiveness to the policy. Since the diffusion process involves the accumulation of policy over space and time arising from adoption decisions, both the ability to spread and absorb new policies are interrelated and important. In aggregate, main hubs are Minnesota, California and Florida while District of Columbia, South Carolina and Alaska have less than ten connections each (worst performers). With respect to closeness centrality, which provides an indication of which states can reach all other reachable nodes quickly, Minnesota, California, Florida and Massachusetts are among those taking top positions. Again, South Carolina and South Dakota take the last rankings.

Moving to betweenness centrality measure, results are particularly insightful. As previously discussed, it determines the relative importance of a state by measuring the amount of flows through that state to other states in the network, thus acting as a bridge. This relates back to the importance of the network approach discussed previously, and in particular, the value of policy intermediaries encouraging interaction within a system (IPCC, 2019). The visualization of the network based on the betweenness indicator (Figure 2.4)<sup>11</sup> highlights the importance of several hubs in the environ-

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<sup>10</sup>Although not being a state, the District of Columbia is also among the less integrated nodes in the network.

<sup>11</sup>See [Appendix, Section 5](#).

mental policy diffusion network. For example, Minnesota, California, Florida, Utah, Hawaii and Missouri are among the top (opposite to South Carolina and Alaska). With respect to eigenvector centrality - builds upon degree centrality, also taking into account the quality of the connections, i.e. how connected a state is to hubs in the environmental policy network - Minnesota, Idaho, Hawaii, Missouri and Louisiana are the most important states in the network. It should be noted that some of these are also hubs themselves, while states such as Missouri and Idaho do not overlap with other measures. Hence, the comparison between centrality measures reinforces the conclusion of the previous section : there is only partial overlap between the different centrality measures and the distribution of centrality among top nodes and less integrated nodes is relatively uniform. In this sense, the network is multipolar with at least three hubs : Minnesota (Midwest), California (West), Florida (South) and no single node appears as an evident center. Although not being as predominant, New Jersey appears as the main hub in the Northeast region, being top-ranked for several centrality measures. As a result, it is not straightforward to identify a single node, nor a region, as the optimal target for the inception and the diffusion of new environmental and climate policies. However, our analysis suggests that a group of states are prominent spreaders in the process.

### **Overtime Network Formation**

In complex economic systems, a relevant topic to address is the origin of the current structure (Desmarais et al., 2015; Halleck Vega and Mandel, 2018). Our methodology can be used to simulate the network formation process by running the network inference algorithm for sub-periods of increasing lengths. The results of this analysis are presented in [Section 6](#) of the [Appendix](#). We expose maps for periods from 1974 to 2018, cross-cutting historical federal government political terms (Republican vs. Democratic).

A first key observation is that the growth of the network has been remarkable, expand-

ing considerably both in terms of size and of connectivity. Compared to Figure 2.1, the landscape for the earliest sub-period is much less dense (11 nodes in total), made up of a few major states such as Nebraska, Missouri, and Oregon. In the following sub-period 1972-2000, the density of the network has increased and new leading states have emerged (namely Nevada, New Jersey, Connecticut and New Hampshire). The global picture suggests that much fewer states remain outside the network (e.g. North Dakota, Tennessee, North Carolina). From this observation, we can argue that large-scale diffusion started in the late of the 90s and the beginning of the 2000s. Overall, several changes come into play : First, all the nodes are connected to the network (i.e. at least four degrees per node). Second, new hubs appeared with the presence of California, Nebraska and Colorado, although they were not reproducing any specific regional setting. For the 1972-2016 period, the network increased in density and, importantly, Minnesota and California started playing key roles in the diffusion. Though this sub-period is similar to Figure 2.1, in general, there have been small changes in terms of general statistics of the network (diameter, average degree) - converging to the characteristics of the 1992-2018 inferred network.

This historical analysis sheds light on critical tipping points in terms of network formation in the late 90s and the 2000s, embodying a major jump with respect to network density and connectivity. This observation (i.e. the increase in states environmental policies adoption) has been studied by scholars in Law and Political Science ([Andrews, 2018](#)). Research findings suggest that this take-off to stemmed from new approaches of environmental issues. Among them, after the "environmental decade" that has witnessed the launch of the National Environmental Policy Act and the Environmental Policy Agency ([Kepner, 2016](#)), the U.S. reached a turning point in national environmental policy calling for readjustments in terms of federal government's action and states' roles. Indeed, the success of national laws aiming to control major sources of pollution and encouraging conservation (e.g. federal land) came together under public scrutiny, focusing on problems that were harder to solve with a federal action (e.g. for

instance, tackling widely scattered sources of pollution as well as specific conservation opportunities affecting farms and housing developments (Graham, 1998)). As a result, state-based environmental laws progressively started to soar in the 90's. Therefrom, states started to influence each other, generating an unprecedented take-off in states' environmental policy adoption (e.g. California). The historic network formation also highlights the late appearance of California and Minnesota as key states for the diffusion. We argue that the amount of environmental policy diffusion during previous periods was too low to observe the emergence of current key states - especially those at the forefront of clean policies in many sectors. Finally, our results indicate an unstable centrality leadership in the network over time, suggesting possible evolution to come with respect to diffusion patterns observed.

### Regional vs Network Communities Approaches

To further investigate the local structure of the network, we implement a regional-level analysis (geographical) as well as a network communities evaluation. By doing so, we provide complementary perspectives on local characteristics in terms of geographic patterns and nodes' proximity in the network.

Our regional setting takes after that of the U.S. Census Bureau, a federal institution which has classified American regional divisions for more than 100 years. Four regions are then delimited : Northeast, Midwest, West and South.<sup>12</sup> It is apparent from both Table 2.3 and the diagonal elements of the matrix in Table 2.4 that the Northeast has by far the lowest amount of connections (i.e. in/out-degree, total degree), especially when considering target region figures (i.e. targeted by 13% of links). Among those, nearly 40% are intraregional connections, indicating that activity is concentrated and that the Northeast is not highly subject to external diffusion influence.

The South also has the largest off-diagonal elements, meaning it is the most connected region in the diffusion network. A large majority of its out-connections is homoge-

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<sup>12</sup>See [Appendix, Section 3](#) for full description.

neously targeted toward the Midwest, the West, and intraregional states, leaving only 10% of remaining out-degrees to the Northeast region. Overall, nearly a 32% of out-degrees and in-degrees are associated with the South region (i.e. 32% of total network connections). As a comparison, Northeast connections represent respectively 20%, 13% and 17% (i.e. out-degree, in-degree, total).

Table 2.3: Regional-level statistics.

<b>Region</b>	<b>No. of states</b>	<b>Out-degree</b>	<b>In-degree</b>	<b>Source region (%)</b>	<b>Target region (%)</b>	<b>Total degree</b>
Northeast	9	89	59	20.23	13.41	148
Midwest	12	98	109	22.27	24.77	207
West	13	113	130	25.68	29.54	243
South	17	140	142	31.82	32.27	282

Although the South has the most states coverage, it is the most targeted region as well as the largest source area. The most interregional flows are between the South and the West, followed by the South-Midwest pair.

Table 2.4: Matrix of intra-interregional connections.

<b>Region</b>	Northeast	Midwest	West	South
Northeast	23	14	24	28
Midwest	10	30	29	29
West	11	29	34	39
South	15	36	43	46

From a complex networks perspective, it is interesting to compare previous results with a community-based approach. The notion of “community” corresponds to a subset of nodes that are more densely connected among themselves than with the nodes outside the subset. Several definitions and methods to detect communities have been proposed

in the literature (see Fortunato (2010) for a review). Most algorithms can be distinguished in divisive, agglomerative and optimization-based (Abraham et al., 2012). In the latter case, the goodness of the partitions is commonly assessed in terms of the so-called “modularity” (Lambiotte et al., 2015). The modularity takes values between -1 and 1 and compares the density of the links within the communities with those across communities. It is positive if the number of edges within groups exceeds the number expected on the basis of chance. Then, for a given division of the network’s vertices into some partitions, modularity reflects the concentration of edges within groups compared with random distribution of links between all nodes regardless of modules. In our case, modularity takes the value 0.425, confirming the sophisticated properties of the network<sup>13</sup> (Becatti et al., 2019). We map in Figure 2.3 a graph perspective of communities of the inferred network.

Overall, communities analysis hints at the presence of cross regional states belonging to same clusters.<sup>14</sup> The latter suggests the existence of multiple inter-states dynamics of diffusion across the country - providing different insights with respect to the regional perspective. As an example, the smallest community gathers four states (Arizona, California, Indiana and South Dakota) while the largest represents 19 states (Alaska, Colorado, Illinois, Kansas, Kentucky, Louisiana, Michigan, Mississippi, North Dakota, New Mexico, Nevada, Ohio, Oklahoma, Texas, Virginia, Washington, Wisconsin and Wyoming). Interestingly, all states belonging to the Northeast region - except Pennsylvania - take part in the same community (i.e. red) while other regional settings become weak nor nonexistent. These results confirm the highly concentrated intra-states diffusion activity in the Northeast part of the U.S. and the existence of groups of states narrowly intertwined across the country (i.e. clusters). The latter explains the macroscopic level of clustering observed previously (i.e. 0.211).

The network of U.S. environmental policy diffusion we have observed is inefficient. Our

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<sup>13</sup>Compared to random graphs.

<sup>14</sup>See Appendix, Section 4 for full description.

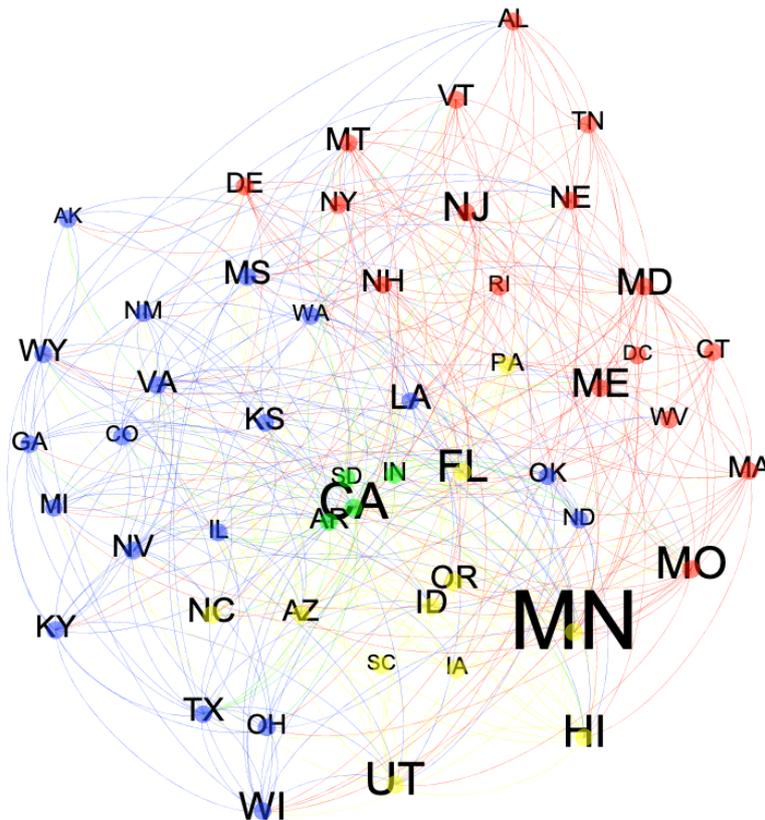


Figure 2.3: Reconstructed network using Force Atlas layout. The node size is proportional to betweenness centrality, a centrality measure capturing the notion of hubs facilitating policy flows. Position of nodes depends on associated connections in the network.

analysis shows that network's structure hints at the existence of lags in policy transmission (e.g. network diameter) while the ability of states to spread a policy is highly unequal. The network also exhibits characteristics matching geographic patterns. That is, in the Northeast region of the U.S., the activity of policy transmission is highly concentrated between states. To enhance our understanding of the current diffusion structure, the next part evaluates the impact of several attributes on the formation process. By doing so, we add up to the literature on policy diffusion by focusing on the determinants of environmental policy transmission across American states. In addition, policy-makers might be interested in modifying the network to reach higher levels of diffusion. In the context of climate change, this part brings them new insights to foster the implementation of pro-environmental policy.

## 2.5 Estimating the Determinants of the Diffusion Network

### 2.5.1 Modelling strategy and data

In this section, we base our econometric approach on the recent works of [Wu et al. \(2013\)](#) and [Halleck Vega et al. \(2018\)](#). We only expose the general framework and we refer to their papers for the econometric approach.

We now consider diffusion rates  $\alpha_{j,i}$  previously exposed, as the probability for a policy to diffuse from state  $j$  to state  $i$ . We argue that this probability depends on a range of characteristics about the source state, the target state and their relationship. For example, it might depend on the level of GDP of the source state, the expected climate change economic cost (% GDP) by the end of the century in the target state, on geographic proximity between the two states (e.g. contiguity).

Then, in all generality, one can consider three main types of variables : a first set of variables  $x_i := (x_i^1, \dots, x_i^{n_1}) \in \mathbb{R}^{n_1}$  characterizing the source state, a second set of variables  $y_j := (y_j^1, \dots, y_j^{n_2}) \in \mathbb{R}^{n_2}$  characterizing the target state, and a third set of dyadic variables  $z_{(i,j)} := (z_{(i,j)}^1, \dots, z_{(i,j)}^{n_3}) \in \mathbb{R}^{n_3}$  characterizing the relationship between the two state ( $z_{(i,j)}$  shall in general be a multi-dimensional variable accounting for the range of bilateral features). A natural approach would then be to try to estimate the diffusion probability between states  $i$  and  $j$  using a logistic model of the form:

$$\alpha_{i,j} = P_{\alpha,\beta,\gamma}(x_i, y_j, z_{i,j}) := \frac{1}{1+e^{-(\alpha x_i + \beta y_j + \gamma z_{i,j})}}$$

where  $\alpha \in \mathbb{R}^{n_1}$ ,  $\beta \in \mathbb{R}^{n_2}$  and  $\gamma \in \mathbb{R}^{n_3}$  are the vector of coefficients associated respectively to the characteristics of the source state, the target state, and their relationship. Based on [Halleck Vega, Mandel and Millock \(2018\)](#), we then infer the determinants of network formation as above using the independent cascade assumption and maximum likelihood estimation. Precisely, we seek to find  $(\alpha, \beta, \gamma)$  that maximize the

likelihood of diffusion observed. This yields the following equation for the likelihood of the set of observed cascades  $S = (S_v)_{v \in V}$  corresponding to  $V$  different policies :

$$\mathcal{L}_{\alpha, \beta, \gamma}(S) = \prod_{v \in V} P_{(\alpha, \beta, \gamma)}^v(X, Y, Z)$$

Therefrom, we apply this methodology to evaluate the determinants of the formation of the environmental policy diffusion network from 1974 to 2018.

In order to proceed, we enrich our policy dataset with characteristics that can be associated to a state as a source (of the type  $x_i$ ) and as a target (of the type  $y_j$ ) of policy diffusion, as well as characteristics of the relationship between pairs of states (of the type  $z_{i,j}$ ). By construction, the model accounts for the fact that the identity of previous adopters matters because they are the only potential sources of diffusion. This applies in particular to the initial adoption state. With respect to policy drivers, key variables are included to capture the impacts of states' economic and political characteristics, as well as environmental features on policy diffusion.<sup>15</sup> As regards the former, we include commonly examined variables such as GDP per capita, population density, citizen ideology as well as partisan control of state government (Berry et al., 1998; Klarner, 2003; Desmarais et al., 2015). We add a variable dealing with the political party in charge of the federal government overtime (e.g. Republican/ Democratic). By doing so, we complement the literature by investigating if the federal government party in office has an impact on the network formation process. In addition, we take into account contiguity of states as results presented in the literature are not clear-cut. Since this variable is dyadic by nature, it is included as a  $z_{i,j}$  feature, with the expectation that the impact will be positive and significant, as contiguity should facilitate diffusion flows of environmental policies (Bromley-Trujillo et al., 2016).

For environmental variables, we focus on different types of indicators ranging from policy directed at tackling climate change to the expected economic risks due to global warming. Controlling for these variables allows us to estimate whether diffusion is

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<sup>15</sup>For full variables description, see [Appendix, Section 8](#).

more likely to occur from/toward states coping with climate change in different ways (i.e. policy, risks). We control for the level of state coal mining production as well as the green performance of its economy. To do so, we include the Genuine Progress Indicator (GPI) of American States constructed by [Fox and Erickson \(2018\)](#) for the year 2011. This indicator, largely commented in the literature on economic welfare assessment ([Kubiszewski, 2013](#)), "provides citizens and policy-makers fruitful insight by recognizing economic activity that diminishes both natural and social capital. Further, the GPI is designed to measure sustainable economic welfare rather than economic activity alone" (cf. [Maryland Department of Natural Resources](#)). Therefrom, we can assess if diffusion from sustainable states (i.e. greener economic system) is more likely to occur or not. Finally, we introduce a new variable referring to the expected economic cost of climate change for US states. Based on the analysis of [Hsiang et al. \(2017\)](#), a county scale expected economic impacts (i.e. GDP losses; 8.5 RCP scenario) of global warming at 2080-2099 horizon, we constructed an index to classify American states with respect to their vulnerability.<sup>16</sup> Overall, combining these indicators aims to cover a large scope of possible environmental determinants of the network and evaluate if states environmental attributes (e.g. policies, risks toward climate change) increase the likelihood of states-pair diffusion.

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<sup>16</sup>We sum state's counties median expected economic losses (% of GDP) and take the average with respect to GDP weights.

## 2.5.2 Empirical results

Table 2.5: Estimation results of diffusion network approach.

	Model A_Eco-Pol	Model B_Eco-Pol- Clim	Model C_Eco-Pol- Env	Model D_Eco- Pol-Clim-Env
<b>Constant</b>	-4.10** (-163.74)	-3.61** (-118.22)	-4.15** (-72.89)	-3.67** (-128.51)
<b>Contiguity (<i>Relationship</i>)</b>	1.46** (33.52)	1.64** (40.22)	1.93** (48.80)	1.69** (41.09)
<b>GDP per capita (<i>Source</i>)</b>	0.01** (2.65)	0.03** (5.13)	0.01** (2.58)	0.03** (4.60)
<b>Population Density (<i>Source</i>)</b>	-0.37** (-22.94)	-0.40** (-24.21)	-0.53** (-30.67)	-0.49** (-28.78)
<b>States Governors Party</b>	-0.00 (-1.20)	-0.00 (-0.12)	-0.03** (-5.10)	-0.03** (-4.71)
<b>Federal Government Party</b>	0.03** (2.78)	0.01 (1.39)	-0.00 (-0.12)	-0.00 (-0.62)
<b>Citizen Ideology</b>	0.00** (17.02)	0.00** (4.56)	-0.00** (-5.18)	-0.00** (-9.00)
<b>Climate change Economic Impacts (&gt;5% GDP)</b>				
• <i>Source</i>		-0.37** (-23.02)		-0.34** (-21.04)
• <i>Target</i>		-0.68** (-6.32)		
<b>Genuine Progress Indicator (<i>source</i>)</b>				
• <i>Source</i>			0.55** (36.41)	0.51** (33.84)
• <i>Target</i>			0.44** (6.81)	
<b>Coal Mining State (<i>Source</i>)</b>		-0.13** (-8.64)	-0.14** (-10.07)	-0.04** (-2.69)
<b>McFadden R<sup>2</sup>*</b>	0.02	0.04	0.04	0.05

Notes: For state-specific explanatory variables, the number of observations are  $51 \times 45$ , where number of nodes is 51 and number of time periods is 45. For dyadic variables, there are  $51 \times 50 \times 45$  observations; for geographic contiguity this is symmetric. t-values are reported in parentheses. \*\*Significant at the 1% level.

From a policy point of view, the results presented in Table 2.5 provide interesting insights on accelerating the diffusion of environmental policy in the U.S., which forms a key component in the energy transition as highlighted in the introduction.

First, in our models, contiguity has a strong impact on policy spreading. This corroborates previous studies (e.g. [Berry and Berry, 1990, 1992](#); [Mooney and Lee, 1995](#); [Wong and Shen, 2002](#); [Bromley-Trujillo et al., 2016](#)), that neighbor states tend to mimic each other with respect to policy implementation. This result was expected as our regional-level analysis pointed out the following pattern : the Midwest, West and South regions have more in-degree than out-degree. Consequently, the latter increases the probability of neighbor states to target each other. As can be noticed, from a source state perspective, GDP per capita is significant for each model specification. In particular, *ceteris paribus*, an additional unit in the level of GDP increases the odds ratio of transmission by 1.03-fold (model B). The latter suggests that wealthier states are more likely to transmit a policy. This finding matches past research suggesting that environmental policies are considered by wealthy countries/states ([Ringquist, 1994](#); [Matisoff and Edwards, 2014](#)).

Population density is associated with a decreasing likelihood of transmission for source states. Though contradicting the literature ([Volden, 2006](#)), this result is rather intuitive as a large number of highly densely populated states are located in the Northeast region where we have observed the fewest amount of diffusion links in total (i.e. out-degree, in-degree). Although this geographic part of the U.S. exhibits a concentrated transmission activity, this finding suggests that diffusion rates of states belonging to this region are not larger compared to other states in the country (i.e. source perspective).

Moving to political consideration, it is expected that state partisanship control positively influence the acceleration of environmental policy diffusion. However, an unexpected result is found as the coefficients are negative (cf. models C, D). Although reaching relatively low levels, this contradicts with the literature (i.e. identical political party fosters diffusion ([Huang et al., 2007](#))). Keeping in mind that variables cover a period from 1974 to 2018, we assume that successive political switches in different states over that time frame scrambled states-pair partisanship proximity impacts on

transmission. It turns out, however, that the party of the federal government ruling the country is significant in one configuration (model A). Although it should not be over-interpreted, this outcome is of great interest as moving from a Republican to a Democrat leadership increases the odds of transmission ( $\exp(0.03) = 1.03$ , model A). This stems from two possible factors : as climate change has historically been more politically considered by Democrats (Leiserowitz, 2018), blue states' governors tend to implement pro-environmental policies. Moreover, pro-environmental federal ambitions can foster the willingness of states to act against global warming with clean policies and divest from a dirty economic system (e.g. Obama Administration climate policy).

With respect to climate change economic impacts, we have estimated the impact of economic damages with treatment coding (with the reference group being less than 5% GDP climate change median expected economic losses =0; median economic losses greater than 5% GDP = 1). Results are shown in the second and fourth columns. Overall, the impact is highly significant. With respect to targeted states facing a high expected climate economic cost, the odds ratio of transmission are 50% lower compared to the reference category (i.e. model B). As Southern states are among the most vulnerable to climate change, our centrality analysis indicates that they are often less integrated in the diffusion network (cf. Appendix, Section 4). These states are also more dependent on fossil energies (Energy Information Administration, State profile, 2017), which implies lower willingness to adopt and transmit green policies (Matisoff and Edwards, 2014). To further investigate this issue, we included the source states perspective in the same model. As expected, the odds of transmission are also lower compared to the reference category. Here again, we argue that non-environmental-friendly states, accounting for a large part of the considered scope, are reluctant to adopt environmental policies and to transmit such actions. The same argument holds for the coal mining state variable we have included (top coal producers tend to not transmit the policy).

On the opposite, both from source and target perspectives, Genuine Progress Indicator has a significant positive impact, the greatest with contiguity. This suggests that diffusion flows are more likely to come from sustainable states toward other greener states (i.e. economic system). Here again, this also matches the literature, suggesting that wealthier states are more likely to implement environmental policies and spread them (Volden, 2006). In addition, a majority of states belonging to the Northeast region together with identified central states in the network (i.e. facilitators) display a high Genuine Progress Indicator. From this view, GPI's effect on policy transmission is consistent.

Overall, our results show that contiguity and GDP are key determinants in the network formation process while environmental characteristics such as sustainable economic systems and expected climate change economic losses are relevant indicators to understand environmental policy flows.

## 2.6 Conclusion

In this paper, we propose a methodology to estimate the network of environmental policy diffusion across American states and evaluate the determinants from adoption data. By doing so, we contribute to the understanding of environmental policies diffusion and give policy-makers insights to maximize the spreading of green policies in the U.S.. We first infer environmental policy diffusion patterns from a built dataset covering 74 green policies (e.g. energy, climate, waste recycling) from 1974 to 2018. We then build a database of economic, political as well as environmental features for each considered state. Finally, we combine both of them in order to estimate the determinants of environmental policy diffusion.

Precisely, we estimate, via maximum likelihood, the parameters that best explain the observed patterns of environmental policies diffusion at the U.S. scale. This approach allows us to overcome the issue that bilateral diffusion events are generically not ob-

served. We have applied this methodology to environmental policies that were enacted across American states but not at the federal scale. Our framework treats each type of policy enacted by member states as a different policy, but does not use information about the strength of the policy. In this sense, our focus is much more on the extensive than on the intensive margin of environmental policy diffusion. We apply an epidemic-like model of network diffusion and we then assume that bilateral diffusion can be explained by a logit model taking into account the characteristics of source and target states as well as that of their bilateral relationship.

Our results emphasize the central role of Minnesota, California and Florida in the diffusion process while Alaska, South Carolina and South Dakota are among the less integrated states. These central states are among the most ambitious to tackle climate change as reported in recent studies (e.g. [Statista, 2019](#)). Our findings also suggest a disconnected dynamics of policy transmission between states belonging to the Northeast region and the rest of the country. Mainly, Eastern states tend to influence each other and are not sensitive to legislative actions occurring outside their region. Therefore, we evaluated the determinants of the network structure. We find that contiguity, economic and political aspects as measured by GDP per capita, Genuine Progress Indicator are key drivers of environmental policy diffusion. It is also found that the level of expected cost of climate change has a negative impact on the diffusion likelihood among considered states. Nevertheless, other specific characteristics are less relevant for the diffusion per se, although they might play a crucial role in the forthcoming years (i.e. in the large scale implementation of policies to limit climate change). As a result, this paper offers an in-depth analysis of the environmental policy diffusion network in the U.S., calling for regular updates to capture new emerging dynamics.

## Appendices of Chapter 2

### Description of Policies Database

*Adaptation to climate change:* Climate Adaptation Plan, Fire prevention policies, General Hazard Plan, Water Plan, Droughts Plan, Droughts Laws (NCLS), Flood Programs, Adaptation plan, Harvesting Water Program;

*Renewables support:* Wind Energy Support, Interconnection Standards, Electricity Portfolio Standards, Standards for Electricity Power plants, Solar rebate, Water rebate program (solar heating), Energy Efficiency Loan, Solar/Wind access Policy, Public Funds for RES, Performance Based Incentives, Training Program, Sales Tax Incentives, Loan Program, Personal Tax Credit, Property Tax Exemptions, Pace Program, Grant Program, Green Purchasing Power, Hydrogen, Biogas, Solar/Wind Permitting Standards, Mandatory Net Metering, Renewables Portfolio Standard, Corporate Tax Credit;

*Circular economy:* Water Efficiency, Composting, Beverage Program Nuclear Waste, Stewardship Recycling, Plastic Bag Recycling Policies, Electronic Recycling Program;

*Climate Policies:* Carbon pricing, GHGs Regulation, Carbon Capture and Storage, GHGs Emissions Targets, US Climate Action Plan;

*Energy Efficiency:* Smart Meter Policies, Energy Audits Refrigerator/Cooling, Air Conditioner Policies, Energy Efficiency - Analysis/services, Rebate Program, Energy Efficiency standards and targets, Building Energy Code, Energy Standards for Public Buildings;

*Environmental Concerns:* GMO Laws, Wildlife Conservation, Bees Keeping Policies, Land conservation, Fracking/Shale gas restrictions, Pollinator Laws, Farmers Markets, Drinking Water Conservation, Forests Management, Environmental Cleanup, Pesticides, Indoor Air Quality;

*Transportation :* Biofuel Policies, LEV Californian standards, Motor Fuel gas Tax Increase (2013 and so forth), Hydrogen Vehicle, Natural Gas Vehicle, Electric Vehicle Policies, Alternative Fuel Policies, Plug in electric vehicle Policies.

### **US Congress Platform : Keywords List**

*Circular economy:* Water Efficiency, Compost, Nuclear Waste, Recycling, Plastic Recycling, Electronic Recycling;

*Environmental Concerns:* GMO, Wildlife, Bees, Land conservation, Shale gas, Pesticides, Farmers Markets, Water Conservation, Forests, Environment Cleanup, Air Quality;

*Transportation :* Biofuel, LEV California, Motor gas Tax, Hydrogen Vehicle, Natural Gas Vehicle, EV, Alternative Fuel, PEV.

### Description of U.S. Census Bureau - Regions

<b>Northeast</b>	<b>Midwest</b>	<b>South</b>	<b>West</b>
Connecticut	Indiana	Delaware	Arizona
Maine	Illinois	District of Columbia	Colorado
Massachusetts	Michigan	Florida	Idaho
New Hampshire	Ohio	Georgia	New Mexico
Rhode-Island	Wisconsin	Maryland	Montana
Vermont	Iowa	North Carolina	Utah
New Jersey	Kansas	South Carolina	Nevada
New York	Minnesota	Virginia	Wyoming
Pennsylvania	Missouri	West Virginia	Alaska
	North Dakota	Alabama	California
	South Dakota	Kentucky	Hawaii
	Nebraska	Mississippi	Oregon
		Tennessee	Washington
		Arkansas	
		Louisiana	
		Oklahoma	
		Texas	

### Communities description

<b>1 - Blue</b>	<b>2 - Red</b>	<b>3 - Yellow</b>	<b>4 - Green</b>
Wyoming	Alabama	Arizona	Arkansas
Alaska	Connecticut	Florida	California
Colorado	District of Columbia	Indiana	Idaho
Georgia	Delaware	Iowa	South Dakota
Illinois	Massachusetts	Idaho	
Kansas	Maryland	Minnesota	
Kentucky	Maine	North Carolina	
Louisiana	Missouri	Oregon	
Michigan	Montana	Pennsylvania	
Mississippi	Nebraska	South Carolina	
North Dakota	New Hampshire	Utah	
Nevada	New Jersey		
Ohio	New York		
Oklahoma	Rhodes Island		
Texas	Tennessee		
Virginia	Vermont		
Washington	West Virginia		
Wisconsin			
New Mexico			

## Centrality Analysis

- The degree centrality of node  $i$ , which is simply given by its degree.
- The closeness of node  $i$ ,  $1/\sum_j d(j,i)$ , is based on the average distance of  $i$  and hence measures how fast a policy adopted in one state would, on average, reach another state in the network.
- The betweenness centrality of node  $i$  measures the share of shortest paths in the network on which node  $i$  lies. Hence, in our context, it measures to which extent a state can serve as a hub in the diffusion process.
- The eigenvector centrality is a recursive measure that assigns a high value to nodes which are connected to other important nodes. In this context, it can be seen as a measure of the total diffusion range (direct and indirect) of a policy, as a function of the initial adopting state.

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Table 2.6: Centrality Measures (1/2).

<b>Id</b>	<b>Label</b>	<b>Name</b>	<b>In-degree</b>	<b>Out-degree</b>	<b>Total degree</b>	<b>Closeness</b>	<b>Betweenness</b>	<b>Eigenvector</b>
2	AK	Alaska	5	4	9	0.403226	9.964373	0.266815
3	AL	Alabama	6	8	14	0.46729	32.094172	0.33571
4	AR	Arkansas	15	4	19	0.416667	41.055787	0.602801
6	AZ	Arizona	10	11	21	0.505051	48.239245	0.523698
7	CA	California	16	14	30	0.561798	141.143666	0.551276
8	CO	Colorado	2	10	12	0.505051	14.114863	0.087953
9	CT	Connecticut	6	9	15	0.490196	27.686538	0.28126
10	DC	Disctrict of Columbia	4	3	7	0.423729	5.891048	0.201624
11	DE	Delaware	10	6	16	0.442478	38.776702	0.361921
12	FL	Florida	13	15	28	0.561798	113.570467	0.547631
14	GA	Georgia	7	7	14	0.47619	26.518929	0.307814
16	HI	Hawaii	14	8	22	0.505051	115.124238	0.783867
17	IA	Iowa	5	9	14	0.471698	20.424889	0.229987
18	ID	Idaho	19	6	25	0.431034	60.88448	0.849111
19	IL	Illinois	6	7	13	0.5	29.107493	0.27493
20	IN	Indiana	6	7	13	0.462963	28.459926	0.263861
21	KS	Kansas	10	7	17	0.471698	52.518223	0.491029
22	KY	Kentucky	9	7	16	0.47619	49.7837	0.350142
23	LA	Louisiana	19	6	25	0.42735	67.385037	0.736789
24	MA	Massachusetts	4	13	17	0.555556	46.955657	0.234508
25	MD	Maryland	6	17	23	0.595238	78.798627	0.19677
26	ME	Maine	11	9	20	0.515464	91.453098	0.479913
27	MI	Michigan	5	9	14	0.49505	34.83789	0.142184
28	MN	Minnesota	23	16	39	0.568182	284.536563	1
29	MO	Missouri	11	10	21	0.510204	114.052441	0.680193
31	MS	Mississippi	13	8	21	0.47619	59.65885	0.580629
32	MT	Montana	10	10	20	0.49505	54.12704	0.3719
33	NC	North Car- olina	9	7	16	0.47619	65.095336	0.334858
34	ND	North Dakota	7	5	12	0.423729	19.040408	0.288743
35	NE	Nebraska	13	6	19	0.471698	51.14652	0.655084
36	NH	New Hamp- shire	8	9	17	0.505051	52.300423	0.332812

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Table 2.7: Centrality Measures (2/2).

<b>Id</b>	<b>Label</b>	<b>Name</b>	<b>In-degree</b>	<b>Out-degree</b>	<b>Total degree</b>	<b>Closeness</b>	<b>Betweenness</b>	<b>Eigenvector</b>
37	NJ	New Jersey	12	10	22	0.515464	94.389463	0.493553
38	NM	New Mexico	5	10	15	0.531915	22.768328	0.106734
39	NV	Nevada	10	8	18	0.47619	51.162607	0.376089
40	NY	New York	3	12	15	0.537634	34.535164	0.14357
41	OH	Ohio	6	7	13	0.438596	36.367952	0.244487
42	OK	Oklahoma	5	8	13	0.446429	30.605094	0.153615
43	OR	Oregon	6	10	16	0.505051	55.651683	0.332255
44	PA	Pennsylvania	5	10	15	0.537634	23.343624	0.211064
46	RI	Rhode Island	2	10	12	0.520833	12.871703	0.066546
47	SC	South Carolina	1	7	8	0.47619	7.576828	0.06823
48	SD	South Dakota	8	4	12	0.381679	17.641288	0.429481
49	TN	Tennessee	4	8	12	0.49505	26.905995	0.175553
50	TX	Texas	8	11	19	0.505051	58.7092	0.444035
51	UT	Utah	14	8	22	0.480769	118.636159	0.601942
52	VA	Virginia	7	13	20	0.520833	50.923421	0.285089
54	VT	Vermont	8	7	15	0.47619	46.132237	0.30207
55	WA	Washington	5	9	14	0.515464	15.410143	0.2304
56	WI	Wisconsin	9	11	20	0.520833	87.318358	0.420461
57	WV	West Virginia	6	5	11	0.423729	23.606168	0.148295
1	WY	Wyoming	14	5	19	0.413223	50.697955	0.552087

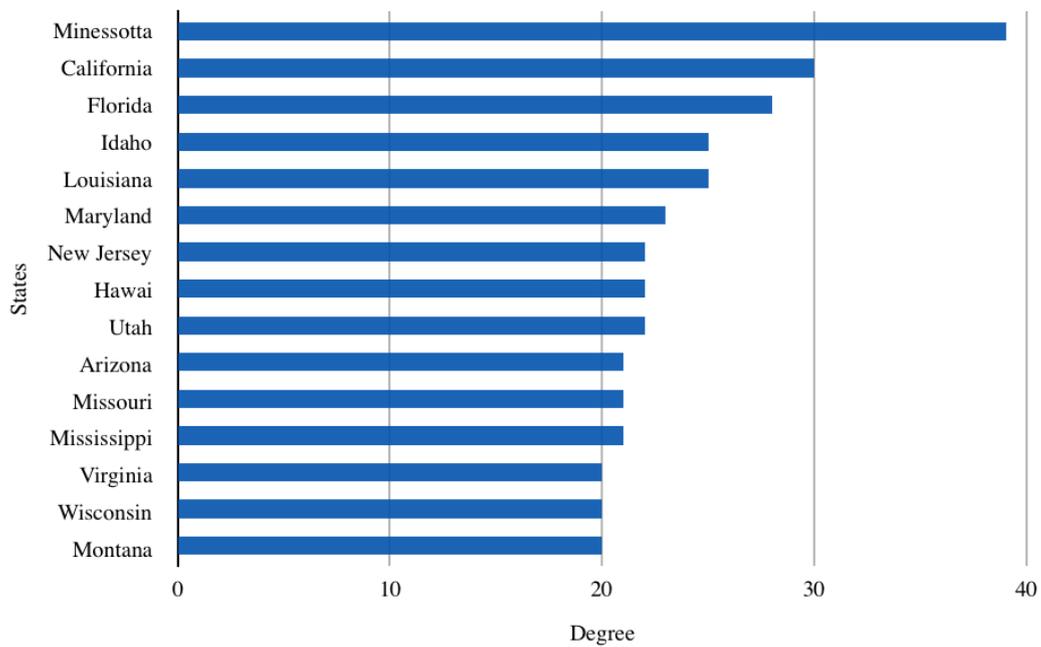


Table 2.8: Top rankings according to centrality indicators (1/6).

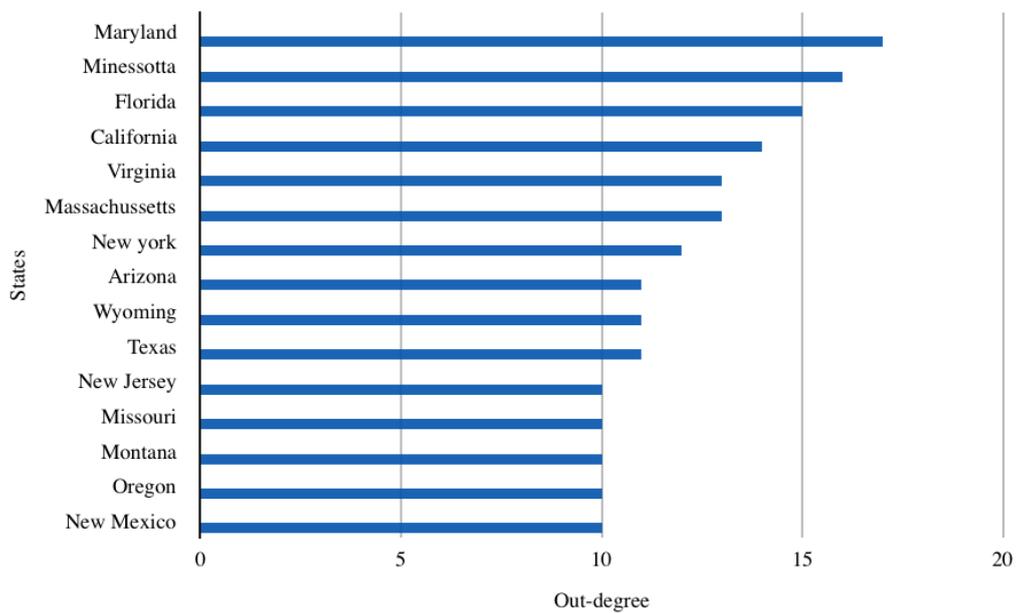


Table 2.9: Top rankings according to centrality indicators (2/6).

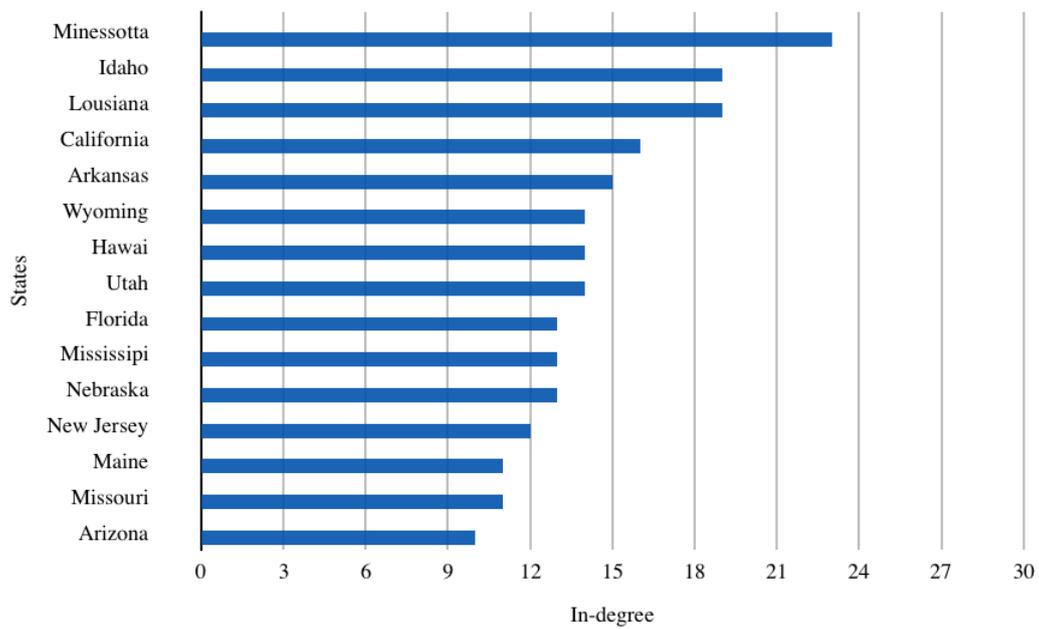


Table 2.10: Top rankings according to centrality indicators (3/6).

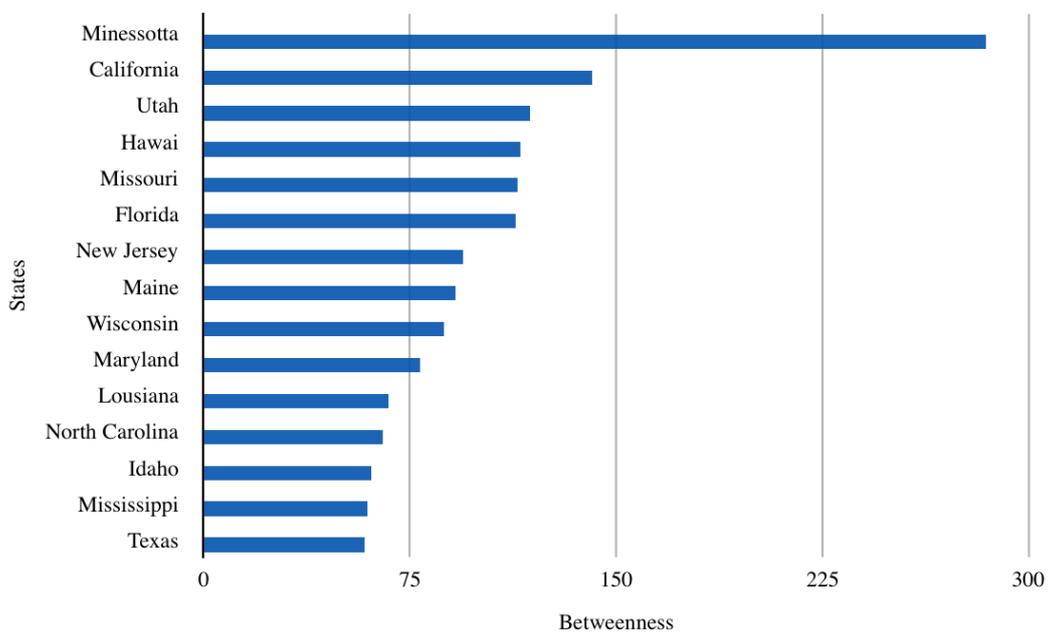


Table 2.11: Top rankings according to centrality indicators (4/6).

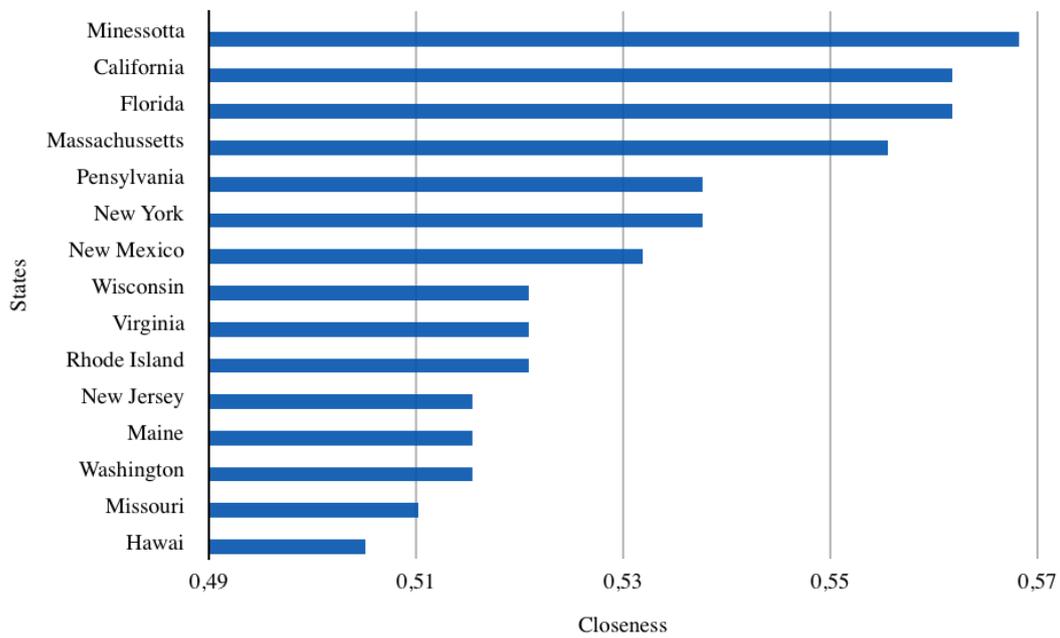


Table 2.12: Top rankings according to centrality indicators (5/6).

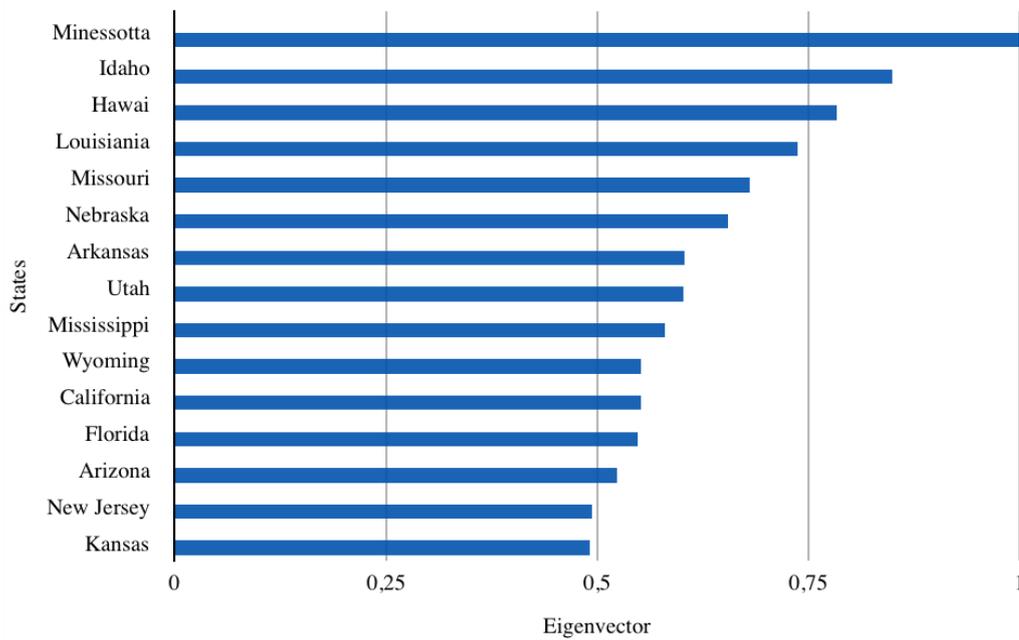


Table 2.13: Top rankings according to centrality indicators (6/6).

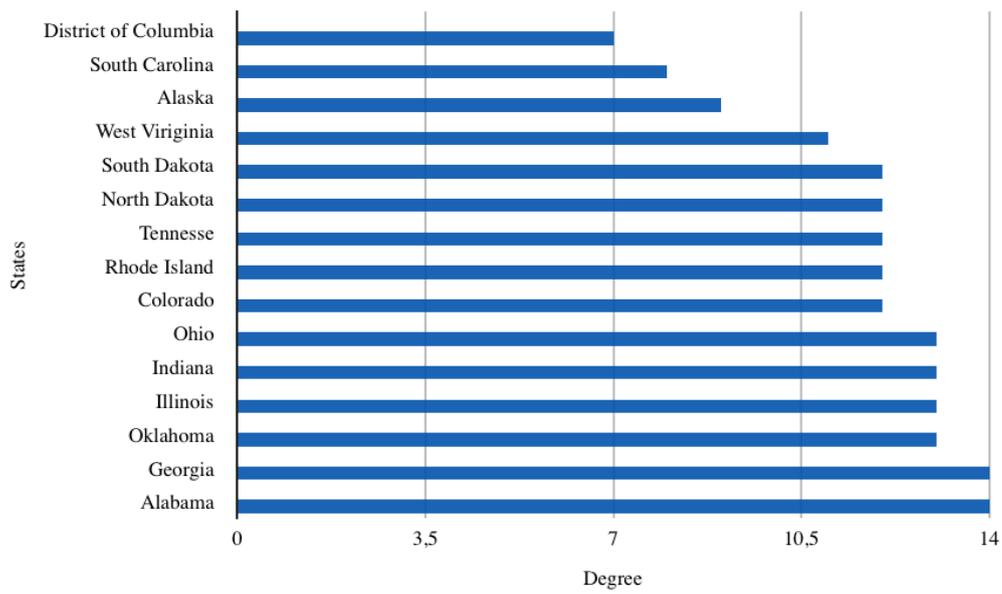


Table 2.14: Ranked last according to centrality indicators (1/6).

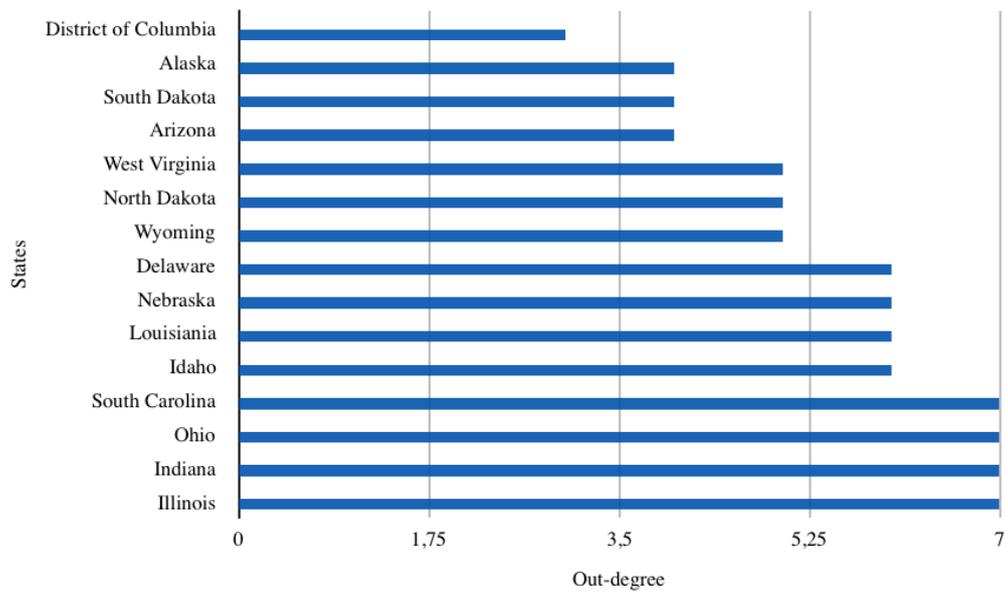


Table 2.15: Ranked last according to centrality indicators (2/6).

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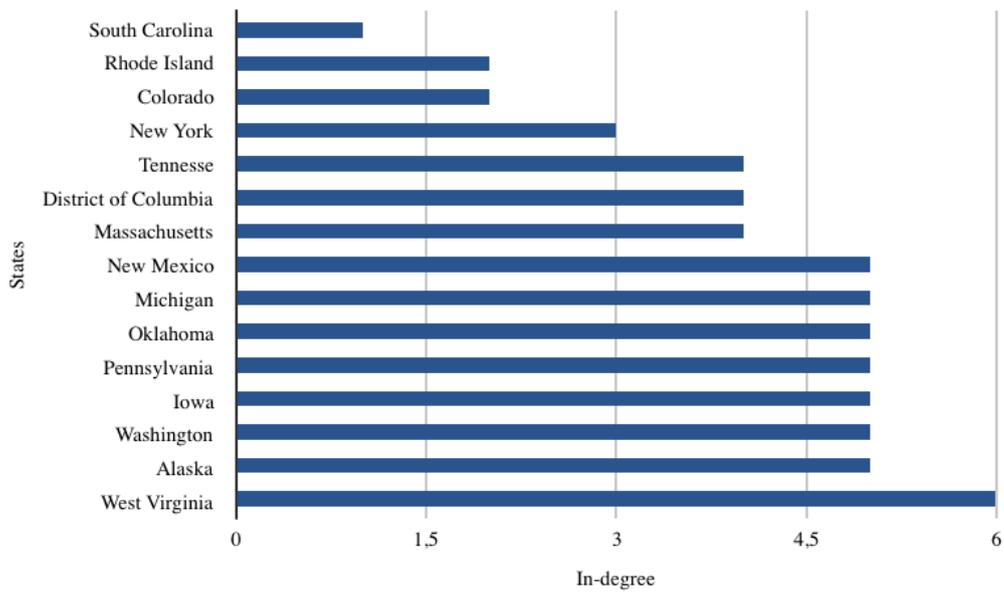


Table 2.16: Ranked last according to centrality indicators (3/6).

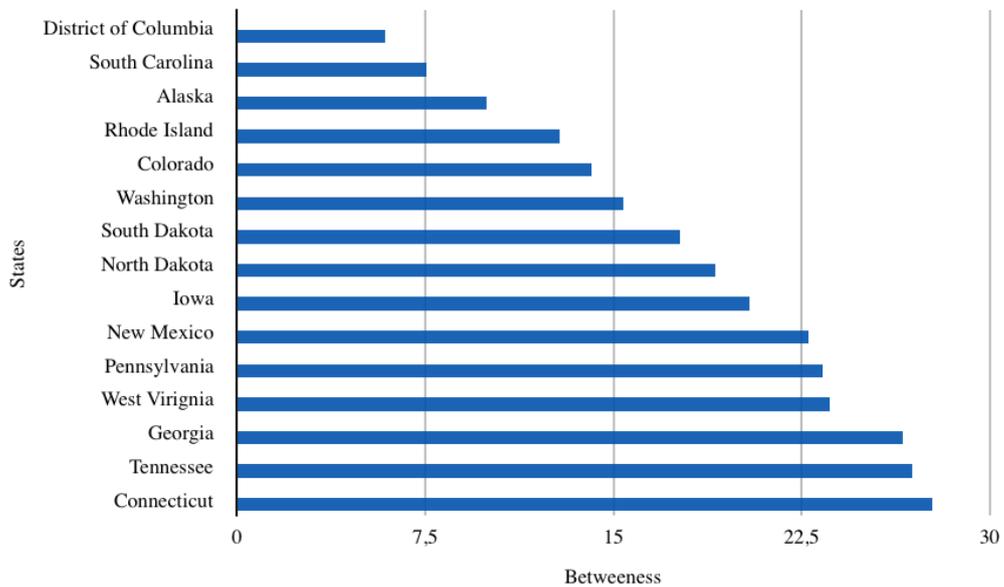


Table 2.17: Ranked last according to centrality indicators (4/6).

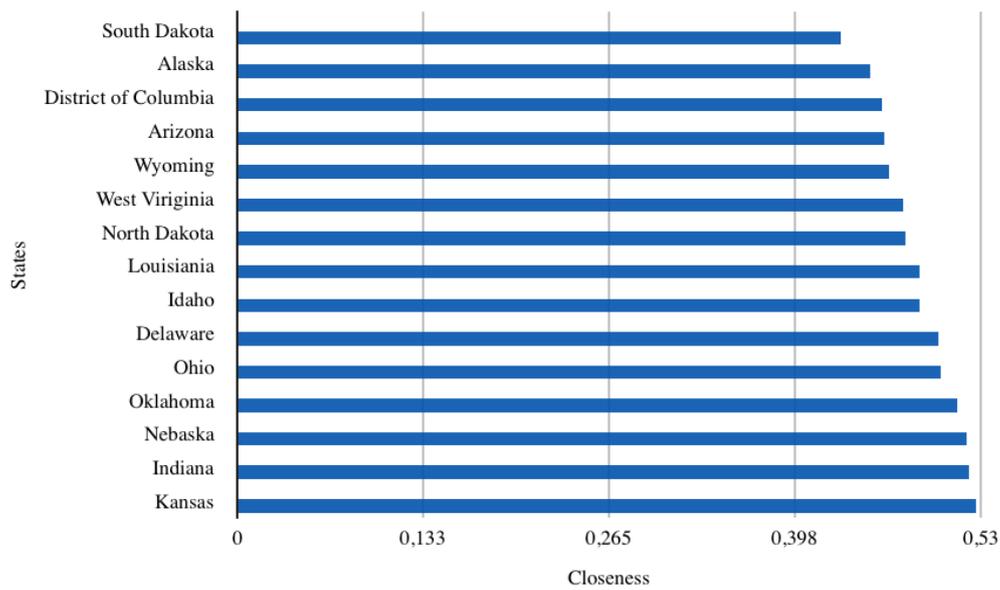


Table 2.18: Ranked last according to centrality indicators (5/6).

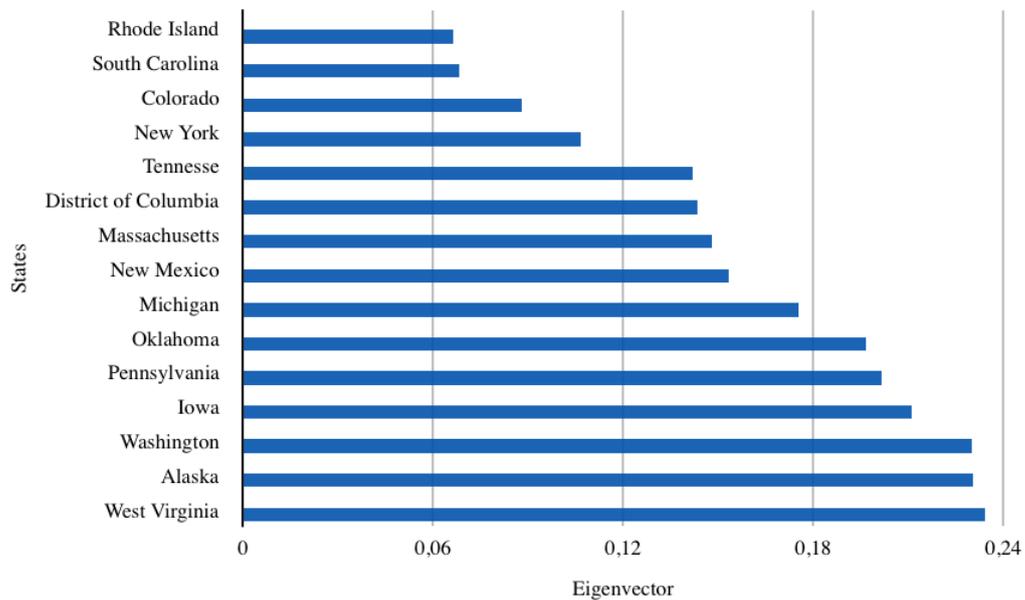


Table 2.19: Ranked last according to centrality indicators (6/6).

## Figures A - Networks

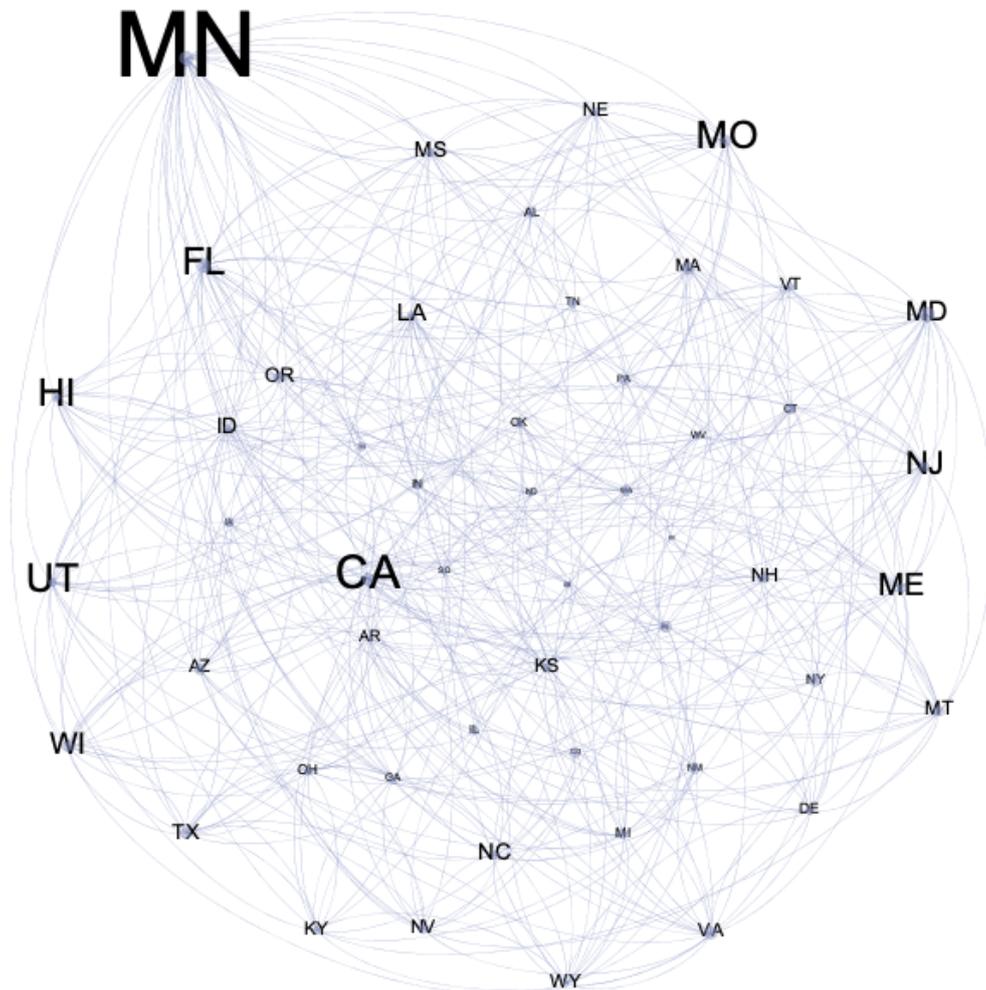


Figure 2.4: Reconstructed network using Force Atlas layout. The node size is proportional to betweenness centrality, a centrality measure capturing the notion of hubs facilitating policy flows.

CHAPTER 2. HOW ENVIRONMENTAL POLICIES SPREAD ? A NETWORK APPROACH TO DIFFUSION IN THE U.S.

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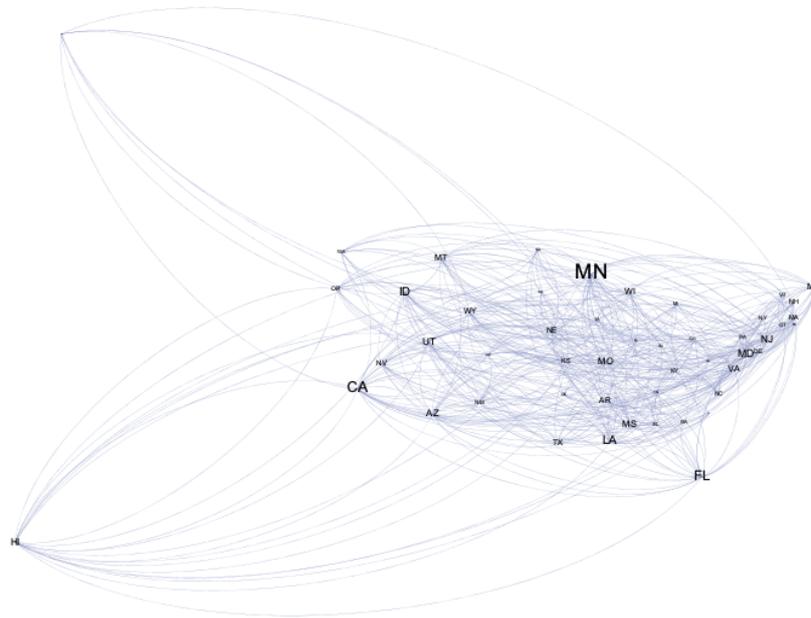


Figure 2.5: Reconstructed network using geographical layout. The node size is proportional to the degree centrality.

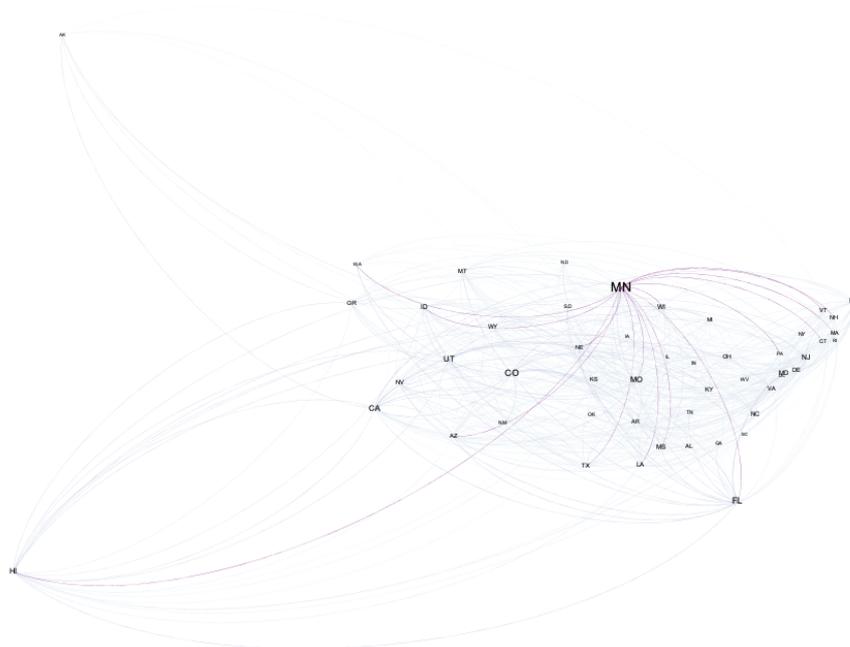


Figure 2.6: Reconstructed network using geographical layout. The node size is proportional to the betweenness centrality.

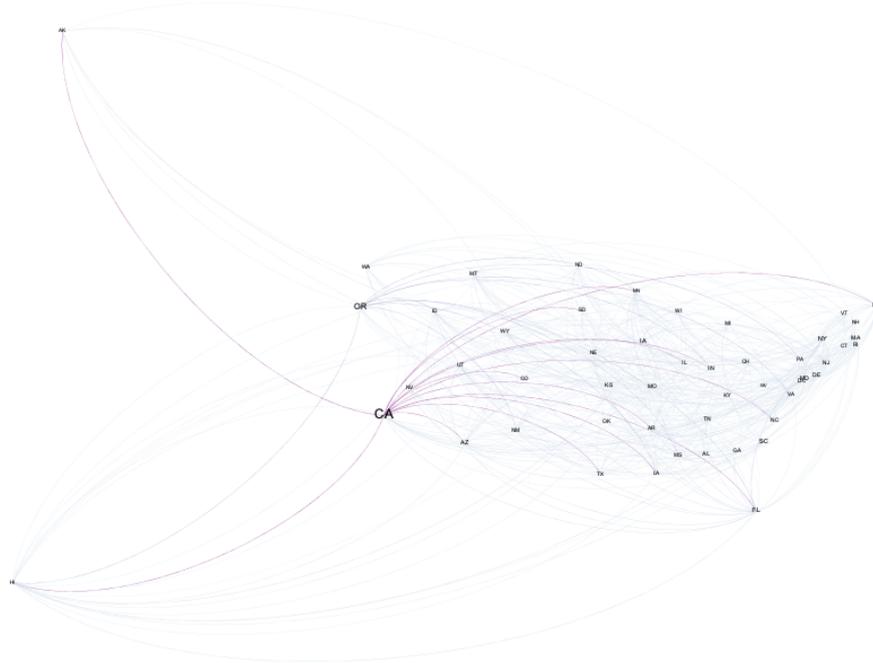


Figure 2.7: Reconstructed network using geographical layout. The node size is proportional to the weighted out-degree ranking.



Figure 2.8: Reconstructed network using geographical layout. The node size is proportional to the weighted in-degree ranking.

## Figures B - Evolution of network

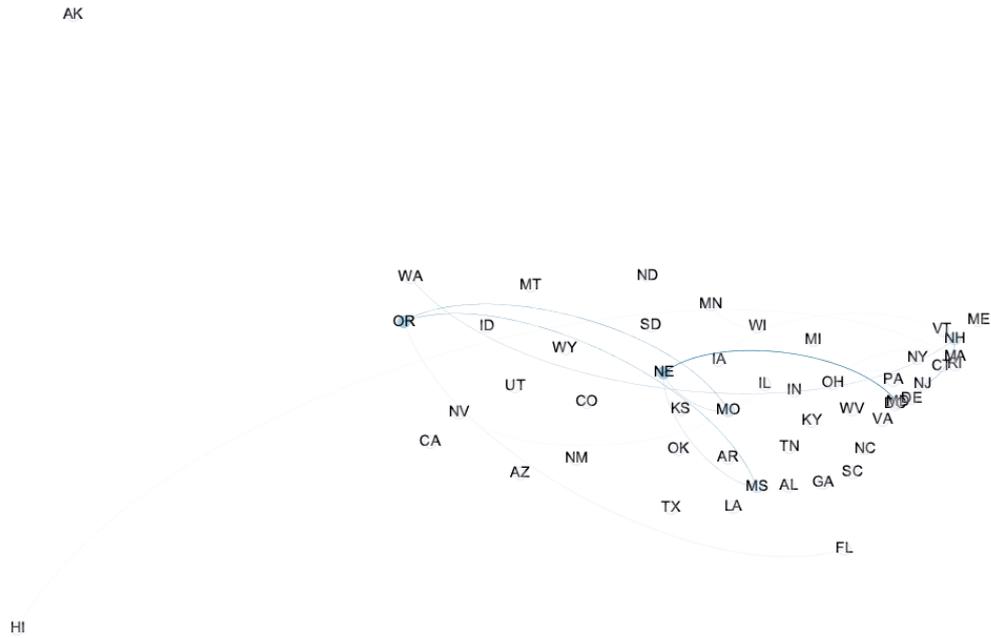


Figure 2.9: 1974-1992

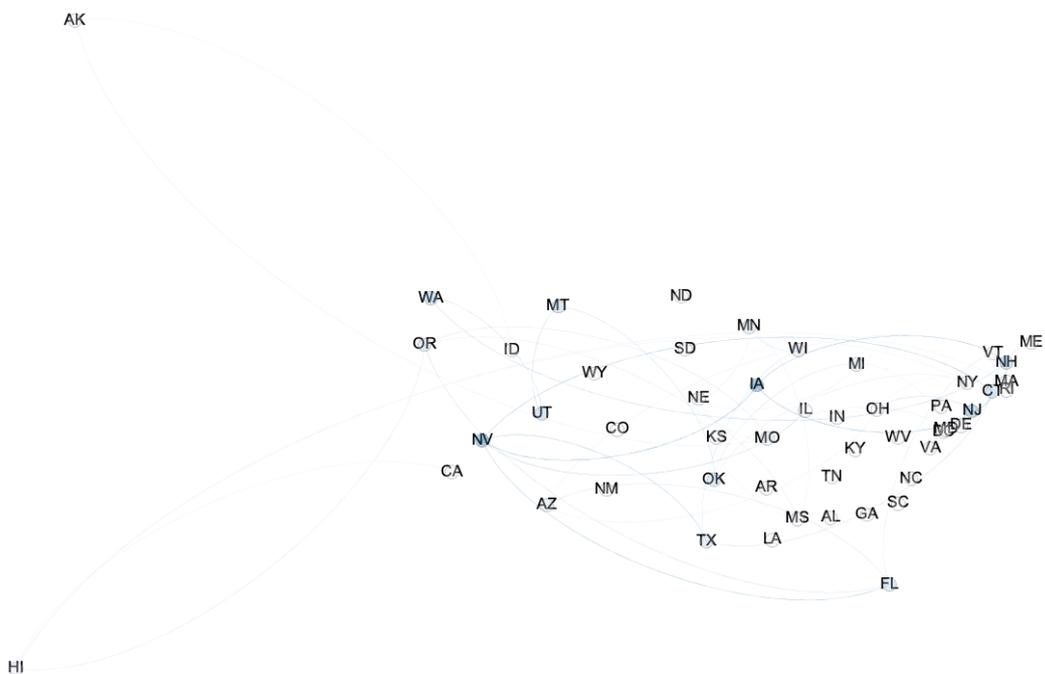


Figure 2.10: 1974-2000

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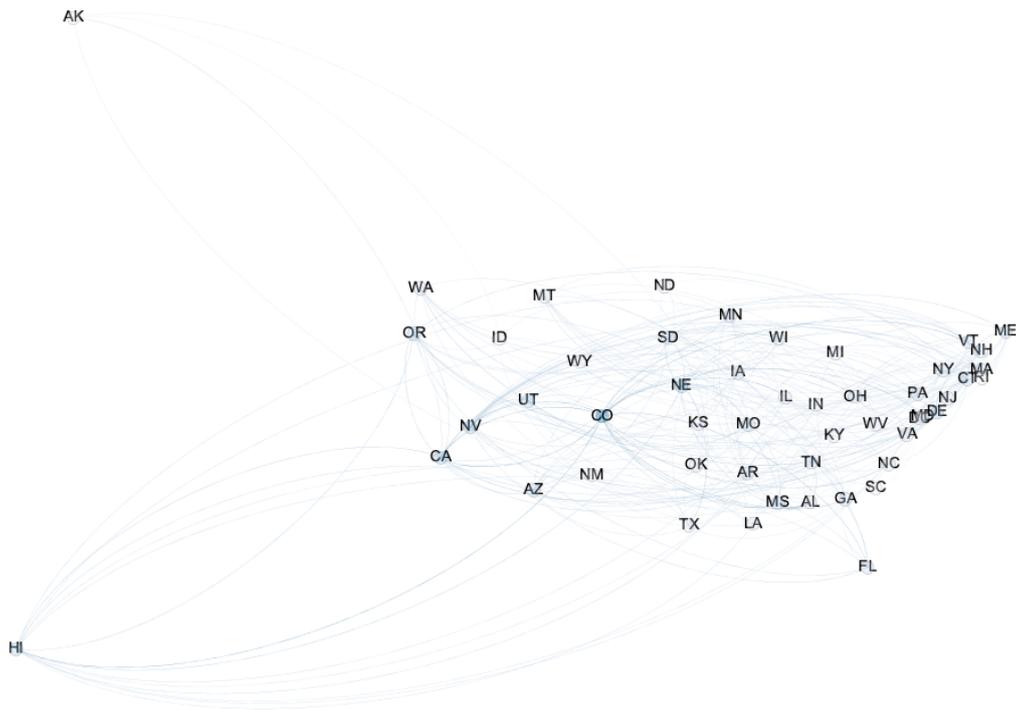


Figure 2.11: 1974-2008

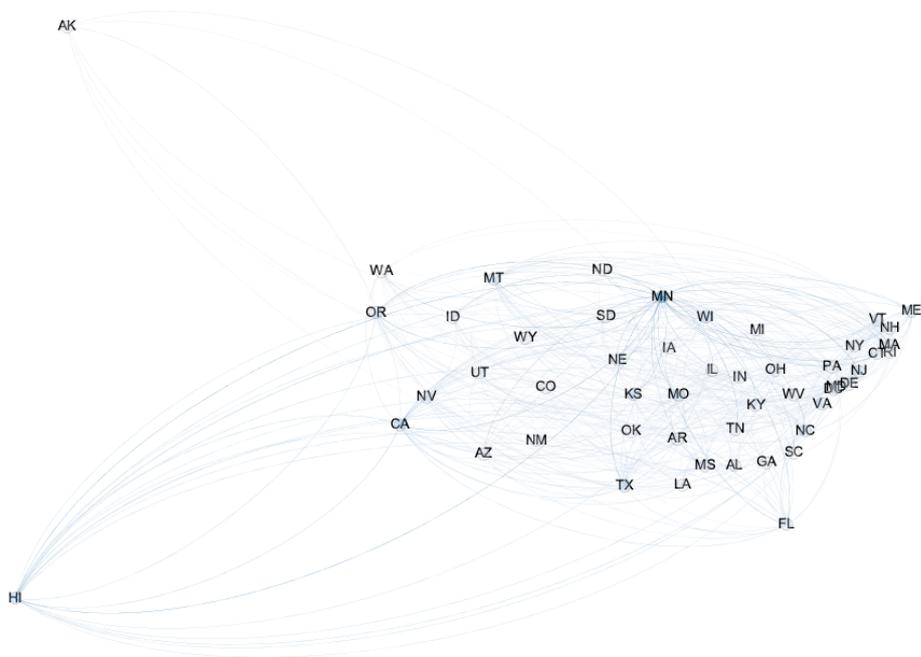


Figure 2.12: 1974-2016

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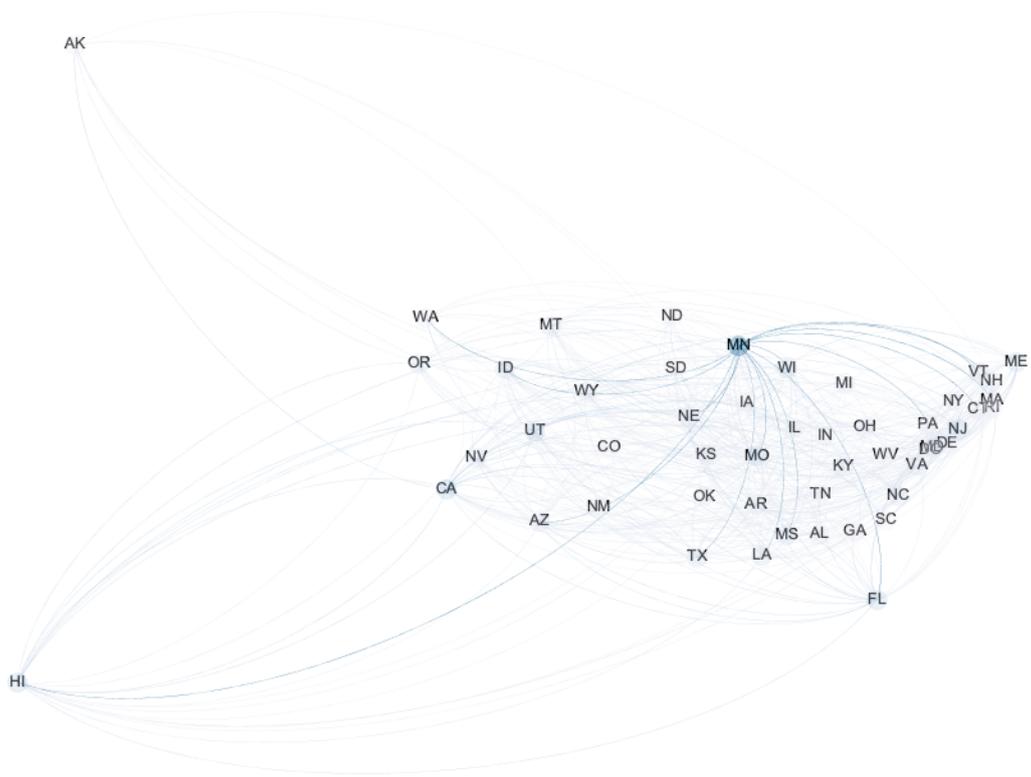


Figure 2.13: 1974-2018

## Determinants of Network Formation

**Contiguity** : Depending on the geography, 0 = not neighbors, 1 = neighbors.

**GDP per capita** : Overtime.

**Population Density** : Overtime, 0 = from 13th to 51st rank , 1 = from 1st to 12th most densely populated states.

**States Governors Colors** : Depending on the party, 0 = Republican, 1 = Split, 2 = Democratic.

**Federal Government Party** : Depending on the party, 0 = Republican, 1 = Democratic.

**Citizen Ideology** : Overtime.

**Climate Change Economic Impacts** : We create 4 categories : 0 = -5% of GDP losses, 1 = +5% GDP losses. Initial Dataset from Hsiang et al. (2017) : <http://www.globalpolicy.science/econ-damage-climate-change-usa>.

**Genuine Progress Indicator** : Based on Fox and Erickson (2018), depending on the level, low = 0, high = 1.

**Coal Mining State** : Based on the EIA coal data production, we select the top States appearing in blue color in the coal data browser map (<https://www.eia.gov/coal/data>).

## Additional Networks

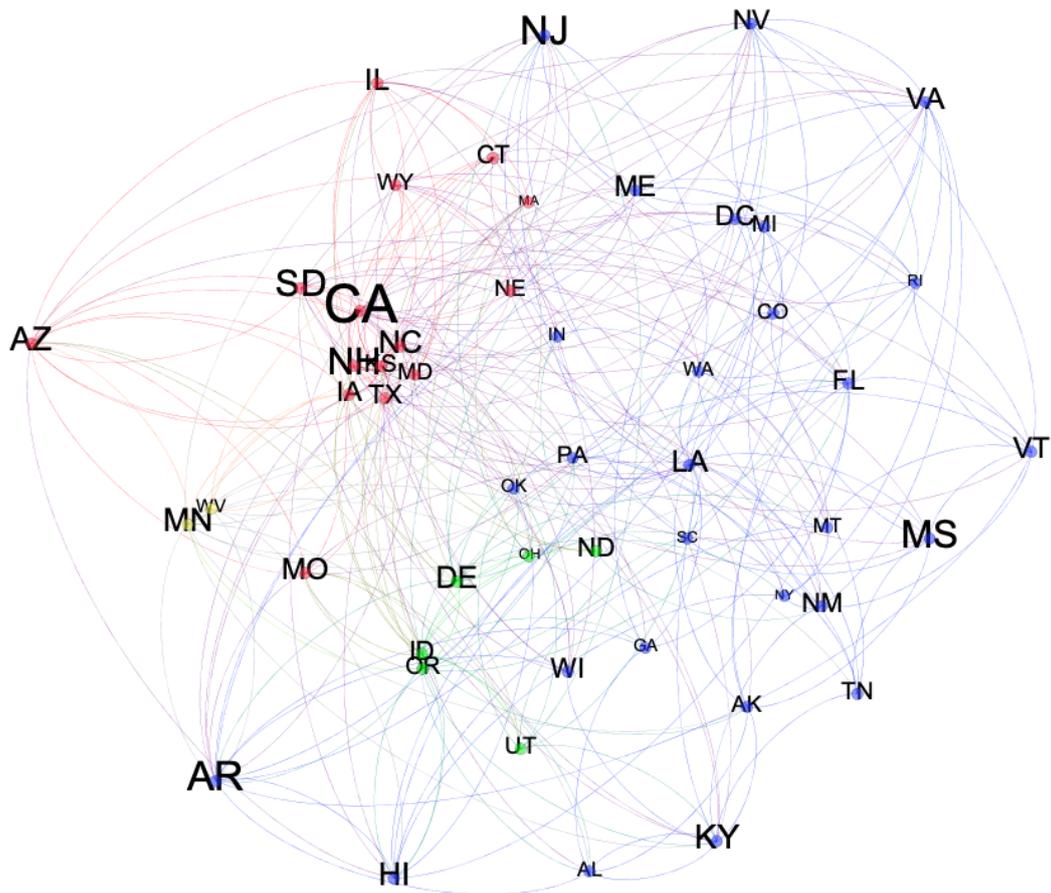


Figure 2.14: Energy Network inferred using Force Atlas Layout. Communities are colored and the node size is proportional to the betweenness centrality indicator.

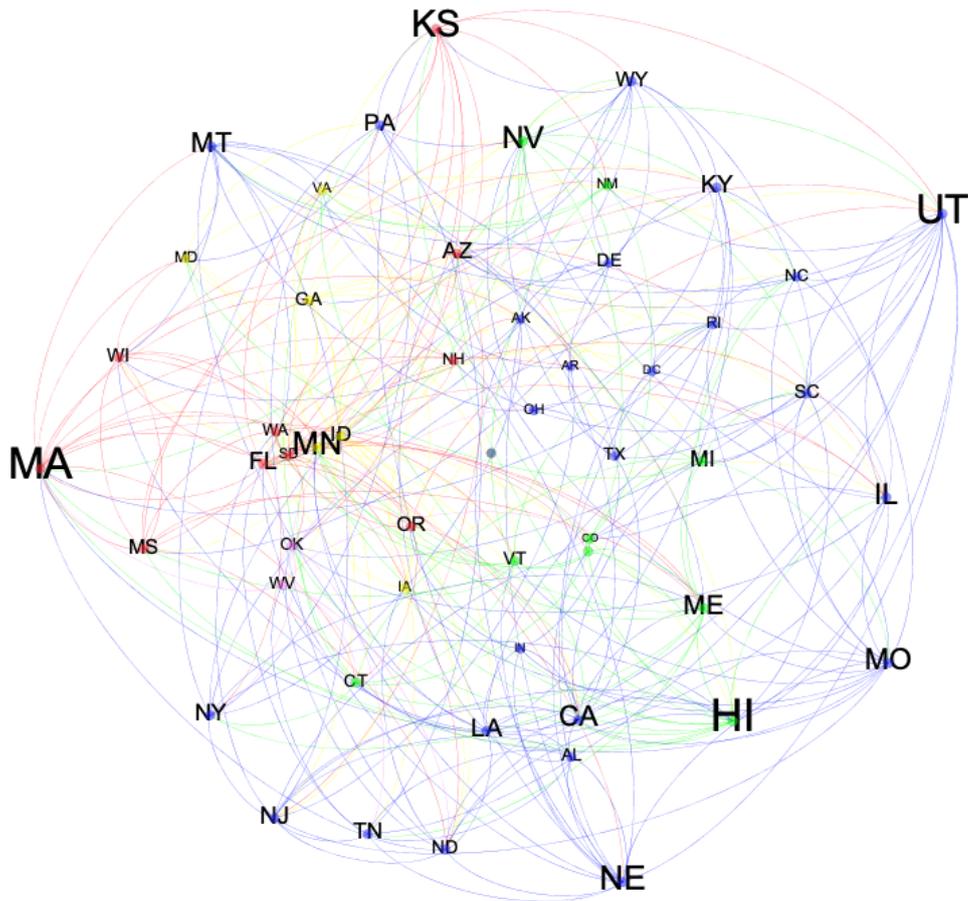


Figure 2.15: Environmental and Climate Network inferred using Force Atlas Layout. Communities are colored and the node size is proportional to the betweenness centrality indicator.

\* \* \*



## Chapter 3

# Triggering Reduction of Imported Emissions in the E.U.

\* \* \*

We implement a methodology to identify the sectors likely to trigger relevant imported emission reductions. We show how, in a sample of five European countries, mining as well as basic metals industries are among those with the highest emission reduction coefficients. We then identify the relevant channels of cascades of imports contraction across sectors. Results emphasize the key role of basic metals in reducing imported emissions. Finally, we estimate the short run impact of a \$25 carbon tax on basic metals imported emissions. We show that affected downstream sectors are identical across countries although disparities appear in terms of economic impacts.

\* \* \*

*This chapter is an adaptation of a joint work with Pr. Anna Creti.*

### 3.1 Introduction

In July 2020, the European Council exposed the *NEXT GENERATION EU* plan, a €750 billion economic instrument to "support the recovery and resilience of the economies of the Member States" following the COVID-19 chaotic crisis ([Special meeting of the European Council, 2020](#)). While such instrument aims at repairing the immediate economic and social damages caused by the pandemic, achieving environmental objectives previously set by the European Commission remain a priority of the plan. Back in December 2019, the President of the European Commission exposed her Green Deal project for Europe with the ambition to make the continent climate-neutral by 2050 ([European Commission, 2019](#)). Among the set of announced sectoral targets, the E.U. leader expressed a resurgent interest in tackling imported emissions to limit carbon leakage.<sup>1</sup> The suggested implementation of a border adjustment mechanism<sup>2</sup> to achieve this objective has raised concerns across the globe, especially among EU trading partners ([Financial Times, January 2020](#)). Indeed, such a policy instrument would target carbon-intensive imports, affecting their competitiveness on the market. Although a border tax may create trade partnership issues, it would generate an additional revenue for the Union whilst limiting imported emissions and carbon leakage comes as a prerequisite to reach the climate objectives set in the [Paris Agreement \(2015\)](#) ([Görlach and Zelljadt, 2019](#)).

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<sup>1</sup>Carbon leakage refers to the effect in which carbon prices drive up relative costs and reduce the relative competitiveness of EU firms such that their output falls. Some of the output transfers to overseas producers with the rest accounted for by reduced domestic consumption, which leads to changes in carbon dioxide emissions both within and outside the EU. Carbon leakage refers to the increase in emissions resulting from the relocation of production ([Vivid Economics, 2014](#)).

<sup>2</sup>A trade measure designed to level the playing field between domestic producers facing costly climate policy and foreign producers with no or little constraint on their GHG emissions ([Ismer and Neuhoff, 2007](#)).

The topic of imported emissions has gained a particular attention over the last decade as researchers pointed out a critical gap between territorial and consumption-based emissions<sup>3</sup> (Barrett et al., 2013; Karstensen et al., 2018). Regarding E.U. countries, the United Kingdom provides a good example of such disconnection (Carbon Brief, 2017). Indeed, in 2014 territorial emissions reached 402 million tonnes of CO<sub>2</sub> while emissions embodied in consumption represented 656 million tonnes (Office of National Statistics, 2019). These figures highlight the responsibility of such states in driving foreign countries' territorial emissions, therefore challenging the success of domestic environmental policies addressing carbon leakage. From that perspective, the E.U. political will to limit imported emissions is of significant relevance.

In academia, a large strand of the literature has focused on areas such as evaluating the level of emissions embedded in international trade (Peters et al., 2011; Kanemoto et al., 2014; Kim et al., 2019; Simola, 2020), the legislative design of economic instruments to limit such emissions (Tamioti, 2011; Holzer, 2014; Mehling et al., 2019) and their potential impacts (Monjon and Quirion, 2011; Fisher and Fox, 2012; Droge et al., 2019). While impacts would mainly concern intermediate demand rather than final demand (Simola, 2020),<sup>4</sup> targeting imported products according to their respective emissions is relevant from a carbon intensity perspective. However, if one considers the economy as a system of industries interacting with each others (OECD, 2016), a limit of the aforementioned approach is to fall short on capturing the dynamics of supply/demand for imports and associated emissions. Indeed, imports of an industry might be used directly as inputs or as output supplied to other sectors (e.g. imports of the mining sector are consumed as inputs by that industry or supplied as inputs to the basic metals sector).<sup>5</sup> The reduction in production from the mining sector would

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<sup>3</sup>Territorial emissions are allocated to the country and sector, where the emissions physically are released into the atmosphere, and this principle is used for emission inventories officially reported to the UNFCCC; Consumption-based emissions are allocated to where final consumption of goods and services occurs. The gap between the two represents imported emissions (after removing emissions embedded in exports).

<sup>4</sup>Industries using steel and iron ores as inputs. See Simola (2020) for full analysis.

<sup>5</sup>See E.U. inter-country supply, use and input-output tables (2019), p.17 for description.

reduce the sector output and impact demand-side sectors. Then, following the chain of intermediate demand, industries directly connected such as basic metals would in turn reduce their output, including their imports. Such a cascading mechanism of imports contraction would decrease associated emissions.<sup>6</sup> While some studies have explored phenomenon of economic cascades (e.g. information in financial markets (Romano, 2007), the diffusion of risks in the banking system (Battiston et al., 2017) or the stranding of dirty assets in a low carbon economy (Cahen-Fourot et al., 2019)), the topic of limiting imported emissions has not been investigated thoroughly, and never from a systemic perspective.

This chapter fills this literature gap by providing an original analysis of the process through which a reduction of imports of a specific sector would affect the demand for imports of other sectors and reduce associated emissions. We illustrate our model using data available for five European countries (i.e. France, Germany, Italy, Poland and the United Kingdom).

First, we use national Input-Output (IO) tables to derive economic matrices of *imported emission reduction coefficients* (*ERC*), covering the entire range of the industrial sectors. These coefficients capture the amount of imported emissions that would be cut (i.e. reduced) in a sector due to a unitary drop in primary inputs<sup>7</sup> utilised by another (or the same) sector, considering both direct and indirect impacts. For instance, these matrices are able to provide the imported CO<sub>2</sub> emissions reduction in the textile sector due to a drop in the plastics industry, both directly and through its intermediate effects on, for instance, chemicals. By doing so, we identify the industries most likely to trigger large emission reductions and those most exposed to a reduction of imported emissions (i.e. through the channel of another sector). The relevance of the present analysis is to maintain a systemic perspective of the national economy, and investigate

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<sup>6</sup>In the following, we name "cascading process" such a dynamics of contraction.

<sup>7</sup>We define "primary inputs" as the main factors used in production (labour, capital, land, and others). IO tables report their factor costs (e.g. compensation of employees, consumption of fixed capital or net operating surplus) (Miller and Blair, 2009).

the transmission channels of imported emission contraction across industries (via a cascading reduction of imports).

Whatever the economic system, we highlight how mining<sup>8</sup> as well as manufacture of basic metals<sup>9</sup> are among the sectors with the largest emission reduction coefficients.<sup>10</sup> On the opposite, coke and refined petroleum, basic metals and electricity and gas industries are the most exposed to a reduction of imported emissions in economic systems. Overall, these activities have various ranges of impacts across economies. These results hint at the existence of different national strategies regarding international trade openness (i.e. sectoral level of imports), thus leading to heterogeneous exposures to an economic instrument targeting imported emissions.

Second, we focus our study on the mining industry in order to investigate the most relevant channels of sectoral cascades of emission reductions (imports). By doing so, we are able to evaluate the role of sectors such as basic metals and coke and refined petroleum in the cascading process. While countries exhibit different cascade processes depending on the characteristics of their industrial structure, certain regular patterns emerge. On one hand, together with basic metals (e.g. iron and steel) and the manufacture of coke and refined petroleum products,<sup>11</sup> electricity and gas are the most directly exposed to emission reduction through import contraction from mining. Such results suggest a strong economic connections between the mining industry and these sectors where the former supplies the latter. On the other hand, irrespective to their rankings in the process, chemicals and pharmaceutical products,<sup>12</sup> machinery

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<sup>8</sup>The sector encompasses coal and lignite, crude petroleum and natural gas, metal ores, other mining and quarrying products and mining support services.

<sup>9</sup>The sector covers basic iron, steel, aluminium and ferro-alloys, tubes, pipes, hollow profiles and related fittings, of steel Other products of the first processing of steel, basic precious and other non-ferrous metals.

<sup>10</sup>These results are in line with the imports intensity of the sectors and associated emissions. See [OECD, STAN 2018](#) for a detailed description.

<sup>11</sup>Includes coke oven products and refined petroleum products.

<sup>12</sup>Sector covers basic chemicals, fertilisers and nitrogen compounds, plastics and synthetic rubber in primary forms, pesticides and other agrochemical products, paints, varnishes and similar coatings, printing ink and mastics, soap and detergents and other chemical products.

and equipment<sup>13</sup> and manufacture of other non-metallic mineral products<sup>14</sup> are highly present in the third and fourth layer of the cascading process. In addition, a large share of manufacturing sectors (e.g. motor and vehicles, fabricated metal products, electrical equipment<sup>15</sup>) are impacted by mining reduction through the channel of basic metals. From a policy perspective, these findings emphasize that moving away from mining would have impacts not only on emissions (Fugiel et al., 2017), but would also generate economic effects on other sectors (i.e. from mining to downstream industries such as machinery and equipment through the channel of basic metals). On this issue, our findings complement the flourishing literature on assets at risk due to a low carbon transition (Caldecott, 2017; Creti and de Perthuis, 2019) and calls for a well-designed policy to limit such effects (e.g. loss of competitiveness due to a lack of substitutes for inputs/imports).

Finally, we concentrate our analysis on the basic metals industry as a channel of emission reductions toward downstream industrial sectors. We simulate the full multiplied impact of a uniform \$25 per tonne carbon price<sup>16</sup> on these products. We exclusively focus on these imports as the E.U. has expressed a strong interest in experimenting such a policy (Reuters, October 2019).<sup>17</sup> Our findings suggest that, on the short run, the majority of industries would see their imported input costs increase by less than one per cent (in France, Germany and the United Kingdom). Apart from basic metals, the sector of fabricated metal products is the most affected, reaching more than 1% increase in the total cost of imported input in Italy and Poland (emphasizing how heterogeneous are E.U. economies). By reducing competitiveness, the implementation

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<sup>13</sup>Industry includes general-purpose machinery, other general-purpose machinery, agricultural and forestry machinery, metal forming machinery and machine tools, other special-purpose machinery.

<sup>14</sup>The activities include glass and glass products, refractory products, clay building materials, other porcelain and ceramic products, cement, lime and plaster, articles of concrete, cement and plaster, cut, shaped and finished stone.

<sup>15</sup>The sector includes electric motors, generators, transformers and electricity distribution and control apparatus, batteries and accumulators, wiring and wiring devices, electric lighting equipment, domestic appliances and other electrical equipment.

<sup>16</sup>For easiness, the currency is in \$ as our IO Tables are expressed in that currency.

<sup>17</sup>Precisely, we set a carbon price amount of 25\$ to be aligned with the 2019 average EU-ETS price (cf. International Carbon Action Partnership, 2020).

of such a tool would put the sectors under pressure of competition from other clean substitute products.

The remainder of the article is organised as follows. [Section 2](#) reviews the related literature. [Section 3](#) introduces the method to compute the matrices of sectoral *emission reduction coefficients*. [Section 4](#) presents the results of the analysis for five European countries, discussing the sectors most likely to create large emission reduction coefficients and the ones most exposed to emission reductions. [Section 5](#) focuses on understanding the systemic propagation of shocks starting from mining in order to identify relevant channels of emission reductions and provides insights on the sectors easing the dynamics. [Section 6](#) simulates the impact of a \$25 carbon tax on imported emissions from basic metals. The economic impact on total cost of imported inputs is exposed by sectors. Finally, [Section 7](#) concludes.

## 3.2 Literature : Input-Output, Emissions embedded in Trade and Border Adjustments Mechanisms

Our paper connects different strands of the literature. The first is a fast growing literature that looks at the propagation of shocks in an interconnected economy ([Acemoglu et al., 2012](#); [Acemoglu et al., 2015](#); [Battiston et al., 2017](#); [Cahen-Fourot et al., 2019](#), [King et al., 2019](#); [Mandel et al., 2019](#)). Based on concepts and methods borrowed from IO approaches and network analysis, we complement these studies by providing an alternative methodology to study the shock of transitioning away from carbon imports in an economy. Following [Blochl et al. \(2011\)](#), [Joya and Rougier \(2019\)](#), [Cahen-Fourot et al. \(2020\)](#) and others, we consider input-output linkages as the links of a directed weighted network capturing the complex system of economic interconnections among productive sectors. Unlike most of the previous research, we do not study the effect of

demand-driven sectoral shocks on aggregate output volatility. Indeed, following the objective of our research, the origin of the shock is located into the industrial sectors. The latter makes a supply side approach more relevant compared to a final demand perspective. For this reason, we consider a supply-driven IO model provided by Ghosh (1958) and incorporate emissions data on imported products. The Ghosh model can be implemented to estimate the relevance of industrial sectors in contributing to downstream economic activity through the calculation of sectoral “forward linkages” (see for instance Aldasoro and Angeloni, 2015; Antras et al., 2012) or, in the case of this paper, their relevance in supporting imports demand. On the theoretical side, some studies have questioned the model’s ability to assess forward leakages due to some strong assumptions such as perfect elasticity of demand (facing changes in supply) and perfect substitutability among input factors (Oosterhaven, 1988; Galbusera and Giannopoulos, 2018). As exposed by Dietzenbacher (1997), such criticisms can be solved when treating the model as a price model. In our case, these issues are mitigated as we are not considering the question of excess output supply allocation.

The second strand of the literature our paper connects is a growing bunch of works on measuring emissions embedded in international trade. Many research studies used MRIO (Multi-Regional Input–Output) models to estimate embodied CO<sub>2</sub> emissions in different countries (Machado et al., 2001; Lin and Sun, 2010; Makarov and Sokolova, 2015; Jiang, 2016; Stefan et al., 2019). More recently, MRIO models were used in the assessment of embodied CO<sub>2</sub> emissions of developing countries (e.g. Brazil, Russia, India, China) in a scope of trade globalization. Results emphasized that both Russia and China were the main exporters of CO<sub>2</sub> emissions due to massive exports of energy and carbon intensive final demand goods (Yang, 2012; Boitier, 2012). Regarding methodology for accounting emissions, previous papers have explored the feasibility of using consumption-based emissions to calculate carbon emissions and determine national emission responsibilities, at both global and national levels. At the global level, emission characteristics triggered by multinational trades have been studied (Peters

et al., 2011). At the national level, consumption-based carbon emissions have been assessed in many countries, such as Australia (Wood and Dey, 2009), China (Su et al., 2010), Italy (Mongelli et al., 2006), Turkey (Tunç et al., 2007) and the U.K. (Barrett et al., 2013).

Finally, a large body of studies relates to the impacts of trade measures (e.g. border adjustment mechanisms) aiming at tackling carbon emissions, their associated impacts (e.g. carbon leakage, competitiveness) and the legislative framework allowing such economic mechanisms. First, with respect to competitiveness, previous work by Reinaud (2005) estimates the impact of an extension of free allocation in the EU-ETS (Phase I) on the increase of production cost incurred by emission intensive sectors. Results suggest that higher cost in production raises concerns with respect to future production and employment, leading to a possible carbon leakage outside the EU. From another perspective, Demailly and Quirion (2006) show that output-based allocation is more effective to mitigate carbon leakage in a free allocation setting. Regarding energy intensive sectors (e.g. cement and steel), recent work of Martin, Muûls and Wagner (2016) as well as Dechezleprêtre and Sato (2017) provide insightful reviews of studies estimating competitiveness and leakage impacts of pricing carbon emissions. Overall, a large part of this literature conducts numerical simulations with empirically calibrated computable general equilibrium (CGE) models to estimate the reduction of leakage effects through various forms of economic instruments (e.g. border carbon tax) both at aggregate levels and in particular sectors. They tend to confirm the role of import tariffs in limiting carbon leakage, leading to a noticeable overall reduction of emissions as they also shrink consumption.

Second, the design and implementation of border carbon adjustment mechanisms (BCAs) have been studied through the lens of competitiveness. Böhringer et al. (2012) demonstrate that BCA mechanisms reduce carbon leakage while Fischer and Fox (2012) provide a detailed model-based economic comparison of different approaches to BCA implementation and find that a mix BCA (import and export) is more effec-

tive to limit carbon leakage. Moreover, [Helm, Hepburn and Ruta \(2012\)](#) argue that the adoption of an import-BCA by one region can provide dynamic incentives for stronger carbon pricing in other regions (so as to capture the additional tax revenue). More recently, [Cosbey et al. \(2019\)](#) carried out a global review of the main findings from the BCA literature to date. Finally, [Zachmann and McWilliams \(2020\)](#) exposed a general review of policy implications of a BCA at the EU scale, suggesting unclear effects on carbon leakage and emphasizing potential negative impacts.

Lastly, regarding the legislative design of BCA, [Ismer and Neuhoff \(2004\)](#) suggested that a BCA targeting imports and exports would fit the World Trade Organization legislation if it is calculated on the basis of best available technology standard. Although [De Cendra \(2006\)](#) analysis of the legality of border adjustments for exports conclude that WTO legalisation is unclear on such a mechanism, [Holzer \(2014\)](#) develops that exports would only be eligible for adjustment at the border if the costs accruing under an European Trading Scheme could be considered an indirect tax, which is unlikely to happen for the author. [Mehling et al. \(2019\)](#) take a more favourable view on the possibility for emission permits to be classified as an indirect tax.

Overall, our paper is at the interface between different strands of the literature. The first focuses on understanding how the structures of network affect diffusion to then identify the propagation of economic shocks within an economy. The second are non-network studies mostly using empirical, analytical and/or simulation tools to measure amounts of emissions embedded in trade. Finally, the third evaluates the potential impacts of economic instruments to limit imported emissions as well as associated impacts (e.g. carbon leakage, competitiveness).

## 3.3 Methodology & Data

### 3.3.1 The Emission Reduction Multiplier Matrix

Following Cahen-Fourrot et al. (2020), we start with the national inter-industry matrix  $\mathbf{Z}$ , a square matrix exhibiting amounts of sectoral intermediate consumption. In broad terms, such a matrix is called "Input-Output matrix" and captures exchanges of goods and services among industrial sectors in monetary units.<sup>18</sup>

In input-output tables (IOTs), the  $\mathbf{Z}$  matrix usually comes with an additional set of column vectors displaying final consumption (i.e. demand ( $\mathbf{f}$ )) and row vectors representing value added items ( $\mathbf{v}$ ) (i.e. compensation of employees, fixed capital consumption, gross operating surplus). Sectors appear both as producers of goods and services (rows) and as consumers of intermediate inputs (columns). More specifically, IOTs are commonly defined as monetary industry balances, where total supply  $\mathbf{x}^T = \mathbf{i}^T \mathbf{Z} + \mathbf{v}$  equals total use  $\mathbf{x} = \mathbf{Z} \mathbf{i} + \mathbf{f}$  of products and services per sector.<sup>19</sup> Therefrom, the total amounts of all transactions over a row (industry output allocated to each category of user (i.e. intermediate and final consumption)) equals the sum over the corresponding column (total industry input flowing from upstream sectors - other industries and value added items). The IOT also reports imported goods and services, which are again used either as intermediate inputs or as final demand. Figure 3.1 below shows a stylized version of an IOT.

In economics, IOTs have been mainly used to evaluate direct and indirect effects of changes in final demand based on the Leontief inverse matrix (Leontief, 1951; Metzler, 1951; Chen, 1973; Velázquez, 2006). Although both demand and supply dynamics will be critical in defining the process of imported emission reductions, we believe that the demand-driven Leontief model is not appropriate to evaluate cascades of reduction of imported emissions. Indeed, we expect that changes in consumption behaviour

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<sup>18</sup>See Miller and Blair, 2009; Cahen-Fourrot et al., 2020.

<sup>19</sup>Note that  $\mathbf{i}$  is a column vector of the same dimension of  $\mathbf{Z}$

Inter-Industry matrix ( $\mathbf{Z}$ )		Intermediate uses		Final uses ( $\mathbf{f}$ )			Total use (TU)
		Sector A	Sector B	Cons.	Inv.	Exp.	
<b>Production</b>	Sector A	Products of A used as inputs by A	Products of A used as inputs by B	Final use of products by A			Total use of products of A
	Sector B	Products of B used as inputs by A	Products of B used as inputs by B	Final use of products by B			Total use of products of B
<b>Total</b>		Total intermediate inputs		Total final uses			Total uses
<b>Value added (<math>\mathbf{v}</math>)</b>	Comp. of employees	Total value added					
	Cons. of fixed capital						
	Operating surplus						
<b>Output</b>		Total domestic output					
<b>Imports</b>		Total imports					
<b>Total supply (TS)</b>		Total supply					

Figure 3.1: A stylized Input-Output Table (Cahen-Fourot et al., 2020)

due to an environmental policy (e.g. carbon taxation) would generate shifts of final demand from high to low-carbon products belonging to the same category of goods (i.e. same NACE category) - rather than creating new patterns of consumption across different categories of products.<sup>20</sup> Second, as heavy polluting raw materials (e.g. coal, gas, iron ores) are essentially consumed as inputs by other industries, "greening" imports will impact production processes of goods and services rather than final demand (Cahen-Fourot et al., 2020). As the *Leontief model* is useful to address questions of changing patterns in final demand, we take an opposite view to focus on the supply side (i.e. productive sectors).

A relevant approach for our study is the *Ghosh (1958) supply-driven model*.<sup>21</sup> The output of the *Ghosh model* is a matrix  $\mathbf{B} = \mathbf{x}^{-1}\mathbf{Z}$  of *allocation* coefficients of the supply of a sector (i.e. output) to all other sectors. In the matrix  $\mathbf{B}$ , each element  $b_{ij}$

<sup>20</sup>Here, we believe that consumers will mostly shift their preferences towards energy-efficient durable goods and electricity produced via low-carbon energy sources, rather than shifting preferences from one category of goods to another (e.g. from manufactured goods to food products).

<sup>21</sup>Augustinovic, 1970; Beyers, 1976.

quantifies the share of sector  $i$ 's output consumed by sector  $j$ . Then, the Ghosh matrix  $\mathbf{G}$  is defined as :

$$\mathbf{G} = (\mathbf{I} - \mathbf{B})^{-1}$$

Therefrom, to capture the supply and demand patterns for imports, we implement the proxy measurement approach developed by the U.S. National Research Council of the National Academies (2006). Based on assumption of input similarity,<sup>22</sup> we measure the proportion of imports in the total supply of each sector to estimate the share of imports that is allocated to each sub-industry. In the next part (i.e. description of data), we provide a description of this proxy measurement approach. As a result, we are able to estimate the share of imported products used by each industry in their total domestic output and the matrix of coefficients  $\mathbf{B}$  now represent the share of imports in the total output of a sector used by other sectors. We then transpose  $\mathbf{G}$  to be able to read the effects of changes in sectoral primary inputs over the columns (similarly to the Leontief system) of  $\mathbf{G}^T$ , where  $T$  denotes the matrix transposition. Each entry  $g_{i,j}$  of  $\mathbf{G}^T$  shows the change in output  $\mathbf{x}$  in sector  $i$  that would result from a unitary change of primary inputs used in sector  $j$  (through the channel of supplied imports). In general terms, a drop (or increase) of one monetary unit in primary inputs supporting production in sector  $i$  will generate a drop (increase) in the output of sector  $j$  by an amount equivalent to  $g_{i,j}$ .<sup>23</sup> In IO analysis, primary inputs cover items appearing on the rows below the inter-industry matrix (e.g. compensation of employees). As exposed in Cahen-Fourrot et al. (2020), primary inputs represent the societal effort to produce the output of a sector, captured by factor payments.

We innovate by combining the obtained Ghosh matrix with sectoral data of imported emissions  $e$ .<sup>24</sup> To do so, we define  $E_i = e_i/M_i^d$  as the imported emission intensity of sector  $i$ , where  $M^d$  represents the domestic output of the sector. By multiplying the

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<sup>22</sup>Import similarity : Within the product categories of the input-output table, the mixes of imports and country-made goods are the same and therefore have the same destinations.

<sup>23</sup>Note that  $g_{i,j}$  includes both direct and indirect effects.

<sup>24</sup>Cf. part next part for full description of data.

diagonalised form of the vector of emission intensities by the Ghosh matrix, we find the matrix  $\mathbf{S}$  of *emission reduction coefficients* :

$$\mathbf{S} = \hat{E} \mathbf{G}^T$$

Each element  $s_{ij}$  of matrix  $\mathbf{S}$  represents the change in imported emissions in sector  $i$  generated by a unitary change of primary inputs used by sector  $j$ . For our purpose, the elements of  $\mathbf{S}$  capture the amount of imported emissions of a sector  $i$  that could be reduced because of a unitary decrease in primary inputs used in the production of goods and services of another sector  $j$  (e.g. hard coal, iron ores). The column sum of matrix  $\mathbf{S}$  gives a measure of the total amount of emission reductions resulting from a unitary reduction of primary inputs in a sector  $j$ . We define this as the total *emission reduction coefficient* of a sector :

$$s_j^{TOT} = \mathbf{i}^T \mathbf{S}$$

where  $n$  is the dimension of matrix  $\mathbf{S}$ . In our case, we assume the values of  $s_i^{TOT}$  to be largely driven by  $i$  emission intensity of imports and therefore, by potential amounts of internal emission reduction from imports.<sup>25</sup> On the opposite, to estimate external *emission reduction coefficient* (i.e. the impacts of a sector reduction of primary inputs on imported emissions of all other sectors), we proceed as follows :

$$s_j^{EXT} = s_j^{TOT} - s_j^{diag},$$

where  $s^{diag}$  refers to the  $j$ -th element of the diagonal of  $\mathbf{S}$ . In the end, we define the sum of the rows of  $\mathbf{S}$  as the exposure of a sector to imported emission reductions (i.e. the reduction of imported emissions following a unitary loss in primary inputs used in all other sectors) :

$$s_i^{EXP} = \mathbf{S} \mathbf{i}$$

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<sup>25</sup>Remember that imports might be used as inputs for the considered sector.

Overall, this methodological approach allows us to investigate both internal and external emission reductions generated by sectors. A sector might have a large emission reduction coefficients mainly driven by internal reductions - suggesting a poor economic connection with other sectors (supply). We capture this feature in [Section 5](#) by constructing the channels of reduction cascades across economies.

### 3.3.2 Datasets : Input-Output Tables and Imported Emissions

We apply the methodology described above to five European economies : France, Germany, Italy, Poland as well as the United Kingdom. Although the UK might officially leave the E.U. at the beginning of 2021 ([European Commission, 2020](#)), including the country in our sample allows us to cover the four top economies of the region ([Statista, 2020](#)). Moreover, data available for our study are provided for the year 2015. The latter prevents us from the Brexit referendum economic impacts (2016).

The main source of IO tables data we employ are extracted from the [OECD](#) for the year 2015.<sup>26</sup> More precisely, we use symmetric input-output tables at basic price by industry.<sup>27</sup> Although IO tables exhibit the total amount of imports for each sector (cf. Figure 3.1, imports per sector), estimating the allocation of such imports to each sub-sectors remains a hard task. The latter stems from the lack of accuracy regarding the type of imports in each sectors (i.e. different types of products - exhibiting different prices - fall in the same category (e.g. Basic metals)). To cope with this issue, we argue that we can implement a proxy measurement form of imports sub-allocation based on assumptions regarding the similarity of imported intermediate inputs. Namely, within product categories of input-output tables, the mixes of imports and country-made products are the same and therefore have the same destinations. Although acting as a proxy measurement in which larger amount of aggregated data impact the accuracy,

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<sup>26</sup>OECD Statistics : <https://stats.oecd.org/Index.aspx?DataSetCode=IOTSI42018>.

<sup>27</sup>Total economy, product by product in million \$.

such approach has been promoted to address further issues such as estimating imports embodied in exports (cf. for the U.S., [U.S. National Research Council of the National Academies \(2006\)](#)). Following the similarity assumption, we measure the proportion of imports in the total supply of each sector to estimate the share of imports that is allocated to each sub-industry (for instance, if mining imports 90% of its total supply, we consider this amount to be uniformly distributed across downstream sectors (i.e. 90% of the total value supplied by mining to basic metals comes from imports)). By doing so, we give an approximation of import allocation of a sector across each sub-sector in the industrial system. Then, Table 3.4 in the [Appendix, 1.1](#) lists NACE level 1 categories,<sup>28</sup> while Table 3.1 below offers the detailed disaggregation of industries we investigate in this paper.<sup>29</sup> We deliberately exclude business services (Table 3.4, from G to S) as it represents a very small share of imported emissions and covered sectors are less likely to be targeted by a potential EU policy (e.g. administration, accommodation services).<sup>30</sup>

Regarding imported emissions, we constructed our dataset from the [OECD](#) accounts on CO<sub>2</sub> emissions intensity embodied in gross imports (see [Wiebe and Yamano \(2016\)](#) for full methodology description).<sup>31</sup> More precisely, we matched our constructed IOTs of imports and the sectoral intensity (CO<sub>2</sub> tonnes per million \$) of imported input to calculate the total amount of imported CO<sub>2</sub> emissions of each sector. By summing the amount of imported CO<sub>2</sub> tonnes over each column sector, we are able to provide the total amount of CO<sub>2</sub> tonnes for each sector total domestic output. For instance, if basic metals imports 5 million \$ of mining and 2 million \$ of coke and

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<sup>28</sup>The Statistical classification of economic activities in the European Community, abbreviated as NACE, is the classification of economic activities in the European Union (EU).

<sup>29</sup>For further descriptions, refer to the [Appendix](#).

<sup>30</sup>Exposed by [Cahen-Fourot et al. \(2020\)](#) : the decarbonisation process might not be particularly detrimental for business activities (low dirty capital levels, low demand for fossil fuel).

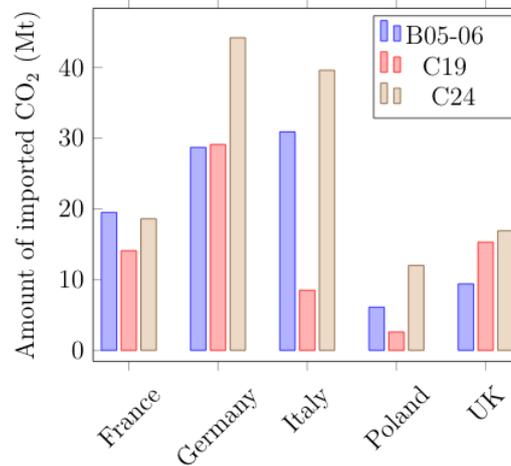
<sup>31</sup>[OECD Statistics](#) - CO<sub>2</sub> emissions intensity embodied in gross imports (2015) : "This indicator shows the intensity of CO<sub>2</sub> emissions, tonne CO<sub>2</sub> per Million USD, in gross imports of importing country/region c with origin in industry i in exporting country/region partner p.". See [https://stats.oecd.org/Index.aspx?DataSetCode=IO\\_GHG2019](https://stats.oecd.org/Index.aspx?DataSetCode=IO_GHG2019). [Wiebe and Yamano \(2016\)](#) provide an in-depth description of methodological process to obtain CO<sub>2</sub> emissions intensity embodied in gross imports.

refined petroleum products, we proceed as follow : emission intensity for imports of mining per million \$ x Imported inputs + emission intensity for imports of coke and refined petroleum products per million x Imported inputs. We consider intensity of CO<sub>2</sub> emissions embodied in gross imports as it includes imports subject to be part of future re-exportation (i.e. products to be transformed as a part of a value chain) and provide a wider perspective of traded items, especially for exporting countries (e.g. Germany). Tables 3.5, 3.6 ([Appendix, 1.1](#)) and Figure 3.2 below summarize the distribution of imported emissions across each country.

Table 3.1: Breakdown of examined NACE Sectors.

<b>Sector</b>	<b>Code</b>	<b>Sector description</b>
A	1	Agriculture, forestry and fishing
B05-06	2	Mining and extraction of energy producing products
B07-08	3	Mining and quarrying of non-energy producing products
B09	4	Mining support service activities
C10-12	5	Food products, beverages and tobacco
C13-15	6	Textiles, wearing apparel, leather and related products
C16	7	Wood and of products of wood and cork (except furniture)
C17-18	8	Paper products and printing
C19	9	Coke and refined petroleum products
C20-21	10	Chemicals and pharmaceutical products
C22	11	Rubber and plastics products
C23	12	Other non-metallic mineral products
C24	13	Manufacture of basic metals
C25	14	Fabricated metal products, except machinery and equipment
C26	15	Computer, electronic and optical products
C27	16	Electrical equipment
C28	17	Machinery and equipment n.e.c.
C29	18	Motor vehicles, trailers and semi-trailers
C30	19	Other transport equipment
C31-33	20	Other manufacturing, repair and installation of machinery and equipment
D-E	21	Electricity, gas, water supply, sewerage, waste and remediation services
F	22	Construction

Figure 3.2: Distribution of imported CO<sub>2</sub> emissions across mining (B05-06), coke/petrol. products (C19) and basic metals (C24)



Overall, Germany imported nearly 319 Mt of CO<sub>2</sub> in 2015, making the country the larger importer of our sample.<sup>32</sup> Main sources of imported emissions came from mining, coke and refined petroleum products, chemicals and basic metals (the latter is particularly relevant for Germany as it exhibits the largest share of industrial production in the EU (e.g. motor vehicles, trailers and semi-trailers, machinery and equipment (Eurostat, 2019))).

By combining IOTs and imported emissions, we are able to offer results for the industrial and power sectors (i.e. NACE from A to F) in France, Germany, Italy, Poland and the United Kingdom. In 2015, these countries represented more than 64% of the European Union gross domestic product (Statista, 2020).

## 3.4 Cascading Reduction of Imported Emissions

### 3.4.1 Emission Reduction Coefficients

In this section, we analyse results reported in Table 3.2, namely total emission reduction coefficients (1), external reduction coefficients (2) and exposure to reduction

<sup>32</sup>These data cover the scope of our analysis (e.g. services are not included).

(3). We focus on the top five sectors for each country. Given the import distribution in the economy and leaving all else equal, the first two sets of coefficients show the sectors that are likely to create the largest amounts of CO<sub>2</sub> emission reduction from imports in the economic system following a unitary drop in their primary inputs. The third set of results exhibit instead the sectors that are likely to be most exposed to a reduction of imported emissions from a unitary drop distributed equally across all industries.

Table 3.2: Emission Reduction Coefficients

<b>France</b>	<b>Germany</b>	<b>Italy</b>	<b>Poland</b>	<b>U.K.</b>
<b>Total Emission Reduction Coefficients (1)</b>				
B05-06 (0.0693)	B05-06 (0.0825)	B07-08 (0.0424)	B05-06 (0.0125)	C24 (0.0045)
B09 (0.0037)	B07-08 (0.0089)	B05-06 (0.0284)	C24 (0.0065)	C27 (0.0044)
C24 (0.0007)	C24 (0.0028)	C24 (0.0049)	C28 (0.0029)	B05-06 (0.0041)
C27 (0.0006)	B09 (0.0025)	C26 (0.0024)	C26 (0.0028)	C31-33 (0.0035)
C25 (0.0006)	C26 (0.0024)	C23 (0.0016)	C20-21 (0.0028)	C26 (0.0035)
<b>External Emission Reduction Coefficients (2)</b>				
B05-06 (0.0689)	B05-06 (0.0089)	B07-08 (0.0081)	B05-06 (0.0012)	B05-06 (0.0004)
B09 (0.0034)	B07-08 (0.0018)	B05-06 (0.0024)	C24 (0.0005)	B07-08 (0.0004)
B07-09 (0.0002)	B09 (0.0008)	B09 (0.0008)	B07-08 (0.0004)	C24 (0.0003)
C24 (0.0001)	C24 (0.0001)	C24 (0.0002)	C20-21 (0.0003)	C27 (0.0003)
C27 (0.0001)	C19 (0.0001)	C20-21 (0.0001)	C28 (0.0003)	C26 (0.0002)
<b>Exposure to Emission Reduction Coefficients (3)</b>				
C19 (0.0420)	C19 (0.0053)	C24 (0.0068)	C24 (0.0009)	C31-33 (0.0004)
D-E (0.0222)	C24 (0.0026)	C19 (0.0010)	D-E (0.0006)	C24 (0.0004)
C20-21 (0.0027)	C20-21 (0.0011)	B05-06 (0.0009)	C27 (0.0003)	C19 (0.0003)
F (0.0026)	D-E (0.0009)	C20-21 (0.0008)	C28 (0.0003)	C30 (0.0002)
C24 (0.0011)	B05-06 (0.0007)	C23 (0.0007)	C19 (0.0003)	C27 (0.0002)

Regarding total coefficients, sectors of mining (B) are by far the most prevalent, appearing as the top sectors in France, Germany, Italy and Poland while ranking third for the United Kingdom. At a disaggregated level, this observation is particularly true for

carbon intensive products such as coal and natural gas (B05-06) (cf. France, Germany, Poland and the United Kingdom). This outcome looks intuitive as a large share of EU imports of mining comes from countries both outside and inside the region, using dirty technological processes (e.g. for gas, EU partners are mainly Russia and North African countries such as Algeria (Eurostat, 2019); for hard coal, the main suppliers of the EU are Russia, Colombia, Australia and Poland (Global coal trade, Dec. 2014)).

Studying the S matrix, one can notice that imported emissions of sectors often significantly affected by the reduction of imports originating in the B05-06 industry include those from electricity and gas industry (D-E), basic metals (C24) and chemicals and pharmaceutical products (C20-21). These results emphasize the critical presence of mining as inputs in their production processes (e.g. steel, chemicals). For certain countries (e.g. France, Germany, Poland and the U.K.), the presence of D-E sector is likely to be mainly driven by the proportion of energy producing inputs in the energy mix (e.g. coal/gas) as well as the importance of industrial production.

In addition to B05-06 sector, activities included in category C (manufacturing) such as C24 (basic metals) and C26 (computer and electronics) exhibit large coefficients of emission reductions across economic systems. The latter appear to be strongly intertwined with the level of imports intensity of the sectors (Eurostat, 2019), thus highlighting a significant potential of internal reductions of emissions. Moreover, for the specific case of basic metals industry (C24), the amount of imported emissions for the year 2015 is significantly high.<sup>33</sup> Combined with the import intensity of the sector<sup>34</sup> (U.S. Department of Commerce, 2019), we particularly expect a large internal potential for emission reductions in the basic metals industry too. The latter is confirmed by the following analysis on external emission reductions.

External emission reduction coefficients, which abstract from internal emission reductions of a sector and thus offer an accurate representation of the effect of a drop in a sec-

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<sup>33</sup>Cf. Figure 3.2, more than 10% of total imported emissions for all countries

<sup>34</sup>For instance, for steel it reached 20% of the EU consumption in 2015 (U.S. Department of Commerce, 2019).

toral imports on the rest of the economy, exhibit a significantly different pattern. The relevance of import-intensive activities is drastically reduced (i.e. coefficients), even if mining sectors still exhibit high emission reduction effects in all economies belonging to our sample.<sup>35</sup> Although levels of coefficients are not distributed equally, sectors C20-21 (chemicals and pharmaceutical products), C24 (basic metals) and C27 (electrical equipment) become the most recurrent sectors in our sample. All these sectors appear high in the ranking of external emission reduction coefficients because they provide significant amount of inputs to other import intensive sectors. For instance, both sectors B05-06 and C20-21 provide substantial intermediate goods to coke and refined petroleum products (C19) while basic metals (C24) supplies fabricated metal products (C25) as well as machinery and equipment (C28).<sup>36</sup> Table 3.3 offers a closer look at industries exhibiting largest coefficients, reporting the top 5 sectoral values for the external emission reduction coefficients originating in B.<sup>37</sup>

Table 3.3: Sectoral Emission reduction coefficients for top sectors (excluded).

<b>France</b>	<b>Germany</b>	<b>Italy</b>	<b>Poland</b>	<b>U.K.</b>
B05-06 (0.0817)	B05-06 (0.0089)	B07-08 (0.0081)	B05-06 (0.0012)	B05-06 (0.0004)
C19 (0.0414)	C19 (0.0052)	C24 (0.0060)	D-E (0.0004)	C19 (0.0037)
D-E (0.0212)	C24 (0.0011)	C23 (0.0007)	C24 (0.0003)	C20-21 (0.0000)
C20-21 (0.0025)	C20-21 (0.0009)	C27 (0.0002)	C19 (0.0002)	D-E (0.0000)
F (0.0010)	D-E (0.0008)	C20-21 (0.0002)	C20-21 (0.0000)	C24 (0.0000)
C24 (0.0009)	C23 (0.0001)	C28 (0.0002)	C23 (0.0000)	C23 (0.0000)

As mentioned, C19 (coke and refined petroleum products), C24 (basic metals) as well as D-F (electricity and gas) all appear as the sectors most exposed to a reduction of imported emissions through the channel of mining. Again, this matches previous observations that top industries in external emission reduction coefficients provide inputs to import intensive sectors.<sup>38</sup> Moving back to Table 3.2, several other manufacturing

<sup>35</sup>Note that mining is now ranking first in the U.K..

<sup>36</sup>Note that these sectors exhibit quite large amount of imported emissions too.

<sup>37</sup>We exclude respective country top sector itself, to abstract from internal reductions.

<sup>38</sup>Although for electricity and gas, this arguments depends on considered energy used (gas, coal).

sectors appear among the top 5, activities C28 (machinery and equipment) and C26 (computer and electronics) for Poland and the U.K. respectively.

Finally, looking at the values of total sectoral exposure to emission reductions, we can identify four main sectors at risk, repeatedly appearing among the sectors with the highest row sums in  $S$ : C19 (coke and refined petroleum products); C20-21 (chemicals and pharmaceutical products); C24 (basic metals) and D-E (electricity and gas). These sectors, in addition to having high imports intensities, are affected by multiple relevant inward economic links. To investigate these features, we consider the  $S$  matrix as an adjacency matrix for a directed network (Godsil and Royle, 2013; Halleck-Vega et al., 2018; Cahen-Fourot et al., 2020), interpreting productive sectors as the vertices of the network and the  $s_{i,j}$  elements of  $S$  as the weight of the edges going from vertex  $j$  to vertex  $i$ . Then, it is possible to represent the network as a circular layout. Figures 3.3 and 3.4 below show the outcome of this procedure for Germany and Poland, as they exhibit different patterns in terms of sectors' exposure (e.g. strength of coefficients).

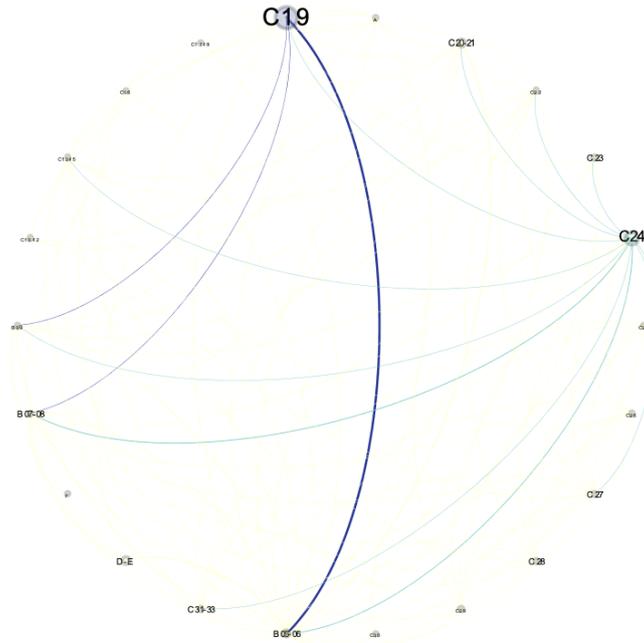


Figure 3.3: Network of imported emission reduction across sectors in Germany. The size of the node is proportional to the number of weighted incoming links (i.e. demand of a sector to another sector).

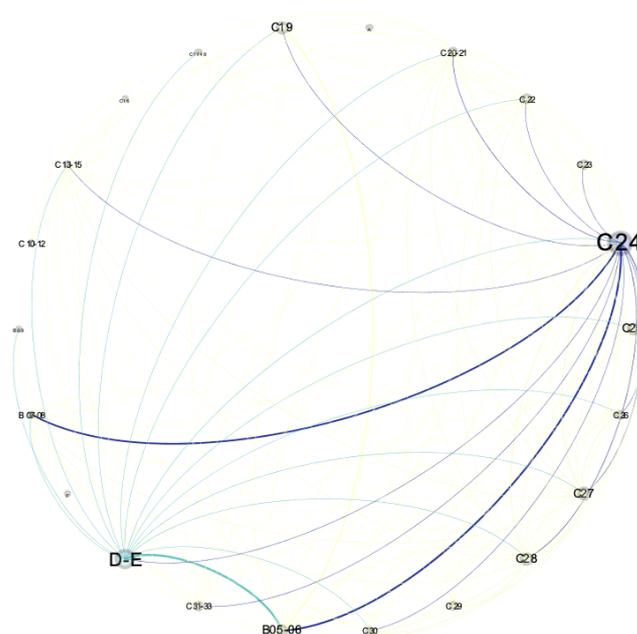


Figure 3.4: Network of imported emission reduction across sectors in Poland. The size of the node is proportional to the number of weighted incoming links (i.e. demand of a sector to another sector).

When studying networks' characteristics, sectors exhibiting the largest numbers of outgoing links and so able to create large cascade of emission reduction in the economy are mining activities (B) in Germany, while chemicals and pharmaceutical, machinery and equipment as well as basic metals are the leading industries in Poland.

However, if one considers the potential strength (weight) of the emission reduction links, mining activities and basic metals display the largest impacts (suggesting a strong effect of a reduction of imports from these sectors on other sectors' imported emissions). Interestingly, the most important emission reduction links starts from B05-06 to electricity and gas industry as well as basic metals in Poland. The former could be partly explained by the coal and gas dominating roles in the Polish power generation system ([International Energy Agency., Key energy statistics, 2018](#)). For Germany, the largest reduction connections start from B05-06 toward coke and refined petroleum products (C19) and basic metals industry (C24).

Overall, our results emphasize different aspects : first, mining (B) is the sector the

most subject to internal emission reductions, exhibiting strong links to internal related activities (i.e. B07-08; B09). The sector also deeply affects basic metals and chemicals and pharmaceutical industries. For this reason, we observe these sectors to be ranked top in exposure category. The ranking of basic metals and chemicals as top external emission reduction sectors suggest a strong connection of these sectors to others across the economy - thus acting as facilitators in the shock propagation process. To better capture this feature, we map in the next section the cascade of emission reductions from top external coefficients activities. The latter brings us a clearer perspective on how cascades propagates in economic systems.

### 3.5 Channels of Reduction Cascades

After having shown the reduction potential and the associated exposure of the entire range of productive sectors, we now shift our attention to top external coefficients sectors (B activities). Our objective is to better investigate the relevance of the potential emission reduction of imports due to a transition away from fossil fuel imports (e.g. coal and gas), and understand how the process originating in the fossil fuel sector propagates throughout the economic system. To do so, we start by identifying the most relevant emission reduction links originating from a unitary loss of primary inputs supporting the production of mining (i.e. the largest values appearing on the B column of matrix S). We retain only the top  $q$  percentile of the values, and position the affected sectors on the first layer of our cascade network. We repeat the procedure for the sectors in the first layer, identifying the sectors within the top  $q$  percentile of emission reductions originating in the layer. The weight of the resulting network edges are re-weighted to take into account that the loss in primary inputs in these sectors will be lower than one and a function of the strength of the upper edges. In other words, the reduction links tend to be stronger the closer they are to the shock origin, and get gradually weaker as they cascade downwards. We then repeat the same

procedure for each layer, excluding the sectors that had already appeared in upper layers, until no new sectors appear. The results of this procedure are shown for each country belonging to our sample following a hierarchical layout (cf. Figure 3.6 - 3.10 in the [Appendix](#), for  $q = 0.15$ ). The numerical weight of the top 10 edges is shown for reference.<sup>39</sup>

As expected, the sectors in the first layer of the network overlap with the ones reported in Table 3.2. The strongest emission reduction link is the one flowing to coke and refined petroleum products (C19) for France, Germany and the United Kingdom. Manufacturing activities, especially basic metals products (C24) and chemicals and pharmaceutical (C20-21), as well as electricity and gas (D-E), also frequently appear among the sector most strongly affected by the immediate reduction caused by B. From the electricity and gas sector (D-E), the reduction cascade often continues affecting other non-metallic mineral products (C23) and basic metals (C24). Given the strength of the original reduction from B to D-E, these links are often the most relevant after the ones affecting sectors in the first layer, and are justified by both the high imports intensity of the sectors and their large consumption of energy products (e.g. electricity, gas). From the coke and refined petroleum products sector (C19), the most common cascades proceed through the chemical sector (C20-21), other non-metallic mineral products sector (C23) and basic metals (C24). The reduction in the basic metals sector (C24) often propagates through to the fabricated metal products (C25), machinery and equipment (C28) and the motor vehicles sector (C29), frequently further affecting other transport equipment (C30) and repair and installation of machinery and equipment (C31-33).

In addition to the sectors mentioned above, several other sectors frequently appear in the cascade networks. For instance, textiles industry (C13-15) often appears on the second or third layer of the network, regularly affected by reduction links originating

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<sup>39</sup> Although most of them exhibit a weight of 0, the impact on downstream sectors remains higher compared to other upstream industries.

chemicals (cf. France, Germany and Italy). The sectors in the C22 category (rubber and plastics) also often appear, largely affected by C20-21 (chemicals) and sometimes by D-E (electricity and gas). Regarding the primary sector, agriculture (A) is not present in the cascade networks (presumably due to low imported emission levels and small share of imports in the total supply of the sector), while food and beverages industry (C10-12) as well as paper and printing services (C17-18) never appear. These sectors mainly supply services and final demand side of the economy, thus not appearing in our framework.

Studying the structure of the networks in conjunction with the weights of its edges, we can identify different relevant cascades across countries. Both in France and Germany, it is possible to observe a strong reduction cascades passing through coke and refined petroleum products (C19) and basic metals (C24), and then affecting a significant number of manufacturing sectors (fabricated metal products, machinery and equipment, electrical equipment, and other non-metallic mineral products). In other countries such as Italy and the U.K., the spreading of the aforementioned cascades across sectors is less wide - following the same trend but with few sectors affected. Italy exhibits a strong link from the textile sector to repair and installation of machinery and equipment, emphasizing the role of the textile industry in this economic system (Eurostat, 2016). Moreover, Italy and Poland display several fairly long reduction cascades, with the most prominent one passing through other non-metallic mineral products (C23), chemicals (C20-21), textiles (C13-15) and, as mentioned, repair of machinery (C31-33) in Italy. The cascade network of the United Kingdom is peculiar, in that it has two particularly deep cascades originating in chemicals (C20-21), with the first one involving several manufacturing sectors and basic metals, and the second one involving plastics and rubber (C22) as well as motor vehicles, trailers and semi-trailers.

More generally, the main structure of the cascades we identify spreads from mining (e.g. coal, gas, iron ores) to manufacturing sectors specialized in material production

(steel, iron, chemicals), then affecting industrial sub-sectors supplying final demand (e.g. vehicles motor, textile, machinery and equipment). In addition, the shape of the cascade differs across economies, suggesting different exposure to the implementation of economic instrument aiming at limiting imported emissions. As exposed by the E.U., imports most likely to face carbon price are those associated with iron, steel and aluminium (C24). In the last section, we focus on basic metals imports to evaluate the impacts of a \$25 carbon price on sectors total cost of imported inputs. The latter brings additional insights to E.U. policy-makers to assess the potential economic impact of such a tool.

## **3.6 Taxing Basic metals Imports : A simulation of short-run impacts**

In the previous sections, we identified the key role of the basic metals industry in the propagation of emission reductions in economies (i.e. starting from mining to downstream sectors supplying final demand, through the channel of basic metals). This sector encompasses different products (e.g. iron and steel) exhibiting carbon intensive production processes ([Financial Time, January 2019](#)). To give more perspective to our work, we first propose a short description of this industry before exposing our findings regarding the implementation of a carbon content tax mechanism.

### **3.6.1 Perspectives on the Basic metals industry**

First of all, the basic metals sector is the first consumer of worldwide produced energy in the world, cumulating at 55% of the total delivered energy in 2018 ([US Energy Information Administration, February 2019](#)). At the industrial level, it represented 12% of global energy consumption. As exposed in the description of NACE sectors, this sector encompasses a wide range of products from iron and steel to aluminium and other metal goods, mainly consumed as intermediate inputs in production processes. To be

produced, such products require large amounts of energy inputs, notably because of the heating process (raw ores and metals). In addition, mining inputs such as metallurgical coal are used for smelting iron. Another critical dimension of the sector is its furniture for world-wide energy networks. For instance, equipment, pipelines and wires are used by several industries such as mining, refining petroleum products and power generation sectors to produce and transport energy (e.g. natural gas).

As this industry is highly energy intensive, it displays a quite high energy intensity per output unit compared to other industrial sectors. From a climate policy perspective, such intensity is heterogeneous when looking at different geographic production areas. In 2015, before Australia and New Zealand, Russia was the most energy-intensive country for producing basic metals goods (68,000 British thermal units (Btu) per dollar). The Russian basic metals sector production was dominated by iron and steel manufacturing while basic metals production in Australia and New Zealand was mainly about by aluminum manufacturing. The manufacturing of these products is the most energy intensive in the all basic metal industry.<sup>40</sup> In comparison, the energy intensity of the U.S. basic metal industry is much lower, at 8,000 Btu/dollar, because the industry is more diverse (production of metals) and stages such as recycling along the production path limit additional amounts of emissions ([US Energy Information Administration, International Energy Outlook 2019](#)).

From an environmental perspective, around 21% of global greenhouse gas (GHG) emissions are generated by industrial sectors, of which steel, iron and aluminum industries account for around 7-9% ([International Energy Agency, 2018](#); [Lehne and Preston, 2018](#), [Gautam et al., 2018](#)). In a business as usual scenario (in which no more environmental policies are implemented), we expect such sectors production to double by 2060, leading to large environmental impacts ([OECD, 2019](#)). Although the COVID-19 pandemic might affect the dynamics of the sector, global steel demand is likely to soar by 15-40%

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<sup>40</sup>Note that production of basic metals in these country is mainly due to the fact that ores resources required to produce steel and iron are available in the ground.

by 2050 while iron demand is also predicted to increase in the coming years ([Accenture Strategy, 2017](#)). In the context of the European Green Deal and the recovery package *Next Generation EU*, the European Commission has set a target of reducing carbon emissions of at least 40 percent by 2030. The success of this objective is likely to depend on a well-designed carbon pricing policy at the regional scale. However, higher carbon prices can lead to carbon leakage outside the E.U., thus undermining climate efforts. To address this perceived threat, the European Commission is currently considering the implementation of a carbon border adjustment mechanism “*for selected sectors, to reduce the risk of carbon leakage*”. Such an instrument is likely to first target steel, iron and aluminium imported products as these products are energy intensive and exposed to potential carbon leakage ([S&P Global Platts, July 2020](#)).

### 3.6.2 Pricing carbon content of imported basic metals

In the wake of the E.U. willingness to target such imported products to limit carbon leakage, this section provides a short analysis of the impacts of a \$25 carbon price on basic metals imports and the associated economic effects on the total cost of imports used as inputs in each sector. We set this price amount to be aligned with the 2019 EU-ETS price which was oscillating around \$25 ([International Carbon Action Partnership, 2020](#)).<sup>41</sup> As we are not including any elasticity dimension (i.e. elasticity of demand for other energy intensive goods), the following results should be perceived as potential short-term sectoral impacts of pricing imported emissions from basic metals.

Applying the import price increase resulting from such a tax simulates how the effect of a uniform carbon price would be born across industries in terms of imported input price increases. As in the [Stern Review \(2006\)](#), the implicit assumption of using a fixed Input-Output methodology for our purpose is that sectors pass on the entire cost increase associated with the carbon price (i.e. their profit margins do not change and

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<sup>41</sup>Moreover, the European Commission suggested that carbon price on imports should be aligned with ongoing EU-ETS carbon permit price ([S&P Global Platts, July 2020](#)).

they do not change their behaviour to optimise their input costs in response to changes in relative prices). It is also assumed that secondary energy producers and all other industries that use any imported basic metals inputs pass on the entire cost increase that they bear to final goods prices. In our case, we only focus on the impact on the total cost of imported inputs. Again, this trace-through process assumes no behaviour change or input substitution. This is a pure arithmetical analysis for a single year and the analytical framework is therefore static (Grover et al., 2016).

Therefrom, we use IOTs constructed in Section 3 and we only consider the basic metals CO<sub>2</sub> intensities of imports. The latter allows us to capture the carbon content of basic metals imports.<sup>42</sup> By applying the methodology exposed by Grover et al. (2016), we are able to evaluate the economic impact of a \$25 carbon price on the total cost of imported inputs across the economy.

In the short run, the introduction of a uniform \$25 per tonne carbon price results in a whole-economy imports cost increase between 0.1% and 0.24%.<sup>43</sup> This results looks intuitive as we only focus on imported emissions from a specific sector of the economy. However, several industries bear different proportions of this increase, with large disparities across countries. The bar chart below shows the sectors the most affected by a \$25 per tonne carbon price. Results suggest a common pattern across countries : industries of basic metals, fabricated metal products, electrical equipment and machinery and equipment are those the most exposed to the implementation of such an economic instrument. Interestingly, these activities are the same (that were shown above) to depend heavily on basic metals imported inputs. Again, this observation confirms the role of basic metals as a channel for the emission reduction propagation

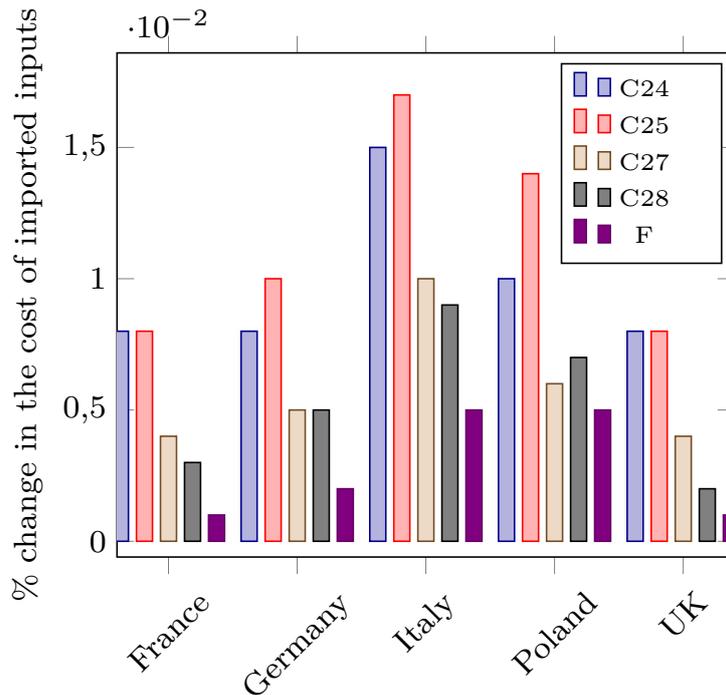
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<sup>42</sup>The multiplier is calculated in two stages. First the new product price reflecting a carbon price is calculated as: Input with carbon price = initial unit price + (carbon content (ton) per million \$ \* cost per ton of carbon). Numerically for basic metals in Germany : 1 million \$ (unit) + (1156 T/CO<sub>2</sub> per million \$ \* 25 \$) = 1 028 9000. We then multiply the value by the amount of million \$ imported. Second, this is expressed as per cent change from the initial total cost of imported input (sum of column for each sector intermediate imported inputs and then we calculate the variation between new and initial total cost of imported inputs (see Grover et al., 2016)).

<sup>43</sup>France : 0.1%; Germany : 0.1%; Italy : 0.2%; Poland : 0.1%; U.K. : 0.1%.

process toward other manufacturing sectors. More precisely, sectors of basic metals and fabricated metal products are experiencing the largest increase with a variation of more than 1% of imported inputs price in Italy and Poland, while the variation is capped below in other countries. From a cross-economy perspective, the latter suggests heterogeneous sectoral exposures to a uniform E.U. tax targeting imports, largely driven by unequal emission intensities (and/or different imported products belonging to Basic Metals category). Finally, although reaching low levels, the appearance of the construction sector (F) among the most exposed sectors emphasizes the role of basic metals as input provider to the industry.

Figure 3.5: % increase cost of sectoral domestic imported inputs, top sectors.



Overall, this analysis sheds light on two main aspects. First, it confirms our previous findings on the strong economic connections between the industry of basic metals and other manufacturing activities such as fabricated metal products (C25), machinery and equipment (C28) and electrical equipment (C27). Second, taxing imported emission from basic metals would affect, in the short-run, identical economic sectors across

E.U. countries (e.g. France, Germany, Italy) but with an unequal strength. Namely, in Poland and Italy, sectors mentioned above are more exposed in terms of variation of imported input cost compared to other economies in our sample. These results suggest that the implementation of a uniform tax across E.U. countries would generate different sectoral impacts, depending on the economy over which it takes place. The latter gives insights to understand the position of E.U. countries with respect to the implementation of such policies ([Financial Times, June 2019](#)). From a policy perspective, we observe that pricing basic metals imported emissions has a low impact on the total imported input cost of sectors (a maximum of 0.25% increase in total imported input cost for the fabricated metal products cost, cf. bar chart). Although such sectors are subject to heavy international competitions, our findings suggest that the potential economic impact remains limited.

### 3.7 Conclusion

The presentation of the EU Green Deal project (2019) has brought back the issue of imported emissions in the E.U. political debate. While an expanding literature has been investigating both the economic repercussions of instruments targeting such emissions and possible legislative designs, less attention has been devoted to understanding the potential reduction of imported emissions, and how this would cascade within a network of economic sectors' interdependencies. This article contributes to filling this gap by providing an original measure to quantify the amount of emission reductions of a sector that could be reduced because of a reduction of primary inputs flowing into another sector.

Analysing the data available for five European countries, we have shown the sectors with the highest “emission reduction coefficients” to be linked to mining activities (B), basic metals (C24) and computer and electronics (C26). This result is mainly driven by the high imported emission intensity of the sectors and the consequent significance of

sectoral internal emission reductions. When abstracting from internal effects with the aim of identifying the sectors that are likely to have the strongest reduction impacts on the rest of the economic system, we have found the mining and quarrying sector (B) to be particularly relevant, together with basic metals (C24) and chemicals products (C20-21) (for some countries (i.e. Italy and Poland)). These sectors are key in providing essential inputs to other sectors with high imported emission intensity. Finally, we have shown how the sectors most exposed to the risk of emission reductions include coke and refined petroleum products (C19); Basic Metals (C24); and electricity, gas, steam and air conditioning (D-E).

When focusing more specifically on the mining and quarrying sector in the attempt of studying the cascading process of imported emission contraction, we have shown how moving away from fossil fuel would have a particularly strong effect on sectors linked to coke and refined petroleum products (C19), basic metals (C24) and electricity and gas (D-E). We have identified regular patterns in cascade structures, such as the links from electricity and gas (D-E) to other non-metallic mineral products (C23) and basic metals (C24); from coke and refined petroleum products (19) to chemicals and pharmaceutical products (C20-21) and then to rubber and plastics products (C22); from the basic metals sector (C24) to fabricated metal products (C25), machinery and equipment (C28) and then to other transport equipment (C30). Other sectors often present in the cascading networks include : textiles (C13-15), electrical equipment (C27), motor vehicles and trailers and semi-trailers (C29).

Finally, we have provided an estimate of the overall and sectoral economic impacts of a 25\$ carbon price on basic metals imported emissions across sectors. The figure is in the range of 0.10-0.24% increase of the total imported inputs for our sample of countries. In absolute terms, Italy and Poland have the largest total increase, respectively 0.19% and 0.24%, a result driven by the emission intensities of basic metals imports. These countries are followed by Germany (0.13%), France (0.10%) and the United Kingdom (0.10%). From a sectoral perspective, top exposed industries are identical

across countries, with basic metals (C24) and fabricated metal products (C25) taking the first ranks. However, the strength of the sectoral exposure is unequal across economies (e.g. fabricated metal activity is more affected in Poland compare to those in France or the U.K). On the short run, the latter suggests different cost on economies following the implementation of such a uniform tax.

The results of our analysis suggest that the reduction of imported emissions triggered by an abrupt green transition might be substantial and systemic. While our methodological framework is not able to provide insights regarding the transition dynamics, the large proportion of imports and associated emissions directly or indirectly used as inputs across sectors indicate that cascading emission reductions is a likely scenario to consider. This offers valuable insights for two main areas of work. First, current research studying the implications of limiting imported emissions using trajectories through numerical simulations might be underestimating the global repercussion of economic effects from a transition away from mining. Second, the burgeoning literature on the macro-financial repercussions of the decarbonisation process might improve its analytical power by considering the effects of activity contraction in a wider range of productive sectors than just fossil extraction and power generation. Enhancing these strands of research with the inclusion of imported inputs and capital utilisation considerations will support policy-makers in the management of a rapid and smooth transition to a low-carbon economic system.

## Appendices of Chapter 3

### Tables

Table 3.4: NACE Sectors

<b>Sector code</b>	<b>Sector description</b>
A	Agriculture, forestry and fishing
B	Mining and Quarrying
C	Manufacturing
D	Electricity, gas, steam and air conditioning
E	Water supply; sewerage; waste management and remediation services
F	Constructions and construction works
G	Wholesale retail trade; repair of motor vehicles and motorcycles
H	Transportation and storage
I	Accommodation and food services activities
J	Information and communication
K	Financial and insurance activities
L	Real estate activities
M	Professional, scientific and technical activities
N	Administrative and support service activities
O	Public administration and defence: compulsory social security
P	Education
Q	Human health and social work activities
R	Arts, entertainment and recreation
S	Other services activities

Table 3.5: CO<sub>2</sub> emissions (Mt) in gross imports by sectors (A-F), year 2015.

Sector	France	Germany	Italy	Poland	U.K.
Agriculture, forestry and fishing	3,4	9,1	3,9	1,2	3,9
Mining and extraction of energy producing products	19,5	28,7	30,9	6,1	9,4
Mining and quarrying of non-energy producing products	1,1	4,1	1,5	0,8	1,5
Mining support service activities	0,3	0,1	0	0	0,1
Food products, beverages and tobacco	7,8	12,2	6	2,2	9,8
Textiles, wearing apparel, leather and related products	9,6	13,4	9	3,2	16,6
Wood and of products of wood and cork (except furniture)	1,1	2,1	1	0,4	1,8
Paper products and printing	2,9	4,9	2,3	1,5	3,4
Coke and refined petroleum products	14,1	29,1	8,5	2,6	15,3
Chemicals and pharmaceutical products	19,8	28,8	15,4	7,6	19,5
Rubber and plastics products	8,7	11,8	5,8	3,7	8,8
Other non-metallic mineral products	7	10,3	4,3	2,5	7,9
Manufacture of basic metals	18,6	44,2	39,6	12	16,9
Fabricated metal products, except machinery and equipment	7	12,2	4,7	3,2	7,9
Computer, electronic and optical products	12,6	22,7	6,1	5,4	14,5
Electrical equipment	12,8	18,9	8,3	5,4	12,8
Machinery and equipment n.e.c.	12,1	18,9	9,6	5,4	11,2
Motor vehicles, trailers and semi-trailers	11,2	20,5	8,5	3,8	15,2
Other transport equipment	10,8	5,5	3,6	2,7	20
Other manufacturing; repair and installation of machinery and equipment	11,6	13,3	5,5	2,1	18,6
Electricity, gas, water supply, sewerage, waste and remediation services	3,3	7,7	2,4	6,1	2,6
Construction	0,3	0,4	0,1	0,1	0,2

Table 3.6: CO<sub>2</sub> emissions in gross imports, year 2015.

<b>Country</b>	<b>CO<sub>2</sub> emissions (Mt)</b>
France	195 600
Germany	318 900
Italy	177 000
Poland	78 000
United Kingdom	217 900

## Cascades Propagation

Figure 3.6: Hierarchical network of imported emission reduction cascades across economic sectors in France.

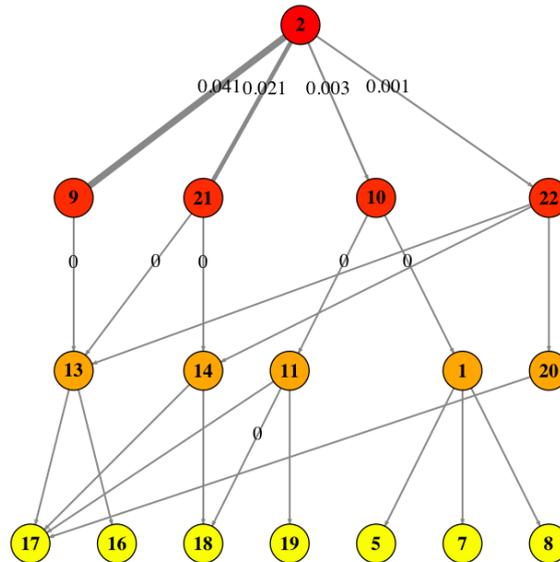


Figure 3.7: Hierarchical network of imported emission reduction cascades across economic sectors in Germany.

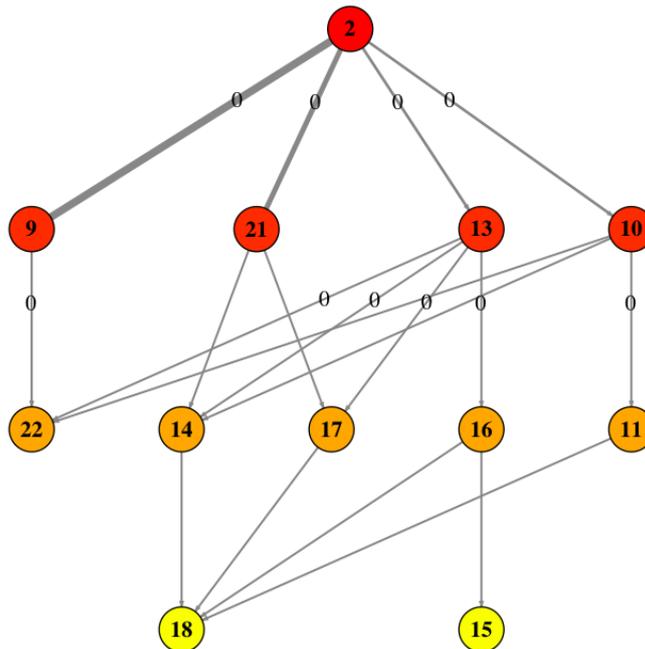


Figure 3.8: Hierarchical network of imported emission reduction cascades across economic sectors in Italy.

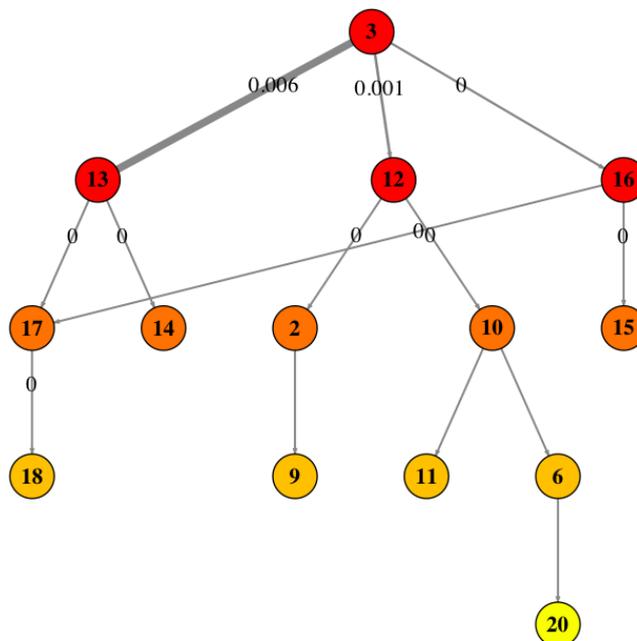


Figure 3.9: Hierarchical network of imported emission reduction cascades across economic sectors in Poland.

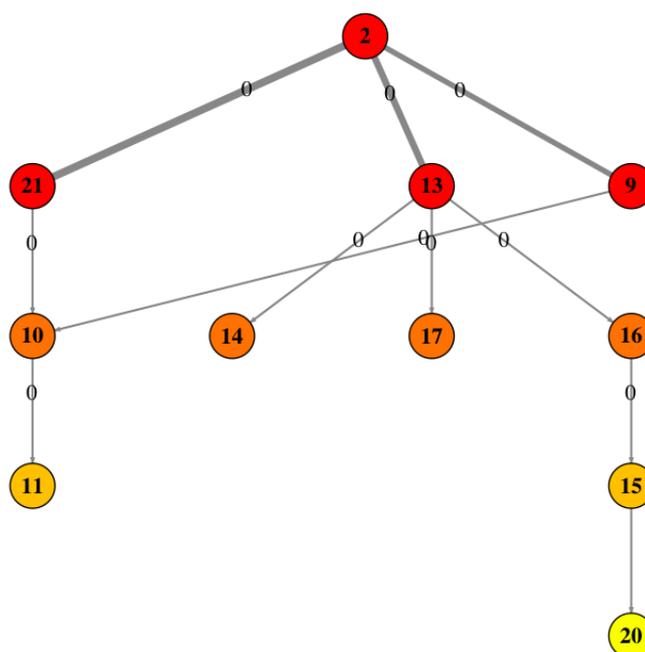
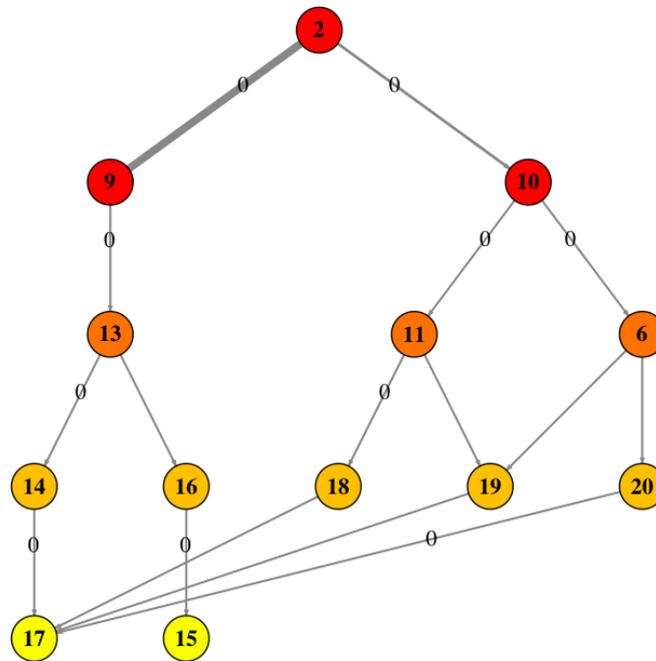


Figure 3.10: Hierarchical network of imported emission reduction cascades across economic sectors in the United Kingdom.



## Additional Informations

*A - Agriculture, forestry and fishing* : Non-perennial crops; Perennial crops; planting material: live plants, bulbs, tubers and roots, cuttings and slips; mushroom spawn; live animals and animal products; agricultural and animal husbandry services (except veterinary services); hunting and trapping and related services; forest trees and nursery services; wood in the rough; wild growing non-wood products; support services to forestry; fish and other fishing products; aquaculture products; support services to fishing.

*B - Mining and extraction of energy producing products* : hard coal; lignite; crude petroleum; natural gas, liquefied or in gaseous state; iron ores; non-ferrous metal ores; stone, sand and clay; mining and quarrying products n.e.c.; support services to petroleum and natural gas extraction; support services to other mining and quarrying.

*C10-12 - Food products, beverages and tobacco* : Preserved meat and meat products Processed and preserved fish, crustaceans and molluscs; processed and preserved fruit and vegetables; vegetable and animal oils and fats; dairy products; grain mill products, starches and starch products; bakery and farinaceous products; other food products; prepared animal feeds; beverages; tobacco products.

*C13-15 - Textiles, wearing apparel, leather and related products* : Textile yarn and thread; woven textiles; textile finishing services; other textiles; wearing apparel, except fur apparel; articles of fur; knitted and crocheted apparel; tanned and dressed leather; luggage, handbags, saddlery and harness; dressed and dyed fur; footwear.

*C16 - Wood and of products of wood and cork (except furniture)* : Wood, sawn and

planed Products of wood, cork, straw and plaiting materials

*C17-18 - Paper products and printing* : Pulp, paper and paperboard; articles of paper and paperboard; printing services and services related to printing; reproduction services of recorded media.

*C19 - Coke and refined petroleum products* : Coke oven products; refined petroleum products.

*C20-21 - Chemicals and pharmaceutical products* : Basic chemicals, fertilisers and nitrogen compounds, plastics and synthetic rubber in primary forms; pesticides and other agrochemical products; paints, varnishes and similar coatings, printing ink and mastics; soap and detergents, cleaning and polishing preparations, perfumes and toilet preparations; other chemical products; man-made fibres; basic pharmaceutical products; pharmaceutical preparations.

*C22 - Rubber and plastics products* : Rubber products; Plastic products.

*C23 - Other non-metallic mineral products* : Glass and glass products; refractory products; clay building materials; other porcelain and ceramic products; cement, lime and plaster; articles of concrete, cement and plaster Cut, shaped and finished stone; other non-metallic mineral products.

*C24 - Manufacture of basic metals* : Basic iron and steel and ferro-alloys; tubes, pipes, hollow profiles and related fittings, of steel; other products of the first processing of steel; basic precious and other non-ferrous metals; casting services of metals.

*C25 - Fabricated metal products, except machinery and equipment* : Structural metal

products; tanks, reservoirs and containers of metal; steam generators, except central heating hot water boilers; weapons and ammunition; forging, pressing, stamping and roll-forming services of metal; powder metallurgy; treatment and coating services of metals; machining; cutlery, tools and general hardware; other fabricated metal products.

*C26 - Computer, electronic and optical products* : Electronic components and boards; computers and peripheral equipment; communication equipment; consumer electronics; measuring, testing and navigating equipment; watches and clocks; irradiation, electromedical and electrotherapeutic equipment; optical instruments and photographic equipment; magnetic and optical media.

*C27 - Electrical equipment* : Electric motors, generators, transformers and electricity distribution and control apparatus; batteries and accumulators; wiring and wiring devices; electric lighting equipment; domestic appliances; other electrical equipment.

*C28 - Machinery and equipment n.e.c.* : General-purpose machinery; other general-purpose machinery; agricultural and forestry machinery; metal forming machinery and machine tools Other special-purpose machinery.

*C29 - Motor vehicles, trailers and semi-trailers* : Motor vehicles; bodies (coachwork) for motor vehicles; trailers and semi-trailers; parts and accessories for motor vehicles.

*C30 - Other transport equipment* : Ships and boats; railway locomotives and rolling stock; air and spacecraft and related machinery; military fighting vehicles; transport equipment n.e.c.

*C31-33 - Other manufacturing* : Furniture; jewellery, bijouterie and related articles;

musical instruments; sports goods; games and toys; medical and dental instruments and supplies; manufactured goods n.e.c.; repair services of fabricated metal products, machinery and equipment; installation services of industrial machinery and equipment.

*D-E - Electricity, gas, water supply, sewerage, waste and remediation services :* Electricity, transmission and distribution services; manufactured gas; distribution services of gaseous fuels through mains; steam and air conditioning supply services; natural water; water treatment and supply services; sewerage services; sewage sludge; waste; waste collection services, waste treatment and disposal services; materials recovery services; secondary raw materials; remediation services and other waste management services.

*F - Construction :* Buildings and building construction works, roads and railways; construction works for roads and railways; constructions and construction works for utility projects; constructions and construction works for other civil engineering projects; demolition and site preparation works; electrical, plumbing and other construction installation works; building completion and finishing works; other specialised construction works.

\* \* \*



## Chapter 4

# COVID-19 Recovery Packages and Industrial Emission Rebounds : Mind the Gap

\* \* \*

Meeting the net-zero climate target by 2050 has become a priority for the European Commission. The success of such objective largely depends on the design of COVID-19 economic recovery plans. In this paper we identify industrial sectors that, if governments are willing to decouple economic growth and emissions, should not benefit from recovery stimuli. Our results suggest that phasing-out the mining sector, a large provider of inputs to heavy polluting activities, would have large impacts on emissions once activity recovers. We also identify coke and refined petroleum products, chemical products and electricity and gas activities as critical downstream industries. Greening their output would limit GHG rebound effects in the coming months.

\* \* \*

*This chapter is an adaptation of a joint work with Pr. Anna Creti.*

## 4.1 Introduction

Since December 2019, the Covid-19 coronavirus has spread quickly from Asia to Europe and America, causing large-scale loss of life and severe human suffering ([Financial Times, April 2020](#)). The pandemic represents the third and greatest economic, financial and social shock of the 21<sup>st</sup> century - after 9/11 and the global financial crisis of 2008 ([OECD, 2020](#)). From an environmental perspective, this unexpected episode could mark a turning point in the fight against global warming. This year, global greenhouse gas (GHG) emissions will fall by around 7% ([Liu et al., 2020](#)), representing the annual rate at which our economies should decarbonize to reach carbon neutrality in 2050.<sup>1</sup> Instead, emissions will rebound once mobility restrictions are lifted and economies recover ([Le Quere, 2020](#)), unless governments take actions.

The expected decline in 2020 GHG emissions comes as a consequence of national policies to prevent the spread of the virus ([Helm, 2020](#)).<sup>2</sup> Indeed, G20 nations have implemented restrictions (e.g. social distancing, mobility) slowing down economic systems ([Thunström et al., 2020](#)). On the supply side, around 81% of the global workforce has been hit by either full or partial lockdown measures, causing unprecedented job losses and furloughs ([International Labour Office, 2020](#)). On the demand side, consumer spending has fallen as it was no longer possible to travel, including to shop for discretionary items, go to restaurants, or for experience-based activities ([Center for Economic Policy Research, 2020](#)). Overall, the crisis has impacted economic activity from both demand and supply sides ([World Economic Forum, 2020](#)), calling

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<sup>1</sup>This objective ensures a temperature rise below 1.5°C degree by 2100 ([UNEP, 2019](#)).

<sup>2</sup>Suggesting we have not decoupled GDP growth and carbon emissions ([Helm, 2020](#)).

governments for unprecedented support policies.

Depending on objectives and timing, government support programs are either part of short-term rescue plans or long-term recovery plans. With respect to the former, numerous EU governments have already exposed and implemented fiscal rescue policies ([International Monetary Fund, 2020](#)). These emergency measures come as a short run safety net to protect business balance sheets, reduce bankruptcies and address immediate human welfare concerns during lockdown periods.<sup>3</sup> Some rescue policies also cover emissions-intensive companies facing bankruptcy or significantly reduced revenue. For instance, this has been the case for airlines companies in France, Australia and the United States.<sup>4</sup> To ensure the success of the Paris Agreement (2015), government support plans (e.g. bailouts) should be conditional on these industries developing a measurable plan of action to transition towards a net-zero emissions future.<sup>5</sup> Indeed, the COVID-19 crisis will reduce global GHG emissions in 2020 but the long-term impact of the pandemic on emissions will be driven by forthcoming investment choices (both public and private). At the European scale, imminent recovery packages soon to be delivered will act as stimuli to restore economic growth in the region ([Hepburn et al., 2020](#)). The design of such packages (e.g. sectoral economic incentives, public investments) will reshape the economy on the long-run, acting as a potential game-changer to reach a post-carbon Union by 2050 ([McKinsey & Company, 2020](#)).

A key objective of any recovery package is to stabilise expectations, restore confidence and to channel surplus desired saving into productive investment ([Hepburn et al., 2020](#)). While most European governments have implemented rescue packages (e.g. France, Germany, Italy, Spain and the United Kingdom), the European Commission announced an additional budget amount of €750 billion to support most affected EU

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<sup>3</sup>In April 2020, all G20 nations (including most EU member states), had signed such fiscal measures into law (see [International Monetary Fund, 2020](#)).

<sup>4</sup>Precisely, France rescue plan for Air France reached €7 billion ([Les Echos, April 2020](#)); Australian government announced AU\$715mn of unconditional Australian airline relief (through the Coronavirus Economic Response Package ([Commonwealth of Australia, 2020](#)), and US\$32bn of bailouts for US airlines (see [Courtney \(2020\)](#) for a review of CARES Act).

<sup>5</sup>Which, for instance, has not been the case for Air France ([Le Monde, May 2020](#)).

economies, representing more than €1100 billion global budget for the period 2021-2027 (European Commission, 2020).<sup>6</sup> If this amount is necessary for EU economies to recover (e.g. France, Italy, Spain), an efficient long-run recovery plan should target sectors able to rapidly create jobs and boost production across other industries in the economy, thus stimulating GDP growth (Allan et al., 2020). Among other factors,<sup>7</sup> those targeted sectors should display high short-run/long-run economic multipliers, or return for every dollar of expenditure (Bussing-Burks, 2011; Ramey, 2019). Such metrics accounts not only for the effects of the spending (government expenses, tax reductions) in the specific sector (e.g. impact on income, output), but also for the subsequent rounds of spending generated by the initial expenditures in other part of the economy.<sup>8</sup> Back during and following the 2008 global financial crisis, expansionary policies, focusing on investments through the lens of economic coefficients, were more effective at restarting economic activity than austerity-based policies (European Central Bank, 2015; Hepburn et al., 2020). Twelve years later, the COVID-19 crisis pushes again policy-makers to decide which key sectors to focus investments on, reflecting changing technologies and the need to stimulate growth and secure job creations for the coming years (DG Tresor, 2020).

From a climate policy approach, the sole consideration of economic multipliers to guide forthcoming economic stimuli does not guarantee a transition toward a post-carbon society by 2050 (Hammer and Hallegatte, 2020). Indeed, recovery plans could be either "brown" or "green" depending on their ability to decouple emissions from economic activity (IFRI, 2020). Sectors exhibiting high economic multipliers could be

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<sup>6</sup>Although governments will have flexibility regarding the allocation of such funds, the main priority is to reach the EU's objectives of climate neutrality and digital transformation, to offer social and employment support as well as to reinforce the EU's role as a global player (European Parliament, 2020).

<sup>7</sup>Several other factors are relevant to the design of economic recovery packages : contributions to the productive asset base and national wealth, speed of implementation, affordability, simplicity, impact on inequality, and various political considerations.

<sup>8</sup>In detail, economic multiplier measures the impact on activity of each additional currency unit of spending/tax cut funded by borrowing. A multiplier of 1 means \$1 extra spending boosts final production and income by £1. A multiplier of 3 implies \$1 spending boosts final income and output by £3.

those acting as big emitters suggesting a tension between short run economic growth and climate targets (see [European Commission, 2007](#)). Then, to decouple GDP growth and emissions, EU governments could be interested in understanding which industrial sectors are driving GHG emissions<sup>9</sup> in the economy. Following the ongoing crisis, the willingness to design green recovery plans could lead to not supporting such industries. By doing so, large amounts of GHG emissions could be avoided once economy recovers, putting the entire EU industrial system on track with respect to the Paris Agreement objectives. Moreover, some industries might not be greenhouse gas (GHG) intensive but might decrease global GHG emissions by limiting provision of inputs to downstream dirty sectors. When designing sectoral support policies, government will have to be aware of such intra-sector dynamics to limit emissions. This paper aims at providing new insights on these issues.

Precisely, we consider the economy as a system of industries interacting with each others ([OECD, 2016](#)) and capture the dynamics of supply/demand between industrial sectors. Indeed, output of an industry might be used directly as input or as output supplied to other sectors (e.g. output of the mining sector are consumed as inputs by that industry or supplied as inputs to other sectors). The decrease in production from the mining sector would decrease the sector output and impact the demand-side sectors. Then, following the chain of intermediate demand, industries directly connected such as basic metals would in turn reduce their output. Such a cascading mechanism of output contraction would decrease associated GHG emissions (i.e. from production).<sup>10</sup> While some studies have explored phenomenon of economic cascades (e.g. information in financial markets ([Romano, 2007](#)), the diffusion of risks in the banking system ([Battiston et al., 2017](#)) or the stranding of dirty assets in a low carbon economy ([Cahen-Fourot et al., 2020](#))), the topic of industrial emissions has never been investigated from a systemic perspective.

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<sup>9</sup>Gases that trap heat in the atmosphere (e.g. carbon dioxide, methane), contributing to global warming. See full description in the Section 2.

<sup>10</sup>In the following, we name "cascading process" such a dynamics of emission contraction.

Overall, we propose a novel analysis of the process through which a contraction of the gross output of a specific sector would decrease the use of inputs in other sectors leading to a drop in associated emissions (i.e. forward oriented sectors). The supply of essential inputs to the rest of the economy is a matter of addressing primarily forward impact effects rather than backward effects (i.e. change in inputs affecting upstream sectors). In the context of post COVID-19 recovery plans, this approach is particularly relevant as supply chains have been severely hit by government restrictions and supply dynamics will be critical to avoid inflation in the post-COVID opening time-window (BNP Paribas - [Economic Analysis, 2020](#)). While governments will implement economic stimuli to secure high levels of supply, our paper identifies the sectors that should not benefit from recovery plans<sup>11</sup> and quantifies the impacts of such deliberate decision on emissions (i.e. avoided emissions). Providing such new results would allow policy-makers to account for these potential "avoided" emissions when designing green economic stimulus. We use data available for five European countries affected by the COVID-19 pandemic (i.e. France, Germany, Italy, Poland and Spain) to illustrate our model and achieve two main objectives.

First, we use Input-Output (IO) concepts to derive national economic matrices of *emission coefficients*, including the entire range of the industrial productive sectors. These coefficients capture the amount of emissions that would be reduced in a sector due to a unitary decrease in primary inputs<sup>12</sup> utilised by another (or the same) sector, considering both direct and indirect effects. For instance, these matrices are able to provide GHG emission reductions in the textile sector due to a drop in the plastics industry, both directly and through its intermediate effects on, for instance, chemicals. By doing so, we identify industries most likely to trigger large emission reduction cascades and those most exposed to a such a dynamics (i.e. increase in internal GHG

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<sup>11</sup>Such sectors drive GHG emissions in the industrial system. Without contributions in terms of climate strategy, government willing to achieve climate goals should not target them.

<sup>12</sup>We define "primary inputs" as the main factors used in production (labour, capital, land, and others). IO tables report their factor costs (e.g. compensation of employees, consumption of fixed capital or net operating surplus) (Miller and Blair, 2009).

emissions through the channel of another sector). The novelty of the present analysis is to maintain a systemic perspective of the national economy, and investigate the transmission channels of GHG emission reductions across industries (i.e. emission cascades). By providing a quantitative estimation of such cross-sectoral GHG emission interactions, our paper brings relevant insights to policy-makers too.

Whatever the economic system, we highlight how mining,<sup>13</sup> coke and refined petroleum products<sup>14</sup> and electricity and gas<sup>15</sup> are among the sectors with the largest emission coefficients. A fall in their activity (i.e. gross output) creates the largest reduction amount of emissions in the system. Leaving all else equal, green recovery packages should ensure their activity to not expand, and even further to contract.<sup>16</sup> On the opposite, coke and refined petroleum, basic metals<sup>17</sup> and electricity and gas industries are the most exposed to such dynamics of emission contraction. All these activities have various impacts in terms of GHG emission reductions (across economies), suggesting different national strategies regarding implementation of recovery plans.

Second, we focus our study on the mining industry in order to investigate the most relevant channels of sectoral cascades of GHG emissions that could be avoided in the future. By doing so, we are able to evaluate the role of energy intensive sectors such as coke and refined petroleum products, basic metals and electricity and gas in the cascading process. While countries exhibit different cascading dynamics depending on the peculiarities of their industrial structure, certain regular patterns emerge. On one hand basic metals, the manufacture of coke and refined petroleum products and electricity and gas are the activities the most directly exposed to a drop in GHG emissions

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<sup>13</sup>The sector encompasses coal and lignite, crude petroleum and natural gas, metal ores, other mining and quarrying products and mining support services.

<sup>14</sup>Includes coke oven products and refined petroleum products.

<sup>15</sup>The sector mainly covers electricity, transmission and distribution services, manufactured gas, distribution services of gaseous fuels through mains, steam and air conditioning supply services, natural water; water treatment and supply services.

<sup>16</sup>If one assumes no shift toward cleaner production in those industries.

<sup>17</sup>The sector covers basic iron and steel and ferro-alloys, tubes, pipes, hollow profiles and related fittings, of steel, other products of the first processing of steel, basic precious and other non-ferrous metals.

through a contraction of production in the mining sector. Such results suggest strong economic connections between the mining industry and these sectors where the former supplies the latter.<sup>18</sup> On the other hand, irrespective to their rankings in the process, chemicals and pharmaceutical products<sup>19</sup> as well as manufacture of other non-metallic mineral products<sup>20</sup> are highly present in the third layer of the GHG cascading process.<sup>21</sup> The latter emphasizes the existence of a significant connection between those activities and aforementioned energy-intensive sectors (e.g. chemicals affected by upstream coke and refined petroleum products activity). In addition, agriculture<sup>22</sup> and construction<sup>23</sup> are often impacted by mining decreasing activity through the channel of basic metals. From a policy perspective, these outcomes suggest that moving away from mining would have impacts not only on emissions (Fugiel et al., 2017), but would also generate economic effects on other sectors (i.e. from mining to downstream industries such as construction through the channel of basic metals). On this issue, our results complement the flourishing literature on assets at risk due to a low carbon transition (Caldecott, 2017; Creti and de Perthuis, 2019). Such findings reinforce the importance of a well-designed recovery plan to limit GHG emission rebound effects and to stimulate sector-based clean solutions (e.g. green inputs).

The remainder of the article is organised as follows. Section 2 introduces the method

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<sup>18</sup>In some countries such as Germany and Poland, this finding is particularly relevant.

<sup>19</sup>Sector covers basic chemicals, fertilisers and nitrogen compounds, plastics and synthetic rubber in primary forms, pesticides and other agrochemical products, paints, varnishes and similar coatings, printing ink and mastics, soap and detergents and other chemical products.

<sup>20</sup>The activities include glass and glass products, refractory products, clay building materials, other porcelain and ceramic products, cement, lime and plaster, articles of concrete, cement and plaster, cut, shaped and finished stone.

<sup>21</sup>For non-metallic mineral products, the sector is present in the second or third layer, depending on the examined country.

<sup>22</sup>The sector includes non-perennial crops, perennial crop, planting material: live plants, bulbs, tubers and roots, cuttings and slips, mushroom spawn, live animals and animal products, agricultural and animal husbandry services (except veterinary services), hunting and trapping and related services, forest trees and nursery services, wood in the rough, wild growing non-wood product, support services to forestry, fish and other fishing products; aquaculture products, support services to fishing.

<sup>23</sup>Represents buildings and building construction works, roads and railways, construction works for roads and railways, constructions and construction works for utility projects; constructions and construction works for other civil engineering projects, demolition and site preparation works; electrical, plumbing and other construction installation works, building completion and finishing works, other specialised construction works.

to compute the matrices of sectoral *emission coefficients*. Section 3 presents the results of the analysis for five European countries, discussing the sectors most likely to create large amounts of emission reductions and the ones most exposed to such dynamics. Section 4 focuses on understanding the systemic propagation of shocks starting from mining in order to identify relevant channels of GHG emission decline. Finally, Section 5 discusses implications of our results for designing effective green recovery packages to avoid a resurgent increase in industrial GHG emissions and exposes elements of conclusion.

## 4.2 Methodology & Data

### 4.2.1 The Emission Reduction Multiplier Matrix

Following Cahen-Fourrot et al. (2020), we start with the national inter-industry matrix  $\mathbf{Z}$ , a square matrix exhibiting amounts of sectoral intermediate consumption. In broad terms, such a matrix is called "Input-Output matrix" and captures exchanges of goods and services among industrial sectors in monetary units.<sup>24</sup>

In input-output tables (IOTs), the  $\mathbf{Z}$  matrix usually comes with an additional set of column vectors displaying final consumption (i.e. demand ( $\mathbf{f}$ )) and row vectors representing value added items ( $\mathbf{v}$ ) (i.e. compensation of employees, fixed capital consumption, gross operating surplus). Sectors appear both as producers of goods and services (rows) and as consumers of intermediate inputs (columns). More specifically, IOTs are commonly defined as monetary industry balances, where total supply  $\mathbf{x}^T = \mathbf{i}^T \mathbf{Z} + \mathbf{v}$  equals total use  $\mathbf{x} = \mathbf{Z} \mathbf{i} + \mathbf{f}$  of products and services per sector.<sup>25</sup> Therefrom, the total amounts of all transactions over a row (industry output allocated to each category of user (i.e. intermediate and final consumption)) equals the sum over the corresponding column (total industry input flowing from upstream sectors - other industries and value

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<sup>24</sup>See Miller and Blair, 2009; Cahen-Fourrot et al., 2020.

<sup>25</sup>Note that  $\mathbf{i}$  is a column vector of the same dimension of  $\mathbf{Z}$

added items). The IOT also reports imported goods and services, which are again used either as intermediate inputs or as final demand. Figure 4.1 below shows a stylized version of an IOT.

Inter-Industry matrix ( $Z$ )		Intermediate uses		Final uses ( $f$ )			Total use ( $TU$ )
		Sector A	Sector B	Cons.	Inv.	Exp.	
Production	Sector A	Products of A used as inputs by A	Products of A used as inputs by B	Final use of products by A			Total use of products of A
	Sector B	Products of B used as inputs by A	Products of B used as inputs by B	Final use of products by B			Total use of products of B
Total		Total intermediate inputs		Total final uses			Total uses
Value added ( $v$ )	Comp. of employees	Total value added					
	Cons. of fixed capital						
	Operating surplus						
Output		Total domestic output					
Imports		Total imports					
Total supply (TS)		Total supply					

Figure 4.1: A stylized Input-Output Table (Cahen-Fourot et al., 2020)

In economics, IOTs have been mainly used to evaluate direct and indirect effects of changes in final demand based on the [Leontief inverse matrix](#) (Leontief, 1951; Metzler, 1951; Chen, 1973; Velázquez, 2006). Although the demand will be critical in defining the forthcoming dynamics of GHG emissions under recovery plans, the novelty of our analysis is to adopt a supply-side perspective. Namely, we capture those sectors providing lower amounts of inputs supplied to other sectors as a result of a one-unit decrease in their gross value added or, generally speaking, gross domestic product (i.e. forward oriented sectors), this allows us to capture associated decrease in emissions (described hereafter). The supply of essential inputs to the rest of the economy is a matter of addressing primarily forward impact effects rather than backward effects (i.e. change in inputs affecting upstream sectors). In the context of post COVID-

19 recovery plans, our methodology is relevant as the supply has been particularly hit by governments restrictions (e.g. mobility) and supply dynamics will be critical to meet forthcoming demand and avoid inflation (BNP Paribas - Economic Analysis, 2020). Governments, while implementing economic policies to support supply-side sectors, will have to be careful on the potential impact on GHG emissions.

A relevant approach for our study is the Ghosh (1958) supply-driven model.<sup>26</sup> The output of the Ghosh model is a matrix  $\mathbf{B} = \mathbf{x}^{-1}\mathbf{Z}$  of *allocation* coefficients of the supply of a sector (i.e. output) to all other sectors. In the matrix  $\mathbf{B}$ , each element  $b_{ij}$  quantifies the share of sector  $i$ 's output consumed by sector  $j$ . Then, the Ghosh matrix  $\mathbf{G}$  is defined as :

$$\mathbf{G}=(\mathbf{I}-\mathbf{B})^{-1}$$

We then transpose  $\mathbf{G}$  to be able to read the effects of changes in sectoral primary inputs over the columns (similarly to the Leontief system) of  $\mathbf{G}^T$ , where  $T$  denotes the matrix transposition. Each entry  $g_{i,j}$  of  $\mathbf{G}^T$  shows the change in output  $\mathbf{x}$  in sector  $i$  that would result from a unitary change of primary inputs used in sector  $j$ . In general terms, a drop (or increase) of one monetary unit in primary inputs supporting production in sector  $i$  will generate a drop (increase) in the output of sector  $j$  by an amount equivalent to  $g_{i,j}$ .<sup>27</sup> In IO analysis, primary inputs cover items appearing on the rows below the inter-industry matrix (e.g. compensation of employees). As exposed in Cahen-Fourrot et al. (2020), primary inputs represent the societal effort to produce the output of a sector, captured by factor payments.

We innovate by combining the obtained Ghosh matrix with sectoral data of GHG emissions  $e$ .<sup>28</sup> To do so, we define  $E_i = e_i/M_i^d$  as the emission intensity of sector  $i$ , where  $M^d$  represents the domestic output of the sector. By multiplying the diagonalised form of the vector of emission intensities by the Ghosh matrix, we find the matrix  $\mathbf{S}$

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<sup>26</sup> Augustinovics, 1970; Beyers, 1976.

<sup>27</sup>Note that  $g_{i,j}$  includes both direct and indirect effects.

<sup>28</sup>Cf. part next part for full description of data.

of *emission reduction coefficients* :

$$\mathbf{S} = \hat{\mathbf{E}}\mathbf{G}^T$$

Each element  $s_{ij}$  of matrix  $\mathbf{S}$  represents the change in emissions in sector  $i$  generated by a unitary change of primary inputs used by sector  $j$ . For our purpose, the elements of  $\mathbf{S}$  capture the amount of emissions of a sector  $i$  that could be reduced because of a unitary decrease in primary inputs used in the production of goods and services of another sector  $j$  (e.g. hard coal, iron ores). The column sum of matrix  $\mathbf{S}$  gives a measure of the total amount of reduced emission resulting from a unitary reduction of primary inputs in a sector  $j$ . We define this as the total *emission coefficient* of a sector :

$$s_j^{TOT} = \mathbf{i}^T \mathbf{S}$$

where  $n$  is the dimension of matrix  $\mathbf{S}$ . In our case, we assume the values of  $s_i^{TOT}$  to be largely driven by  $i$  emission intensity and therefore, by potential amounts of internal emission reduction. On the opposite, to estimate external *emission reduction coefficient* (i.e. the impacts of a sector reduction of primary inputs on emissions of all other sectors), we proceed as follows :

$$s_j^{EXT} = s_j^{TOT} - s_j^{diag},$$

where  $s_j^{diag}$  refers to the  $j$ -th element of the diagonal of  $\mathbf{S}$ . In the end, we define the sum of the rows of  $\mathbf{S}$  as the exposure of a sector to emission reductions (i.e. the reduction of emissions following a unitary loss in primary inputs used in all other sectors) :

$$s_i^{EXP} = \mathbf{S} \mathbf{i}$$

Overall, this methodological approach allows us to investigate both internal and external emission reductions generated by sectors. A sector might have a large emission reduction coefficients mainly driven by internal reductions - suggesting a poor economic connection with other sectors (supply). We capture this feature in [Section 5](#) by constructing the channels of reduction cascades across economies.

## 4.2.2 Datasets : Input-Output Tables and Emissions

We apply the methodology described above to five European economies, heterogeneously affected by the pandemic crisis : France, Germany, Italy, Poland as well as Spain (OECD, *Economic Outlook*, 2020; *The Guardian*, June 2020). The main source of IO tables data we employ are extracted from the OECD for the year 2015.<sup>29</sup> More precisely, we use symmetric input-output tables at basic price by industry.<sup>30</sup> Table 4.4 in the [Appendix, 1.1](#) lists NACE level 1 categories,<sup>31</sup> while Table 4.1 below offers the detailed disaggregation of industries we investigate in this paper.<sup>32</sup> In the following, we deliberately exclude business services (Table 4.4, from G to S) as it represents a small share of emissions (OECD, *Air Emission Accounts*).<sup>33</sup> However, by providing inputs to other sectors, such activities can still play a significant role by driving down emissions. Our model allows us to capture such dynamics through the channel of external coefficients. With respect to emissions, we constructed our dataset from the *OECD - Air emission accounts* on total GHG emissions per sector (CO<sub>2</sub> eq.) for the year 2015.<sup>34</sup> Overall, Germany emitted more than 629 Mt (CO<sub>2</sub> eq.), followed by Poland (297 Mt), Italy (258 Mt), France (247 Mt) and Spain (221 Mt).<sup>35</sup> Although countries exhibit different patterns in terms of sectoral emissions, our dataset suggests that agriculture, electricity and gas, chemicals, fabricated metal products and basic metals were the largest emission intensive activities in 2015.

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<sup>29</sup>OECD Statistics : [https://stats.oecd.org/Index.aspx?DataSetCode=IOTSI4\\_2018](https://stats.oecd.org/Index.aspx?DataSetCode=IOTSI4_2018).

<sup>30</sup>Total economy, product by product in million \$.

<sup>31</sup>The statistical classification of economic activities in the European Community, abbreviated as NACE, is the classification of economic activities in the European Union (EU).

<sup>32</sup>For further descriptions, refer to the [Appendix](#).

<sup>33</sup>Exposed by [Cahen-Fourot et al. \(2020\)](#) : the decarbonisation process might not be particularly detrimental for services activities (low dirty capital levels, low demand for fossil fuel).

<sup>34</sup>OECD Statistics - "Data refer to total emissions of CO<sub>2</sub> (CO<sub>2</sub> emissions from energy use and industrial processes, e.g. cement production), CH<sub>4</sub> (methane emissions from solid waste, livestock, mining of hard coal and lignite, rice paddies, agriculture and leaks from natural gas pipelines), N<sub>2</sub>O (nitrous oxide), HFCs (hydrofluorocarbons), PFCs (perfluorocarbons), (SF<sub>6</sub> +NF<sub>3</sub>) (sulphur hexafluoride and nitrogen trifluoride), SO<sub>x</sub> (sulphur oxides, NO<sub>x</sub> (nitrogen oxides), CO (carbon monoxide), NMVOC (non-methane volatile organic compounds), PM<sub>2.5</sub> (particulates less than 2.5 μm), PM<sub>10</sub> (particulates less than 10 μm) and NH<sub>3</sub> (ammonia)".

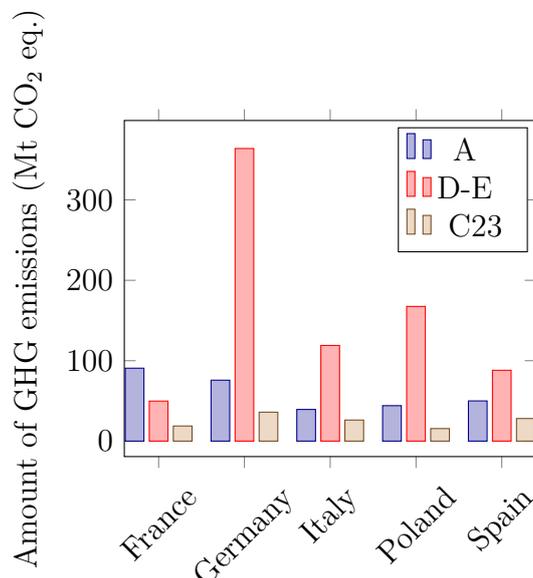
<sup>35</sup>These data cover the scope of our analysis (e.g. services are not included, imported emissions neither).

By combining IOTs and data of emissions, we are able to offer results for the industrial and power sectors (i.e. NACE from A to F) in France, Germany, Italy, Poland and Spain. In 2015, these countries represented more than 60% of the European Union gross domestic product ([Statista, 2020](#)).

Table 4.1: Breakdown of examined NACE Sectors.

<b>Sector</b>	<b>Code</b>	<b>Sector description</b>
A	1	Agriculture, forestry and fishing
B	2	Mining and quarrying activities
C10-12	5	Food products, beverages and tobacco
C13-15	6	Textiles, wearing apparel, leather and related products
C16	7	Wood and of products of wood and cork (except furniture)
C17-18	8	Paper products and printing
C19	9	Coke and refined petroleum products
C20-21	10	Chemicals and pharmaceutical products
C22	11	Rubber and plastics products
C23	12	Other non-metallic mineral products
C24	13	Manufacture of basic metals
C25	14	Fabricated metal products, except machinery and equipment
C26	15	Computer, electronic and optical products
C27	16	Electrical equipment
C28	17	Machinery and equipment n.e.c.
C29	18	Motor vehicles, trailers and semi-trailers
C30	19	Other transport equipment
C31-33	20	Other manufacturing, repair and installation of machinery and equipment
D-E	21	Electricity, gas, water supply, sewerage, waste and remediation services
F	22	Construction

Figure 4.2: Distribution of total GHG emissions (CO<sub>2</sub> eq.) across Agriculture (A), Electricity and Gas (D-E) and Other Non-metallic mineral products (C23).



## 4.3 Cascading Greenhouse Gas Emissions

### 4.3.1 Emission Coefficients

In this section, we analyse results reported in Table 4.2 below, namely total emission coefficients (1), external coefficients (2) and exposure to emissions (3). We focus on the top five sectors for each country. Given the distribution of emissions in the economy and leaving all else equal, the first two sets of coefficients show the sectors that are likely to generate the largest amounts of GHG emission reductions (Mt CO<sub>2</sub> eq.) in the economic system following a unit decrease in their primary inputs. For the purpose of our paper, these sectors are the ones that should not be supported by forthcoming recovery plans if governments are willing to decouple growth and emissions. On the opposite, recovery plans could create economic incentives to engage such sectors in cleaner production processes (cf. Section 5). The third set of results displays instead the sectors that are likely to be most exposed to such dynamics of decreasing emissions

from a unitary drop<sup>36</sup> distributed equally across all industries.

Table 4.2: Emission Coefficients

France	Germany	Italy	Poland	Spain
<b>Total Emission Coefficients (1)</b>				
B (0.0292)	B (0.0190)	B (0.0373)	B (0.0121)	B (0.0286)
C19 (0.0058)	D-E (0.0055)	C19 (0.0081)	D-E (0.0118)	C19 (0.0061)
C24 (0.0035)	A (0.0051)	D-E (0.0044)	C19 (0.0073)	C23 (0.0057)
A (0.0030)	C19 (0.0044)	C23 (0.0032)	C24 (0.0062)	D-E (0.0040)
C23 (0.0028)	C24 (0.0027)	C24 (0.0028)	A (0.0054)	C24 (0.0027)
<b>External Emission Coefficients (2)</b>				
B (0.0287)	B (0.0178)	B (0.0359)	B (0.0088)	B (0.0280)
D-E (0.0004)	C19 (0.0008)	M (0.0007)	C20-21 (0.0019)	C20-21 (0.0008)
C19 (0.0004)	G (0.0005)	K (0.0007)	C19 (0.0016)	D-E (0.0008)
C22 (0.0004)	M (0.0004)	C24 (0.0006)	C24 (0.0015)	C22 (0.0007)
C25 (0.0004)	C25 (0.0004)	C19 (0.0006)	C28 (0.0013)	K (0.0006)
<b>Exposure to Emission Coefficients (3)</b>				
C19 (0.0225)	D-E (0.0114)	C19 (0.0268)	D-E (0.0142)	C19 (0.0205)
D-E (0.0042)	C19 (0.0083)	D-E (0.0141)	C19 (0.0058)	D-E (0.0104)
C24 (0.0029)	C24 (0.0036)	C24 (0.0026)	A (0.0053)	C24 (0.0039)
A (0.0026)	A (0.0017)	C23 (0.0016)	C24 (0.0029)	C23 (0.0031)
C23 (0.0012)	C23 (0.0017)	C20-21 (0.0009)	C23 (0.0021)	A (0.0015)

Regarding total coefficients, sector of mining (B) is by far the most prevalent, appearing as the top sector in every country of our scope.<sup>37</sup> Studying the S matrix, one can notice that emissions of sectors often significantly affected by the drop in primary inputs originating in the mining industry include those from coke and refined petroleum products (C19), electricity and gas industry (D-E), other non-metallic mineral prod-

<sup>36</sup>In primary inputs.

<sup>37</sup>Remember that total coefficients are column sums of the S matrix, thus representing the cumulative impact of a drop in a sector's primary inputs on GHG emissions of other sectors. As to interpret the coefficient of mining : a one unit decrease (in monetary unit = million \$) in mining primary inputs leads to a drop in GHG of 0.029 Mt (CO<sub>2</sub> eq.) across all other sectors in the economy. Looking at the S matrix and the impact of mining on coke and refined petroleum products (C19) we have : a one unit decrease (in monetary unit = million \$) in mining primary inputs leads to a drop in GHG from the coke and refined petroleum industry of 0.020 Mt (CO<sub>2</sub> eq.).

ucts (C23) and basic metals (C24). These results emphasize the critical presence of mining inputs in their production process (e.g. iron ores, coal). For certain countries (e.g. Germany, Italy, Poland), the presence of D-E sector is likely to be mainly driven by the proportion of energy producing inputs in the energy mix (e.g. coal/gas, see [EU data](#), [Energy statistical datasheets](#) for the year 2015).

In addition to B activities, industries included in category C (manufacturing) such as C19 (coke and refined petroleum products), C23 (other non-metallic mineral products), C24 (basic metals) and D-E (electricity and gas) exhibit large coefficients of emission reductions across economic systems.<sup>38</sup> The latter appears to be strongly intertwined with the level of emission intensity of the sectors, thus highlighting a significant potential for an internal emission decline. Moreover, for the specific case of other non-metallic mineral products (C23), examined EU countries were the largest producers in the EU in 2015 ([European Commission, 2017](#)). The strong potential for internal emission contraction in these industries is confirmed by the following analysis on external emission coefficients. Finally, agriculture (A) is among the top sectors of total emission coefficients in France, Germany and Poland. This outcome emphasizes the key role of agricultural practices in climate mitigation strategies ([IPCC, 2014](#)).

External emission coefficients, which abstract from internal emissions of a sector and thus offer an accurate representation of the effect of a sector's activity on GHG emission decline in the rest of the economy, exhibit a different pattern. The relevance of mining (B) as an import-intensive activity is still highly significant (i.e. coefficients), confirming a strong economic connection (i.e. provider of inputs) between this sector and other high polluting sectors (e.g. coke and refined petroleum products (C19) and electricity and gas (D-E)).<sup>39</sup> With respect to other GHG intensive sectors, coefficients

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<sup>38</sup>Note that for France, D-E is not among top sectors. We expect the latter to be due to the large share of nuclear power generation in the country.

<sup>39</sup>Note that mining external coefficients are significantly high, embodying the ability of the sector to generate emissions in other GHG intensive sectors. Moreover, mining products are mainly imported from outside of the EU, thus explaining low amounts of emissions for the sector (although in Poland, the sector displays a high amount of emissions as the country is the biggest EU hard-coal producer

are drastically reduced. Sectors C20-21 (chemicals and pharmaceutical products) becomes particularly relevant in Poland and Spain while C19 (coke and refined petroleum products) and C24 (basic metals) are the most recurrent manufacturing sectors in our sample (except in Spain). All these sectors appear high in the ranking of external emission coefficients because they provide significant amount of inputs to other productive sectors (thus driving up emissions).<sup>40</sup> For instance, both sectors B (mining) and C20-21 (chemicals) provide substantial intermediate goods to coke and refined petroleum products (C19) while basic metals (C24) supplies fabricated metal products (C25) as well as machinery and equipment (C28). Table 4.3 below offers a closer look at industries exhibiting largest coefficients, reporting the top 5 sectoral values for the external emission coefficients originating in mining (B).<sup>41</sup>

Table 4.3: Sectoral Emission Coefficients for top sectors (excluded).

<b>France</b>	<b>Germany</b>	<b>Italy</b>	<b>Poland</b>	<b>Spain</b>
B (0.0292)	B (0.0190)	B (0.0373)	B (0.0121)	B (0.0286)
C19 (0.02094)	C19 (0.0072)	C19 (0.0236)	D-E (0.0038)	C19 (0.0171)
D-E (0.0032)	D-E (0.0070)	D-E (0.0095)	C19 (0.0027)	D-E (0.0061)
C24 (0.0018)	C24 (0.0022)	C24 (0.0012)	C24 (0.0010)	C24 (0.0023)
A (0.0009)	C23 (0.0004)	C23 (0.0005)	A (0.0004)	C23 (0.0012)
C23 (0.0007)	A (0.0003)	C20-21 (0.0002)	C23 (0.0004)	C20-21 (0.0005)

As mentioned, C19 (coke and refined petroleum products), C24 (basic metals) as well as D-E (electricity and gas) all appear as the sectors most exposed to a decrease in GHG emissions through the channel of mining. Again, this matches previous observations that top industries in external emission coefficients provide substantial inputs to GHG intensive sectors.<sup>42</sup> Moving back to Table 4.2, several other manufacturing sectors appear among the top 5. For instance, this is the case for activities C22 (rubber (Reuters, June 2020)).

<sup>40</sup>The low level of external emissions coefficients of energy intensive sectors is due to the fact that downstream sectors are not huge polluting industries (e.g. machinery and equipment (C27), construction (F)).

<sup>41</sup>We exclude respective country top sector itself, to abstract from internal emissions.

<sup>42</sup>Although for electricity and gas, this arguments depends on considered energy used (gas, coal).

and plastics) and C25 (fabricated metal products) in France, Germany and Spain respectively. Note that financial and insurance activities (K) are also present in Italy and Spain.

Finally, looking at the values of total sectoral exposure to emissions, we can identify four main sectors, repeatedly appearing among the sectors with the highest row sums in  $S$  : C19 (coke and refined petroleum products); C23 (other non-metallic mineral products); C24 (basic metals) and D-E (electricity and gas). These sectors, in addition to having high emission intensities, are affected by multiple relevant inward economic links. To investigate these features, we consider the  $S$  matrix as an adjacency matrix for a directed network (Godsil and Royle, 2013; Halleck-Vega et al., 2018; Cahen-Fourot et al., 2020), interpreting productive sectors as the vertices of the network and the  $s_{i,j}$  elements of  $S$  as the weight of the edges going from vertex  $j$  to vertex  $i$ . Then, it is possible to represent the network as a circular layout. Figures 4.3 and 4.4 below show the outcome of this procedure for Germany and Spain, as they exhibit different patterns in terms of sectors' exposure (e.g. strength of coefficients and rankings).

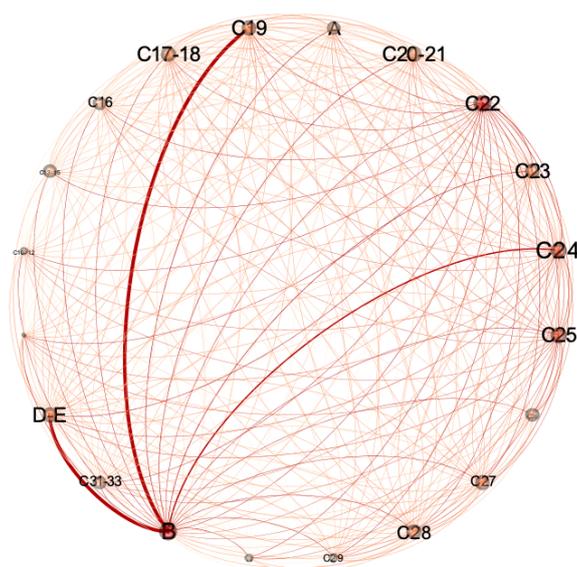


Figure 4.3: Network of emissions across sectors in Germany. The size of the node is proportional to the number of weighted incoming links.

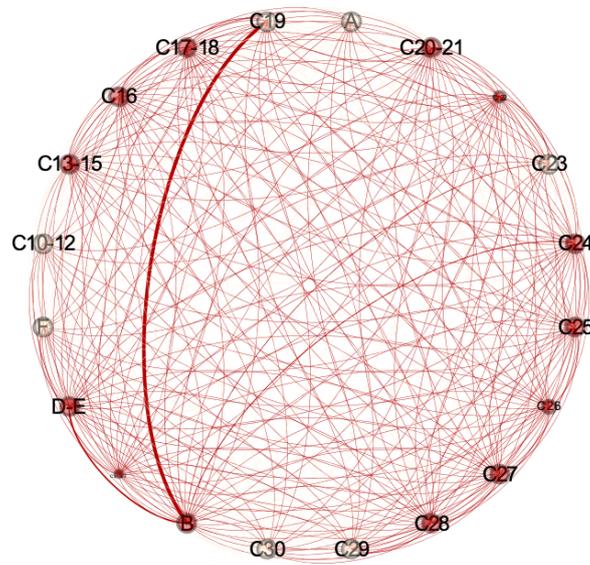


Figure 4.4: Network of emissions across sectors in Spain. The size of the node is proportional to the number of weighted incoming links.

When studying networks' characteristics, if one considers the potential strength (weight) of forward emission links,<sup>43</sup> mining activities (B) as well as coke and refined petroleum products (C19) and fabricated metal products (C25) are the leading sectors in Germany while mining (B) together with chemicals (C20-21) and electricity and gas (D-E) display the largest impacts in Spain. Interestingly, in Germany the most important GHG emission links start from B to coke and refined petroleum products (C19) and electricity and gas (D-E). The latter could be partly explained by the coal and gas dominating roles in the German power generation system ([International Energy Agency, Key energy statistics, 2018](#)). For Spain, top emission connections follow the same pattern : they start from mining (B) toward coke and refined petroleum products (C19), electricity and gas (D-E) and basic metals (C24). Comparing both countries, one can note on Figure 4.3 and 4.4 the significant weight of emission links from mining (B) to electricity and gas (D-E), coke and refined petroleum products (C19) and basic metals (C24) in Germany. The latter provides a clear view of the

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<sup>43</sup>Thus suggesting a strong effect of reducing gross domestic output in these sectors on other sectors' GHG emissions.

strong role of mining (B) in the industrial German ecosystem.

Overall, our results emphasize different aspects : first, mining (B) is the sector the most able to drive down external emissions, exhibiting strong links/connections to high polluting activities.<sup>44</sup> The sector deeply affects coke and refined petroleum products (C19) as well as basic metals (C24) and electricity and gas (D-E) industries. For this reason, we observe these industries to be ranked top in exposure category. Moreover, the ranking of coke and refined petroleum products (C19), chemicals (C20-21) as well as basic metals (C24) among the top external emission activities suggests a strong connection of these sectors to others across the economy - thus acting as facilitators in the shock propagation process originating from mining (B). The strength of such edges informs policy-makers not only on the dependence of sectors to others, but also on the ability of key industries to reduce emissions elsewhere in the economy.

In the next section, we investigate this feature. We map the cascade of GHG emission contractions from top external coefficients activities. By doing so, we are able to capture the key sectors acting as drivers of emission reductions in the industrial system. The latter brings us a clearer perspective on the existence of common or various patterns of cascades of emission contractions across countries.

## 4.4 Channels of Emission Cascades

After having shown the emission potential and associated exposure for the entire range of productive sectors, we shift our attention to top external multiplier activities (B activities). Our objective is to better investigate the propagation channels of decreasing GHG emissions due to an contraction (gross output) originating from the fossil fuel industry (e.g. coal and gas). Precisely, we trace out the propagation process throughout the industrial system to capture relevant patterns across economies.

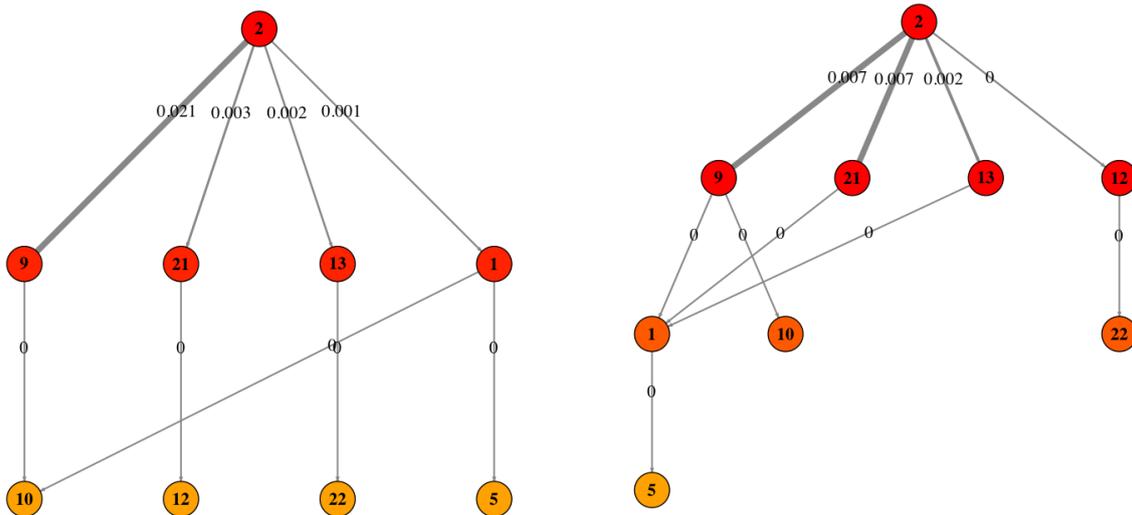
We start by identifying the most relevant emission links resulting from a unitary drop

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<sup>44</sup>Although mining is not emitting large amounts of emissions, cf. Table 4.5 in the [Appendix](#).

of primary inputs supporting the production of mining (i.e. the largest values appearing on the B column of matrix S). We retain only the top  $q$  percentile of the values, and position the affected sectors on the first layer of our cascade network. We repeat the procedure for the sectors in the first layer, identifying the sectors within the top  $q$  percentile of emissions originating in the layer. The weight of the resulting network edges are re-weighted to take into account that the fall in primary inputs in these sectors will be lower than one and a function of the strength of the upper edges. In other words, the emission reduction links tend to be stronger the closer they are to the shock origin, and get gradually weaker as they cascade downwards. We then repeat the same procedure for each layer, excluding the sectors that had already appeared in upper layers, until no new sectors appear. The results of this procedure are shown for each country belonging to our sample following a hierarchical layout (cf. Figures 4.5, 4.6 and 4.7 below, for  $q = 0.2$ ). The numerical weight of the top 10 edges is shown for reference.<sup>45</sup>

Figure 4.5: Hierarchical networks of emission cascades across economic sectors in France (left) and Germany (right).



<sup>45</sup> Although most of them exhibit a weight of 0, the impact on downstream sectors remains higher compared to other industries.

Figure 4.6: Hierarchical networks of emission cascades across economic sectors in Italy (left) and Poland (right).

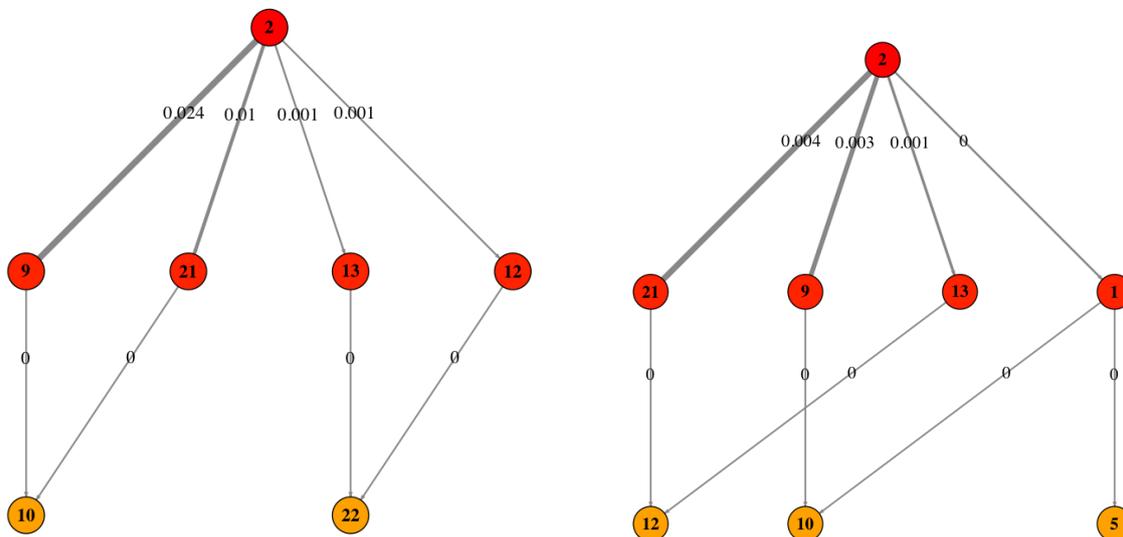
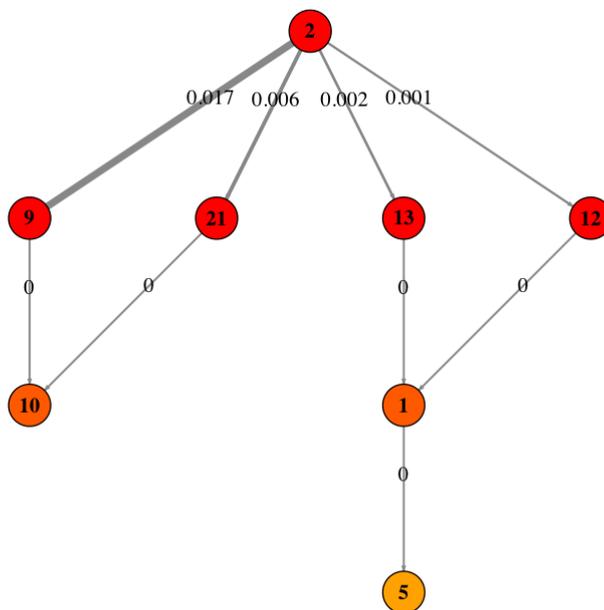


Figure 4.7: Hierarchical network of emission cascades across economic sectors in Spain.



As expected, the sectors in the first layer of the network overlap with the ones reported in Table 4.2. The strongest emission link is the one flowing from mining (B) to coke and

refined petroleum products (C19) for France, Germany, Italy and Spain. Interestingly, the reduction link from mining (B) to electricity and gas (D-E) has a larger weight in Poland while reaching an identical level compare to coke and refined petroleum products (C19) in Germany. The latter confirms previous observations on the carbon intensity of power systems in those economies. Manufacturing activities, especially basic metals products (C24), other non-metallic mineral products (C23) as well as electricity and gas (D-E), also frequently appear among the sector most strongly affected by the immediate contraction caused by mining (B). From the electricity and gas sector (D-E), the emission cascade often continues, further affecting chemicals (C20-21) or other non-metallic mineral products (C23) (cf. Germany, Italy, Poland, Spain). Given the strength of the original emission connection from mining (B) to electricity and gas (D-E), these links are often the most relevant after the ones affecting sectors in the first layer, and are justified by both the high emission intensity of the sectors and their large consumption of energy products (e.g. electricity, gas). From coke and refined petroleum products sector (C19), the most common cascades proceed through the chemical sector (C20-21)<sup>46</sup> while from basic metals sector (C24), GHG emission cascade propagates through the construction sector (F) and agriculture (A). Although surprising for agriculture (A), this finding looks intuitive for construction (F) as the sector relies on a high amount of metallic materials used as inputs (e.g. tubes, pipes).

In addition to the sectors mentioned above, several other sectors frequently appear in the cascade networks. For instance, food products activities (C10-12) often appears on the third or fourth layer of the network, regularly affected by links originating from agriculture (A) (cf. France, Germany, Poland and Spain). The sector in the C23 category (other non-metallic mineral products) also often appear, largely affected by B (mining) and further impacting F industries (construction). Overall, energy intensive sectors are highly present in the second layout of the networks, acting as propagation facilitators toward sectors supplying final demand side of the economy. These sectors

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<sup>46</sup>Note that it is relevant in every country of our sample.

exhibit low levels of emissions, thus not appearing in the network we observe here (e.g. textiles (C13-15), computer and electronics (C26)).

Studying the structure of the networks in conjunction with the weight of edges, we can identify two common cascades across countries. First, in all economies except Poland, a strong reduction cascade passes through coke and refined petroleum products (C19) and then affects chemicals (C20-21). This dynamics is particularly relevant in France, Italy and Spain. Although not appearing, we expect further downstream sectors to be manufacturing sectors (rubber and plastics products (C22), paper products and printing (C17-18)). Second, the cascade starting from mining (B) to electricity and gas (D-E) and then impacting manufacturing sectors such as chemicals (C20-21) and other non-metallic mineral products (C23) is widely present in our sample - and particularly significant in Poland, Germany and Italy.

Overall, the main structure of emission cascades spreads from mining (e.g. coal, gas, iron ores) to energy intensive manufacturing sectors (coke and petroleum products, steel, iron, chemicals) and power generation (e.g. electricity and gas), then further affecting industrial sub-sectors supplying final demand (e.g. construction, agriculture). In addition, GHG emission cascades share common characteristics across countries, suggesting the opportunity for EU governments to design green recovery packages sharing common patterns, aiming at limiting emission rebounds in sectors identified (e.g. mining (B), coke and refined petroleum products (C19), chemicals (C20-21) and electricity and gas (D-E)). The next section concludes by discussing the implications of such results for the design of green recovery packages. Indeed, further contractions of the identified sectors would lead to additional reduction of GHG emissions. However, it is more than likely that governments will create incentives to green the activity of such sectors (e.g. allocation of funds conditional on developing a climate strategy). We expose some policy avenues that could be implemented to limit emissions to rebound in those sectors.

## 4.5 Discussions and conclusion

In the coming months, COVID-19 economic recovery packages will be introduced by governments in the EU. These packages will shape EU's future prosperity and determine the success environmental targets recently set in the Green Deal ([European Commission, 2019](#)). So far, we have identified industrial sectors that, if government wish to decouple growth and emissions in the coming decades, should not be benefit from forthcoming economic stimuli. If mining activities (B) play a significant role (by providing inputs to other sectors), emission intensive industries will have a particular contribution to meet the Paris Agreement targets. For those sectors, forthcoming economic stimuli (e.g. public investments) should be conditional on these industries developing a measurable plan to limit GHG emissions in the future.

Moving back to channels of emissions, coke and refined petroleum products (C19), chemicals (C20-21), other non-metallic mineral products (C23), basic metals (C24) and electricity and gas (D-E) are the most GHG intensive sectors of our sample. A decrease in their inputs (supplied by mining) generates large amounts of avoided emissions. In those sectors, the key challenge for forthcoming recovery plans is to ensure a shift from dirty to low carbon inputs.<sup>47</sup> Starting from the power generation sector, which is among the most emitting industries in some EU countries (i.e. Germany, Poland) and rank top at the regional scale ([European Environment Agency, 2020](#)), shifting from high to low carbon technologies has become a major issue over the last years ([International Renewable Energy Agency, 2018](#)). For instance, the German government recently announced a total phase-out of coal-power plants by 2038, compensated by large scale investments in renewable energy sources (RES) ([Reuters, January 2020](#)) while the French National Energy Roadmap targets 36% of power generation from renewables in the energy mix by 2028 ([Le Monde, May 2020](#)). Although official statements might drive sectoral dynamics (e.g. private investments), barriers to the large-scale deploy-

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<sup>47</sup>Not only to shift away from mining, but also because mining inputs are expected to be phased-out from the economic system by 2050.

ment of RES have remained strong (see [Sen and Ganguly, 2017](#) for a review). Among others, storage capacity issues and energy infrastructures (e.g. cost) have particularly constrained RES expansion ([Jones, 2015](#); [Ruz and Pollitt, 2016](#)). In the wake of current public incentives to promote RES deployment (see [Solorio and Jorgens, 2017](#) for a review), forthcoming green stimulus should enlarge the scope of targeted sectors and tackle such barriers ([Allan et al., 2020](#); [European Commission, 2020](#)). Measures such as public R&D support and EU cross-border cooperation could target technologies that complement renewables (e.g. energy storage, smart grids, interconnectors). The latter would guarantee that capacity exists to facilitate decarbonisation of further downstream industries too (e.g. mobility and heating).<sup>48</sup>

From an economic perspective, the pandemic is unfolding in a policy environment providing strong advantages to a green design of recovery plans. Indeed, since the global financial crisis (2007-2008) and recovery plans that followed, the cost of low-carbon technologies (e.g. solar, wind) has sharply declined compared to other energy sources, making large scale financing affordable and competitive ([Bloomberg NEF, 2019](#)). Importantly, in the short run, green stimulus measures are economically advantageous when compared with traditional fiscal stimuli ([World Resource Institute, 2009](#)), creating higher numbers of jobs ([Pollin et al., 2008](#)). In the long run, these public investments offer high returns by driving down costs of the clean energy transition ([World Bank, 2015](#)). While unemployment rates in EU economies are predicted to soar in 2020 ([Reuters, April 2020](#)), such dimensions are critical to consider when shaping green stimulus.

Moving to GHG intensive industries, transforming industrial energy usage is a major issue to handle for governments. In our paper, we have identified coke and refined petroleum products (C19), chemicals (C20-21) as well as basic metals (C24) to have a significant impact on emissions. For those activities, creating incentives to produce

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<sup>48</sup>Note that in some countries, decarbonising the power sector does not come as a priority compare to, for instance, transport sectors (e.g. France).

low-carbon output would guarantee a slowdown in industrial emissions. The development of programs guaranteeing the purchase of cleaner output at a profitable price could be a first step toward an environmental-friendly shift in production (Allan et al., 2020). In this context, a significant price of carbon (e.g. internal/external carbon tax, EU-ETS market permit) could lead to higher investments in R&D focusing on potential environmental friendly substitutes (CDP, 2017). In the same way, green stimuli should contain large scale investments in greenhouse gas removal technologies including industrial carbon capture and storage. These technologies are necessary to contain emissions from heavy polluting industries. Although barriers exist (e.g. infrastructures, cost), more research and developments targeting such technologies could bring multiple benefits in the long run (Hepburn et al, 2019). Moreover, if rapidly deployed, such technologies could limit emissions during the transition period toward cleaner production processes in GHG intensive industries.

To conclude, our paper has investigated industries that should not benefit from economic recovery stimuli if EU governments wish to decouple growth and emissions once activity recovers (OECD, 2020). Although the mining sector is identified as the sector at the core of potential emission reductions, GHG intensive activities such as coke and refined petroleum products and power generation activities are likely to act as key sectors to reach a post-carbon society. The ongoing COVID-19 pandemic crisis acts as a stalemate in the fight against climate change as recovery plans will shape the economy for the decades to come. Reaching a carbon neutral European Union by 2050 largely depends on the design of forthcoming recovery packages. Decoupling emissions and economic growth will become possible if identified sectors are phased-out or if they implement strategies to clean their production process. Although we have discussed some potential policy strategies for such changes, the latter is unlikely to happen without a strong support from national and EU Institutions. At the EU regional scale, a major issue to come is the allocation of such recovery funds across states - and further, sectors to benefit from such funds within national economies. In

our paper, we have shown that economies display differences in terms of industrial structures and GHG emission levels. The latter calls for different national approaches to tackle GHG emissions. If some countries have a large proportion of mining inputs in the energy mix (e.g. Germany and Poland), a uniform implementation of tools to meet the EU targets would cause heterogeneous impacts across economies, likely reinforcing economic and political divisions within the Union. In the coming months, the EU Commission will have to be aware of such differences when evaluating the effectiveness of recovery plan allocation funds by national states. Whether the supervision of such funds is centralised or decentralised (i.e. EU Institutions or national states), it will have a strong impact on the EU ability to meet its legally mandated environmental targets.

## Appendices of Chapter 4

### Tables

Table 4.4: NACE Sectors

<b>Sector code</b>	<b>Sector description</b>
A	Agriculture, forestry and fishing
B	Mining and Quarrying
C	Manufacturing
D	Electricity, gas, steam and air conditioning
E	Water supply; sewerage; waste management and remediation services
F	Constructions and construction works
G	Wholesale retail trade; repair of motor vehicles and motorcycles
H	Transportation and storage
I	Accommodation and food services activities
J	Information and communication
K	Financial and insurance activities
L	Real estate activities
M	Professional, scientific and technical activities
N	Administrative and support service activities
O	Public administration and defence: compulsory social security
P	Education
Q	Human health and social work activities
R	Arts, entertainment and recreation
S	Other services activities

Table 4.5: Greenhouse gas emissions (Mt CO<sub>2</sub> eq.) by sectors (A-F), year 2015

Sector	France	Germany	Italy	Poland	Spain
Agriculture, forestry and fishing	90.7	75.8	39.4	44.1	50.0
Mining and extraction of energy producing products	1.1	7.2	4.7	22.0	1.5
Food products, beverages and tobacco	11.0	9.9	6.2	5.1	3.5
Textiles, wearing apparel, leather and related products	0.8	0.9	2.9	0.2	0.8
Wood and of products of wood and cork (except furniture)	0.5	1.0	0.3	0.5	1.4
Paper products and printing	2.8	7.8	5.4	2.4	2.7
Coke and refined petroleum products	14.0	22.2	17.9	12.6	16.1
Chemicals and pharmaceutical products	22.8	30.2	11.8	14	11.5
Rubber and plastics products	1.5	3.2	0.4	0.7	0.0
Other non-metallic mineral products	18.8	36.0	26.2	15.6	28.1
Manufacture of basic metals	19.0	44.7	14.1	9.7	13.8
Fabricated metal products, except machinery and equipment	1.0	3.8	0.8	0.5	0.6
Computer, electronic and optical products	0.4	1.1	0.4	0.1	0.0
Electrical equipment	0.5	1.3	0.5	0.2	0.7
Machinery and equipment n.e.c.	0.6	3.2	1.7	0.2	0.6
Motor vehicles, trailers and semi-trailers	1.0	4.6	0.3	0.3	1.0
Other transport equipment	0.4	0.5	0.0	0.1	0.2
Other manufacturing; repair and installation of machinery and equipment	1.2	1.3	0.8	0.3	0.0
Electricity, gas, water supply, sewerage, waste and remediation services	49.8	363.9	119.0	167.5	88.1
Construction	9.1	11.2	5.9	0.9	0.6

Table 4.6: GHG emissions (Mt CO<sub>2</sub> eq.), year 2015.

<b>Country</b>	<b>GHG emissions</b>
France	330.7
Germany	769.5
Italy	314.2
Poland	341.7
Spain	277.9

## **Additional Informations**

*A - Agriculture, forestry and fishing* : Non-perennial crops; Perennial crops; planting material: live plants, bulbs, tubers and roots, cuttings and slips; mushroom spawn; live animals and animal products; agricultural and animal husbandry services (except veterinary services); hunting and trapping and related services; forest trees and nursery services; wood in the rough; wild growing non-wood products; support services to forestry; fish and other fishing products; aquaculture products; support services to fishing.

*B - Mining and extraction of energy producing products* : hard coal; lignite; crude petroleum; natural gas, liquefied or in gaseous state; iron ores; non-ferrous metal ores; stone, sand and clay; mining and quarrying products n.e.c.; support services to petroleum and natural gas extraction; support services to other mining and quarrying.

*C10-12 - Food products, beverages and tobacco* : Preserved meat and meat products  
Processed and preserved fish, crustaceans and molluscs; processed and preserved fruit and vegetables; vegetable and animal oils and fats; dairy products; grain mill products, starches and starch products; bakery and farinaceous products; other food products; prepared animal feeds; beverages; tobacco products.

*C13-15 - Textiles, wearing apparel, leather and related products* : Textile yarn and thread; woven textiles; textile finishing services; other textiles; wearing apparel, except fur apparel; articles of fur; knitted and crocheted apparel; tanned and dressed leather; luggage, handbags, saddlery and harness; dressed and dyed fur; footwear.

*C16 - Wood and of products of wood and cork (except furniture)* : Wood, sawn and

planed Products of wood, cork, straw and plaiting materials

*C17-18 - Paper products and printing* : Pulp, paper and paperboard; articles of paper and paperboard; printing services and services related to printing; reproduction services of recorded media.

*C19 - Coke and refined petroleum products* : Coke oven products; refined petroleum products.

*C20-21 - Chemicals and pharmaceutical products* : Basic chemicals, fertilisers and nitrogen compounds, plastics and synthetic rubber in primary forms; pesticides and other agrochemical products; paints, varnishes and similar coatings, printing ink and mastics; soap and detergents, cleaning and polishing preparations, perfumes and toilet preparations; other chemical products; man-made fibres; basic pharmaceutical products; pharmaceutical preparations.

*C22 - Rubber and plastics products* : Rubber products; Plastic products.

*C23 - Other non-metallic mineral products* : Glass and glass products; refractory products; clay building materials; other porcelain and ceramic products; cement, lime and plaster; articles of concrete, cement and plaster Cut, shaped and finished stone; other non-metallic mineral products.

*C24 - Manufacture of basic metals* : Basic iron and steel and ferro-alloys; tubes, pipes, hollow profiles and related fittings, of steel; other products of the first processing of steel; basic precious and other non-ferrous metals; casting services of metals.

*C25 - Fabricated metal products, except machinery and equipment* : Structural metal

products; tanks, reservoirs and containers of metal; steam generators, except central heating hot water boilers; weapons and ammunition; forging, pressing, stamping and roll-forming services of metal; powder metallurgy; treatment and coating services of metals; machining; cutlery, tools and general hardware; other fabricated metal products.

*C26 - Computer, electronic and optical products* : Electronic components and boards; computers and peripheral equipment; communication equipment; consumer electronics; measuring, testing and navigating equipment; watches and clocks; irradiation, electromedical and electrotherapeutic equipment; optical instruments and photographic equipment; magnetic and optical media.

*C27 - Electrical equipment* : Electric motors, generators, transformers and electricity distribution and control apparatus; batteries and accumulators; wiring and wiring devices; electric lighting equipment; domestic appliances; other electrical equipment.

*C28 - Machinery and equipment n.e.c.* : General-purpose machinery; other general-purpose machinery; agricultural and forestry machinery; metal forming machinery and machine tools Other special-purpose machinery.

*C29 - Motor vehicles, trailers and semi-trailers* : Motor vehicles; bodies (coachwork) for motor vehicles; trailers and semi-trailers; parts and accessories for motor vehicles.

*C30 - Other transport equipment* : Ships and boats; railway locomotives and rolling stock; air and spacecraft and related machinery; military fighting vehicles; transport equipment n.e.c.

*C31-33 - Other manufacturing* : Furniture; jewellery, bijouterie and related articles;

musical instruments; sports goods; games and toys; medical and dental instruments and supplies; manufactured goods n.e.c.; repair services of fabricated metal products, machinery and equipment; installation services of industrial machinery and equipment.

*D-E - Electricity, gas, water supply, sewerage, waste and remediation services :* Electricity, transmission and distribution services; manufactured gas; distribution services of gaseous fuels through mains; steam and air conditioning supply services; natural water; water treatment and supply services; sewerage services; sewage sludge; waste; waste collection services, waste treatment and disposal services; materials recovery services; secondary raw materials; remediation services and other waste management services.

*F - Construction :* Buildings and building construction works, roads and railways; construction works for roads and railways; constructions and construction works for utility projects; constructions and construction works for other civil engineering projects; demolition and site preparation works; electrical, plumbing and other construction installation works; building completion and finishing works; other specialised construction works.

\* \* \*



# Conclusion

This dissertation has investigated how economic networks could improve the understanding of several diffusion dynamics (i.e. environmental technologies, green policies, economic shock effects on emissions). The first chapter theoretically studies the impacts of social underlying structures on technology adoption. It adds up to the literature on diffusion in networks by introducing a cost dimension in the contagious spreading of the technology.<sup>49</sup> The second chapter proposes a complementary approach (empirical). Instead of postulating underlying network structures, it reconstructs the network of environmental policy flows across US states from 1974 to 2018. The third and fourth chapters investigate networks of economic interactions in several European industrial systems to assess how a local contraction of activity influences emissions in downstream activities. While the third chapter explores such dynamics for imported emissions, the fourth follows an equivalent methodology to identify sectors that could act as drivers of emission rebounds in the context of COVID-19 recovery plans. In the remainder of the conclusion, we briefly review exposed contributions as well as policy implications.

## Network Structures, Environmental Technology and Social Contagion

In order to evaluate the role of underlying social network structures on technology adoption, *Chapter 1* implements a novel methodology by adding a cost perspective to the contagious feature of adoption. The technology cost dimension, subject to ef-

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<sup>49</sup>The proposed model is a generalisation of the [Watts model \(2002\)](#).

fects of learning, provides a complementary tool to evaluate how innovations (e.g. clean technologies) spreads in a population of agents. Two main lessons can be drawn from this research. First, clustering of agents is critical for a clean technology to diffuse. This results confirms the literature on complex contagion (Centola, 2018; Beaman, 2018). However, clusters of agents lead to more variability in terms of aggregate adoption. Indeed, diffusion in clustered networks requires at least one initial adopter among clustered groups to make percolation in the whole group possible. Then, in clustered networks, diffusion is exacerbated to one extreme or another, leading to high levels of variance. From a policy perspective, it suggests a possible trade-off between maximising adoption and uncertainty in results. Namely, where aggregate diffusion levels are the highest, dispersion is the largest. If there is a strong connection between diffusion and network structures, this indicates a policy tension : targeting diffusion levels with lower expected variability or favouring maximum adoption with more uncertainty in terms of final results. Second, effects of learning have a key role in diffusion dynamics. Whatever the underlying social structure, higher learning rates leads to higher aggregate adoption (and higher variance in clustered networks). The latter is captured by the following : increasing the learning effect fosters the impact of one agent adopting on the technology cost function. In other words, with higher rates of learning, fewer new adopters are required to reach an equivalent decrease in the cost function. Aggregate diffusion and learning rates are intertwined with one another.

We expose recommendations from these results, which could both be used to ease the deployment of green technologies in a considered population. On the one hand, to target clustered structure, government should be aware of underlying social networks in the selected population. On this issue, the growth of social platforms and the associated increasing amount of data (e.g. social network, geographic data) could help capturing underlying social structures and would provide powerful informations for policy makers. On the other hand, policy makers could limit uncertainty in results in cluster structures by giving access to the technology to agents less able to afford such a

product. Indeed, those agents, exhibiting a low cost threshold (i.e. they cannot afford the technology if the latter does not diffuse massively), are hampering the diffusion as they are not adopting the product. By implementing economic mechanisms to support such population to adopt, diffusion would be less subject to heterogeneity and could reach higher levels. Such policies would allow a large share of the population to adopt the technology, creating feedback effects for the rest of the group. Finally, policy makers should select the "good" innovation to promote - the one that is likely to exhibit some learning effects, then easing the adoption in the population.

## **How Environmental Policies Spread ? A Network Approach to Diffusion in the U.S.**

*Chapter 2* proposes a methodology to infer, from adoption data (i.e. laws enacted), the network structure of environmental policy transmission likelihood between American states. This work provides an empirical contribution by identifying existing influences in the environmental policy diffusion network (i.e. states-pairs) and by assessing the impacts of different attributes (e.g. economic and political proximity, environmental features) on the formation of the existing structure over time. The main innovation is a systemic perspective that accounts for the impact of each state not only on its direct connections, but also on the global diffusion process. The main takeaways are of this research are : First, a relatively inefficient organization, characterized in particular by a great heterogeneity between states in terms of centrality in the network. The latter leads to inefficiencies and induces relatively long lags in the diffusion process. Second California, Minnesota and Florida act as central states in the diffusion process (i.e. facilitators) and there exists a relative disconnection between Northeastern states and the rest of the country. The latter suggests that in this region, transmission activity is concentrated between neighborhood states. Fourth, contiguity, GDP per capita, Genuine Progress Indicator have significant effects (i.e. positive impacts) on policy flows across states while states. The latter brings new insights on the understanding of en-

vironmental policy spreading in the United States.

Among others, an important implication of our results stems from the analysis of states facilitating the spreading of environmental policies across the country. Namely, California, Minnesota and Florida. Targeting such states (i.e. governor, representatives) to maximize the likelihood of diffusion at a larger scale would be a relevant strategy for various types of actors (e.g. NGOs, citizens, companies' representatives), especially those interested in passing pro-environmental laws in "big emitter" states. From another perspective, being aware of policy flows dynamics brings insights to private firms on the possible pattern of environmental regulation diffusion. As differences in legislation across states drive day-to-day business decisions of private actors (e.g. investments, market strategy etc.), our results have critical implications in that respect too (Bradbury et al., 1997).

After evaluating issues of clean technologies and environmental policies, *Chapter 3* and *Chapter 4* of this thesis combine Input/Output tables (IOTs) approach and tools from network theory to spotlight how a local shock in the industrial system impacts generated/imported emissions.

### **Triggering Reduction of Imported Emissions in the E.U.**

The third contribution specifically focuses on imported emissions and aims at identifying industrial sectors that are likely, following a contraction of activity, to generate cascading reduction of imported emissions in the system. Main lessons from this work highlight the role of imported emission intensive activities such as mining activities, basic metals and computer and electronics. Mining sector and basic metals are providing large amounts of essential inputs to other industries with high imported emission intensity, suggesting a strong economic dependence between them (proximate neighbors in the network). Moreover, this chapter emphasizes that moving away from fossil fuel would generate effects on sectors linked to coke and refined petroleum products,

basic metals and electricity and gas. To complement such findings, the impact of a \$25 carbon tax on imported basic metals highlights that exposed industries are identical across countries (although impacts are heterogeneous), with basic metals and fabricated metal products taking the first ranks. This contribution provide insights to policy makers on at least two dimensions. First, tackling the issue of imported emissions will have direct effects on importing sectors (e.g. basic metals, mining) but would also generate indirect impacts on downstream industries (e.g. fabricated metals products, chemicals). From this perspective, there is a critical need to push downstream activities toward cleaner input uses, and to adopt a system-wide approach when designing economic instrument aiming at limiting imports of carbon intensive products. On this issue, the implementation of a carbon tax on basic metal reveals how sectoral exposure is unequal across economies (e.g. fabricated metal activity is more affected in Poland compare to those in France or the U.K). Such dimension is likely to act as an additional barrier to the advent of this mechanism at the European scale.

## **COVID-19 Recovery Packages and Industrial Emission Rebounds : Mind the Gap**

The last contribution implements the same approach to identify industrial sectors that, if governments wish to decouple growth and emissions in the coming decades, should not be benefit from forthcoming economic stimuli. Main outcomes suggest that coke and refined petroleum products, chemicals, other non-metallic mineral products, basic metals and electricity and gas are the most likely to generate emission rebounds supported by economic stimuli (France, Germany, Italy, Poland and Spain). A decrease in their inputs (supplied by mining) generates large amounts of avoided emissions. In terms of policy takeaways, stimuli packages should provide incentives for these activities to shift from dirty to low carbon inputs. If properly defined, including counterparts dealing with environmental dimensions could act as a promising step. From another perspective, results hint at the existence of differences across economies in terms of

industrial structures and GHG emission levels. The latter calls for different national approaches to tackle GHG emissions. If some countries have large share of mining inputs in the energy mix (e.g. Germany and Poland), a uniform implementation of tools to meet the EU targets would cause heterogeneous impacts across economies, likely reinforcing economic and political divisions within the Union.

More broadly, the present dissertation demonstrates how network economics could enhance our understanding of diffusion dynamics on the path toward a cleaner society. Studying clean technology diffusion, environmental policies spreading and economic shocks effects on emissions, we have shown that network structures (*Chapter 1*), position of embedded agents (*Chapter 2*) and the neighborhood environment (*Chapter 3* and *4*) are critical aspects to take into account for the design of interventions (e.g. public). Such elements provide new insights to reach a net zero society by 2050.

Finally, with respect to network economics, a prominent challenge for academics and governments will be to expand the associated toolkit - from innovations in the field of econometrics to the role of policy-makers/Institutions in collecting network data. For the latter, enacted policies targeting the disclosure of information and of some publicly shared social network data could pave the way to a common use of network economics in public policy intervention. In the case of this thesis, we have demonstrated that collecting social/economic data about adoption of technologies, policy flows and economic interactions could enhance our understanding of propagating processes.

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## RÉSUMÉ

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Pour maintenir le réchauffement climatique en dessous de 2°C d'ici la fin du siècle, les économies mondiales doivent atteindre la neutralité carbone d'ici 2050. La diffusion à grande échelle de technologies bas carbone représente une composante majeure des stratégies internationales visant à atteindre cet objectif, largement soutenue par la mise en œuvre de politiques environnementales. Cette thèse s'appuie sur la théorie des réseaux pour étudier théoriquement et empiriquement les dynamiques de diffusion sur le chemin d'une société bas carbone. Elle propose une analyse de trois perspectives de diffusion : les technologies vertes, les politiques environnementales et les effets des chocs économiques sur les émissions (importées/générées).

Ce travail illustre comment les structures de réseaux (sociaux/économiques), les positions des agents et la force des connexions qu'ils entretiennent sont des dimensions essentielles à prendre en compte lors de la conception de politiques visant à accélérer la transition énergétique.

## MOTS CLÉS

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*Réseaux - Diffusion - Technologies bas carbone - Politiques Environnementales*

## ABSTRACT

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To limit global warming to less than 2°C by the end of the century, worldwide economies must reach carbon neutrality by 2050. Large scale diffusion of low carbon technologies represent an important component of international strategies to achieve such a target, largely driven by the implementation of environmental policies.

This thesis builds upon concepts from network theory to investigate both theoretically and empirically diffusion dynamics on the path towards a low carbon society. It provides analysis for three different diffusion perspectives : clean technologies, environmental policies and effects of economic shocks on (imported/generated) emissions. Overall, it illustrates how network structures, positions of embedded agents and the strength of neighborhood connections are critical dimensions to take into account when designing policies aiming at accelerating the green transition.

## KEYWORDS

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*Networks - Diffusion - Clean Technologies - Environmental Policies*