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How Environmental Policies Spread ? A Network Approach to Diffusion in the U.S.[†]

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Abstract

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.

Keywords : Network, United States, Environmental Policy Diffusion, Cascades.

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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 (ie. Paris Agreement withdrawal) and keep the country on track with respect to its COP21 contribution (ie. 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 researches 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 (eg. extreme climate events, proclimate groups) or external (eg. states bilateral/international agreements).[1] 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 ? (eg. 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 ? (ie. 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 (ie. diffusion patterns). Secondly, identifying states facilitating the spreading across the U.S. would bring multiple benefits. Among those, targeting such states (ie. governor, representatives) to maximize the likelihood of diffusion at a larger scale would be a relevant strategy for various types of actors (eg. 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 (eg. 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 transmission between states-pairs ? As suggested in the aforementioned literature, do we observe higher likelihood of transmission between states sharing common characteristics ? (eg. economic, political, climate change risks etc.). Investigating the latter

[1] See Massey et al. (2014) for a review.

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 (ie. 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 (ie. date of the enacted law in the state) were collected from the Database of State Incentives for Renewables & Efficiency (DSIRE),[2] 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 (eg. 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 (eg. 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 (ie. states-pairs) and by assessing the impacts of different attributes (eg. economic and political proximity, environmental features) on the formation of the existing structure over time. Importantly, we implement an ex-post analysis of environmental policies diffusion based on enacted laws. The latter sets our paper apart as previous researches have mainly focused on the rationale of policy adoption (eg. emulation, competition, coercion, and learning).[3]

[2]This database is provided by the U.S. Department of Energy and NC Clean energy Technology Center.

[3]See Dobbin et al., (2007) for a review.

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 (ie. 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 region, 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 (eg. 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 (ie. 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 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 researches on diffusion in networks.

When considering the case of environmental policy adoption in American states, past research has 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; Matisoff, 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, research often indicates 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 is 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 (ie. budgets, politics, and demographic (Volden, 2006)). Recent researches point out the importance of ideological distance between states (Chandler, 2009). Grossback and colleagues (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 (eg. 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 (eg. health, agriculture, transportation, domestic commerce etc.), they propose different 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, researches 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 (eg. 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 (ie. number of observations) to evaluate underlying diffusion dynamics and the rationale behind it, allowing for comparisons with previous findings.

Overall, we can distinguish two main approaches. The first are 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.

3 Methodology : Inferring the network

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[4] $\boldsymbol{t}^c = (t_1{}^c,...,t_N{}^c)$, 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 $C := \{\boldsymbol{t}^1,..., \boldsymbol{t}^{|C|}\}$.

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 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

[4]In this paper, we call "cascade" the diffusion of a policy.

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 $\{\boldsymbol{t}^1,..., \boldsymbol{t}^{|C|}\}$ given a network $A = [\alpha_{j,i}]$ as follows (see Gomez-Rodriguez et al., 2011 for a comprehensive discussion).

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

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

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 :

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

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 :

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

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

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

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 $C = \{\boldsymbol{t}^1,..., \boldsymbol{t}^{|C|}\}$ is maximized. More precisely, we aim at solving the following maximum likelihood (ML) optimization problem:

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

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 $f(t_i|t_j; \alpha_{j,i}) = \alpha_{j,i}\mathrm{e}^{-\alpha_{j,i}}(t_i - t_j)$ (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.

4 The U.S. Environmental Policy Network

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 (ie. 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 (eg. wind energy supports, solar rebate, sales tax incentives) and energy efficiency (eg. 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 (eg. 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 constructed cascades based on the first occurrence of a word (eg. GMO) in the laws of the corresponding state.[5] We gathered 27 policies targeting transportation (eg. biofuel policies, LEV Californian standards), sustainability (eg. 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 1[6] and cover the scope of environmental and climate state-based legislative actions from 1974 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"

[5] See Appendix, Section 2 for keywords list.

[6] For full description, see Appendix, Section 1.

time of a given policy in a state as the enacted date of the policy (ie. 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 1. Environmental and Climate Change Policies collected in Brief.

Scope (Number)	**Policies Description**
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.

4.2 Statistical Analysis of the Network

4.2.1 Generalities

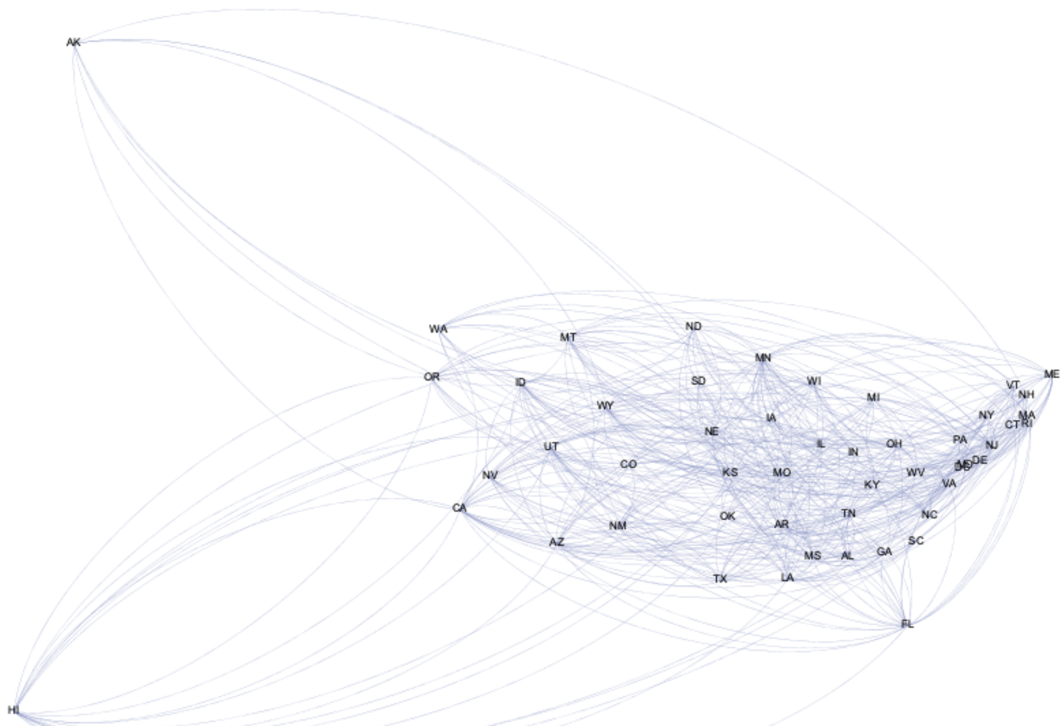
As illustrated in Fig.1, the inferred network[7] first provides a map of existing diffusion routes and hence a much broader view than obtained from the sole consideration of bilateral influences among states. For example, in our setting, it could be the case that California and Oklahoma are not linked 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

[7]We relegate to the Appendix, Section 9 supplementary inferred networks (ie. Energy Network (Renewable Support + Energy Efficiency); Environmental and Climate Network (remaining policy categories)).

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.

Overall, Fig.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.

Fig.1. Reconstructed environmental policies diffusion network in the U.S. using geographical layout.



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[8] 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,

[8]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 Barábasi, 2014).

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 (ie. diameter and average path length) hint at the existence of lags in the diffusion process as well as heterogeneity in terms of nodes attributes (eg. degree, centrality).

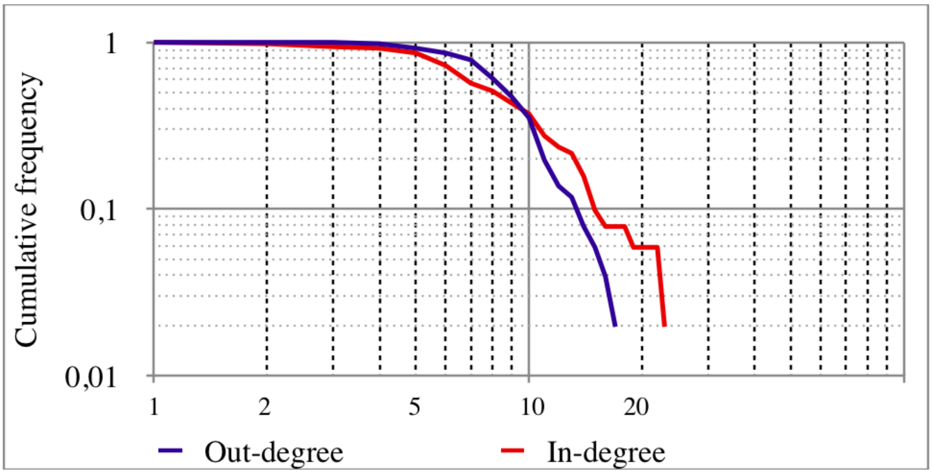
Table 2. General Properties of the Network.

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

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 Fig.3 in log-log scale.

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.

Fig.3. Cumulative distribution of states' out-degree and in-degree.



4.3 Centrality Analysis : Looking for Facilitators

In this section, we analyze how centrality measures are distributed among nodes to capture central nodes and vice versa 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.[9]

Overall, it is clear that among the most prominent states are Minnesota (Midwest), California (West) and Florida (South). In fact, many overlap across the different centrality measures. Maryland and Louisiana also appear among 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

[9]See Appendix, Section 4 Centrality measures description; Table 5. a.b.c.d.

the worst performers with respect to centrality indicators, suggesting a low integration in terms of connections and positions in the network[10]. 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 (Fig.4)[11] highlights the importance of several hubs in the environmental 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

[10] Although not being a state, the District of Columbia is also among the less integrated nodes in the network.

[11] See Appendix, Section 5.

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 put forward 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.

4.3.1 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, expanding considerably both in terms of size and of connectivity. Compared to Fig.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 (eg. North

Dakota, Tennessee, North Carolina). From this observation, we can argue that large-scale diffusion picks up in the late of the 90s and the beginning of the 2000s. The sub-period 1972-2008 reinforces this assumption. Overall, several changes come into view: First, all the nodes are connected to the network (ie. at least four degrees per node). Second, new hubs appear with the presence of California, Nebraska and Colorado, although they are not reproducing any specific regional setting. For 1972-2016, the network increases in density, and importantly Minnesota and California starts playing key roles in the diffusion. Though this sub-period is similar to Fig.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 (ie. the increase in states environmental policies adoption) has been studied by scholars in Law and Political Science (Andrews, 2018). Research findings suggest this take-off to stem 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, 2017), 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 aimed at controlling major sources of pollution and encouraging conservation (eg. federal land) came together with a new public attention focusing on problems that were harder to solve with a federal action. 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 (eg. 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.

4.3.2 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.

We base our regional setting on 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.[12] It is apparent from both Table 3 and the diagonal elements of the matrix in Table 4 that Northeast has by far the lowest amount of connections (ie. in/out-degree, total degree), especially when considering target region figures (ie. targeted by 13% of links). Among those, nearly 40% are intraregional connections, indicating that activity is concentrated and that Northeast is not highly subject to external diffusion influence.

South also has the largest off-diagonal elements, reflecting it is the most connected region in the diffusion network. A large majority of its out-connections is homogeneously targeted toward Midwest, 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 (ie. 32% of total network connections). As a comparison, Northeast connections represent respectively 20%, 13% and 17% (ie. out-degree, in-degree, total).

[12] See Appendix, Section 3 for full description.

Table 3. Regional-level statistics.

Region	**No. of states**	**Out-degree**	**In-degree**	**Source region (%)**	**Target region (%)**	**Total degree**
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

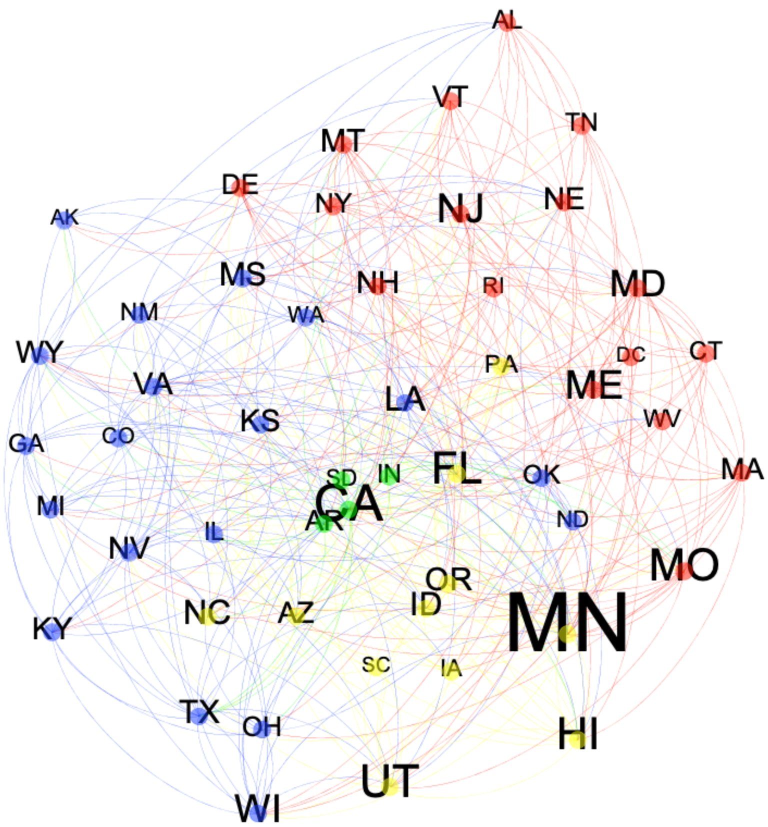
Although South region has the most states coverage, it is the most targeted region as well as the largest source area. The most interregional flows are between South and West, followed by South and Midwest.

Table 4. Matrix of intra-interregional connections.

Region	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, 2012). In the latter case, the goodness of the partitions is commonly assessed in terms of the so-called "modularity" (Lambiotte, 2009). 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[13] (Becatti et al., 2019). We map in Fig.2 a graph perspective of communities of the inferred network.

Fig.2. Reconstructed network using Force Atlas layout. The node size in 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.



Overall, communities analysis points out the presence of cross regional states

[13]Compared to random graphs.

belonging to same clusters.[14] 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 (ie. 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 (ie. clusters). The latter explains the macroscopic level of clustering observed previously (ie. 0.211).

The network of U.S. environmental policy diffusion we have observed is inefficient. Our analysis shows that network's structure hints at the existence of lags in policy transmission (eg. 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.

[14] See Appendix, Section 4 for full description.

5 Estimating the Determinants of the Diffusion Network

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 the aforementioned authors' researches 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 (eg. contiguity).
Then, in all generality, one can consider three main types of variables : a first set of variables $x_i := (x_i^1, \cdots, \mathrm{x}_i^{n_1}) \in \mathbb{R}^{n_1}$ characterizing the source state, a second set of variables $y_j := (y_j^1, \cdots, \mathrm{y}_j^{n_1}) \in \mathbb{R}^{n_2}$ characterizing the target state, and a third set of dyadic variables $z_{(i,j)} := (z_{(i,j)}^1, \cdots, \mathrm{z}_{(i,j)}^{n_1}) \in \mathbb{R}^{n_3}$ characterizing the relationship between the two state ($\mathrm{z}_{(i,j)}$ 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 (α, β, γ) 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 :

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

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.[15] 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 (eg. 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

[15] For full variables description, see Appendix, Section 8.

global warming. Controlling for these variables allows us to estimate whether diffusion is more likely to occur from/toward states coping with climate change in different ways (ie. 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 policymakers 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 (ie. 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 (ie. 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.[16] Overall, combining these indicators aims at covering a large scope of possible environmental determinants of the network and evaluate if states environmental attributes (eg. policies, risks toward climate change) increase the likelihood of states-pair diffusion.

5.2 Empirical results

From a policy point of view, the results presented in Table 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;

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

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 : 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 researches 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 looks 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 (ie. 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 (ie. 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 (ie. identical political party fosters diffusion (Huang et al., 2007)). Having 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 leadership 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), states' governors tend to implement pro-environmental policies as their awareness to climate change increased. 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 (eg. 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 (ie. model B). Being aware that Southern states are among the most vulnerable to climate change, our centrality analysis indicated that they are often less integrated in the diffusion network (cf. Appendix, Section 4). These states are also dependent on fossil energies (EIA, State profile, 2017) which implies a low tendency 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 (ie. economic system). Here again, this 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 (ie. facilitators) display a high Genuine Progress Indicator. From this view, GPI's effect on policy transmission is consistent.

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

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

Overall, results demonstrate 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.

6 Conclusions

In this paper, we have developed a methodology to estimate the network of environmental policy diffusion across American states and evaluate the determinants from adoption data. By doing so, we enhance the understanding of environmental policies diffusion and give policy makers insights to maximize the spreading of green policies in the U.S.. We have first inferred environmental policy diffusion patterns from a constructed dataset covering 74 green policies (eg. energy, climate, waste recycling) from 1974 to 2018. We have then constructed a database of economic, political as well as environmental features for each considered state. Finally, we have combined 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 to overcome the issue that bilateral diffusion events are generically not observed. We have applied this methodology to environmental policies that were enacted across American states but not at the federal scale. Our approach 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. Aforementioned central states are among the most ambitious to tackle climate change as reported in recent studies (eg. 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. Therefrom, 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.

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Appendix

1. 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.

2. 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.

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

Northeast	**Midwest**	**South**	**West**
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	

4. Communities description

1 - Blue	**2 - Red**	**3 - Yellow**	**4 - Green**
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			

5. Centrality Analysis

Description of centrality measures.

- 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.

Table 5.a. Centrality Measures (1/2).

Id	Label	Name	In-degree	Out-degree	Total degree	Closeness	Betweenness	Eigenvector
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 Carolina	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 Hampshire	8	9	17	0.505051	52.300423	0.332812

Table 5.b. Centrality Measures (2/2).

Id	Label	Name	In-degree	Out-degree	Total degree	Closeness	Betweenness	Eigenvector
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 5.c. Top rankings according to centrality indicators (1/6).

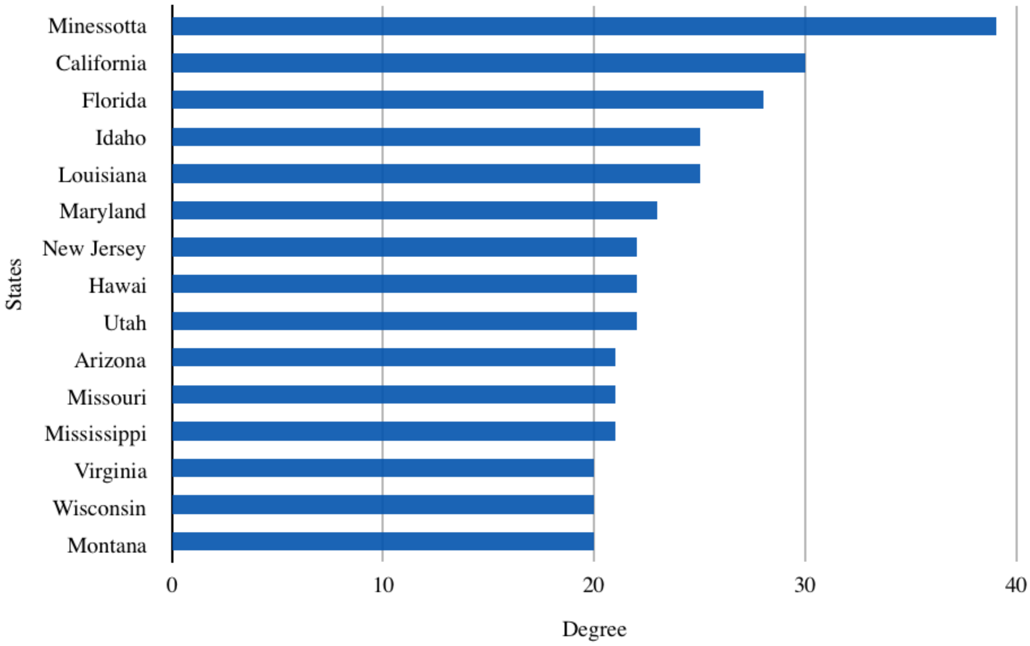


Table 5.c. Top rankings according to centrality indicators (2/6).

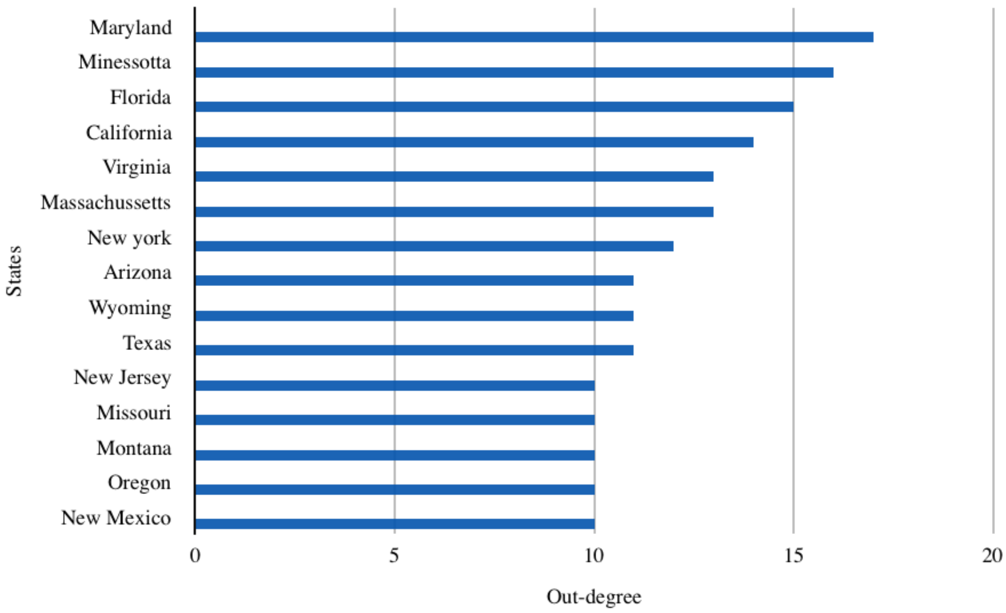


Table 5.c. Top rankings according to centrality indicators (3/6).

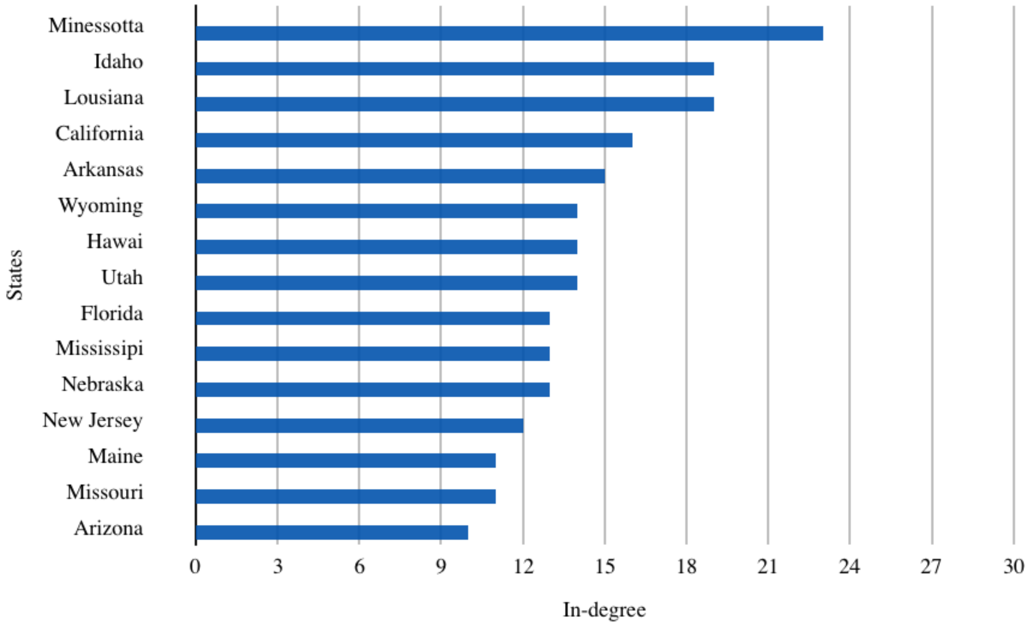


Table 5.c. Top rankings according to centrality indicators (4/6).

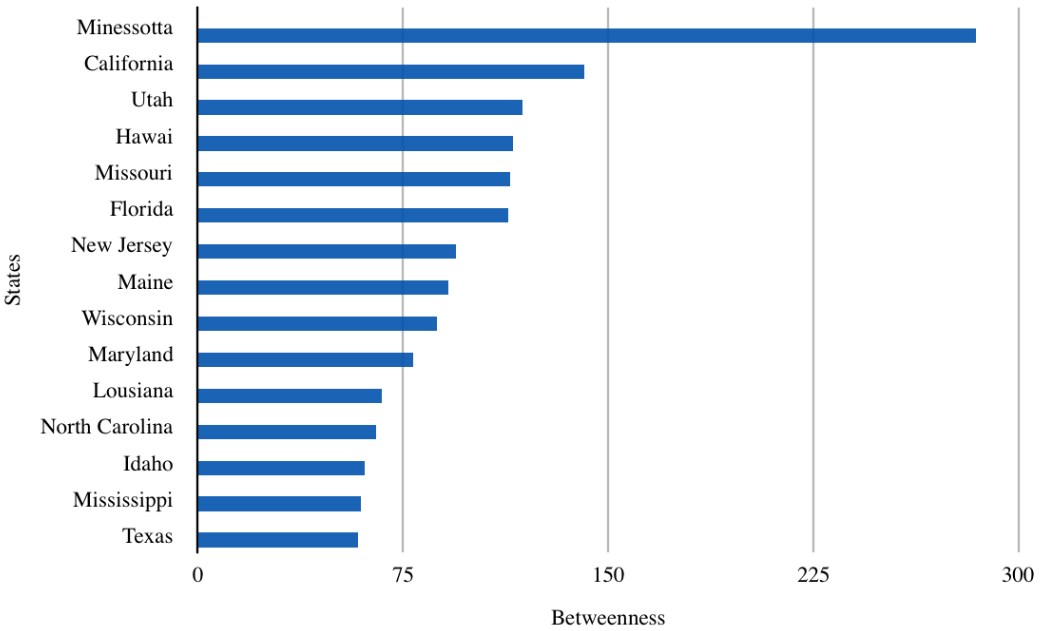


Table 5.c. Top rankings according to centrality indicators (5/6).

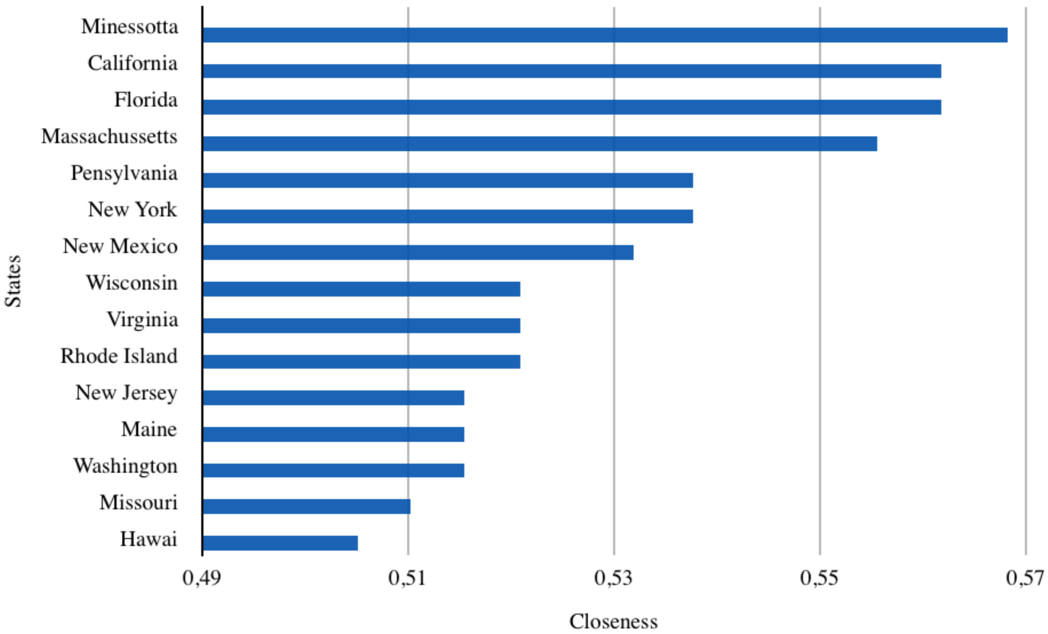


Table 5.c. Top rankings according to centrality indicators (6/6).

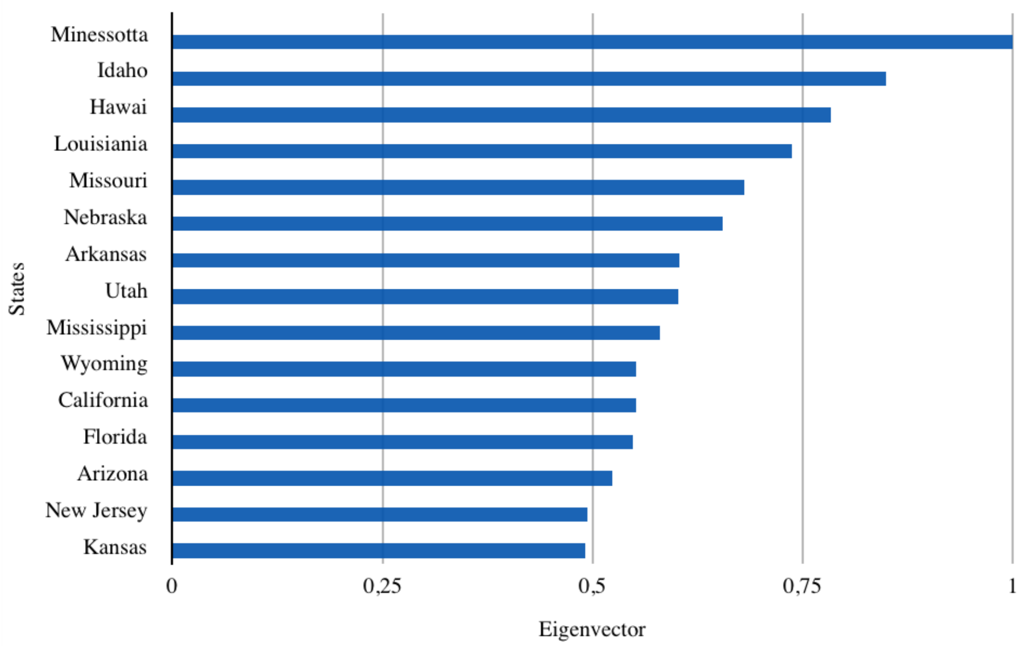


Table 5.d. Ranked last according to centrality indicators (1/6).

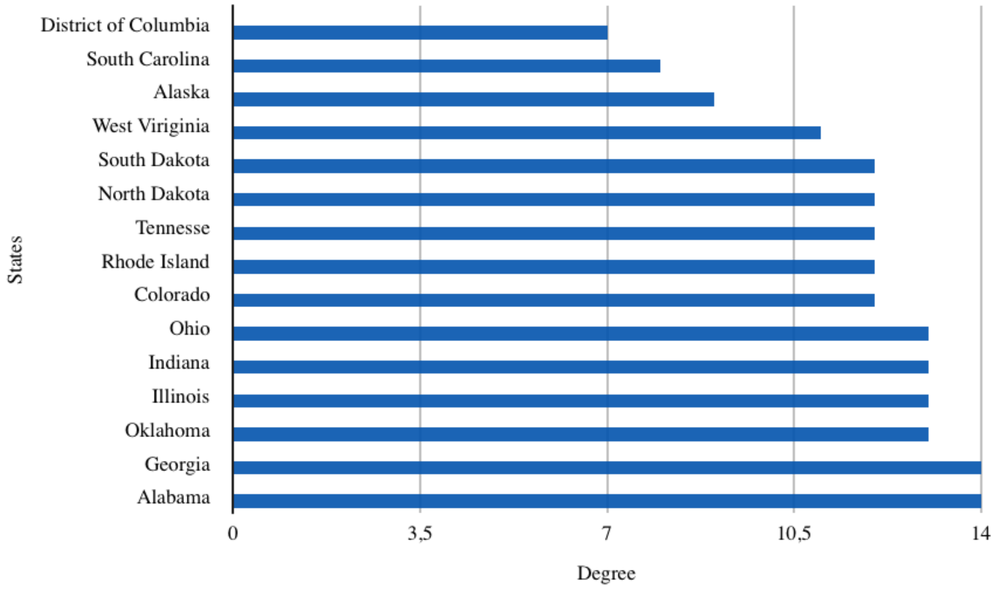


Table 5.d. Ranked last according to centrality indicators (2/6).

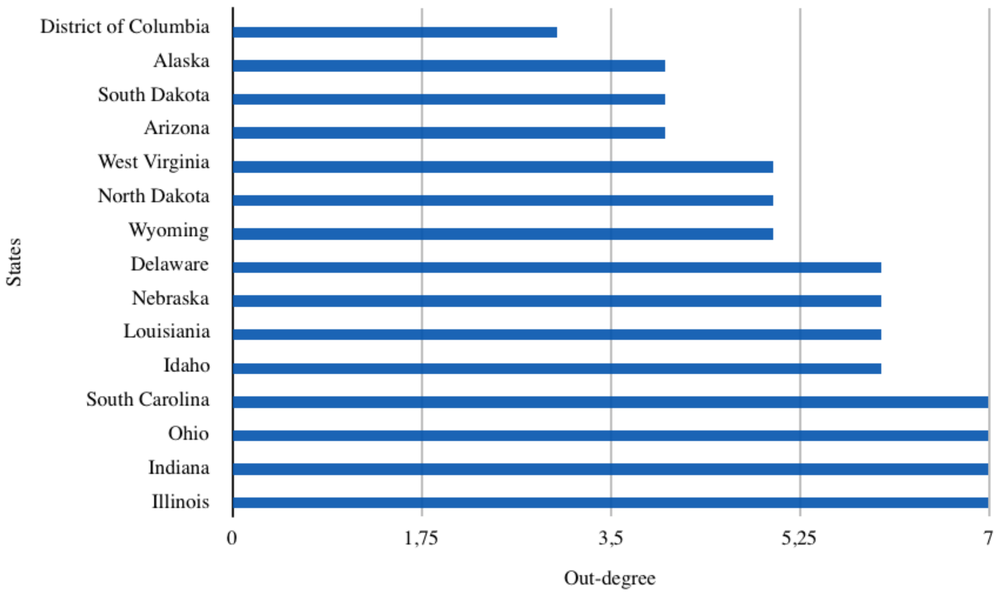


Table 5.d. Ranked last according to centrality indicators (3/6).

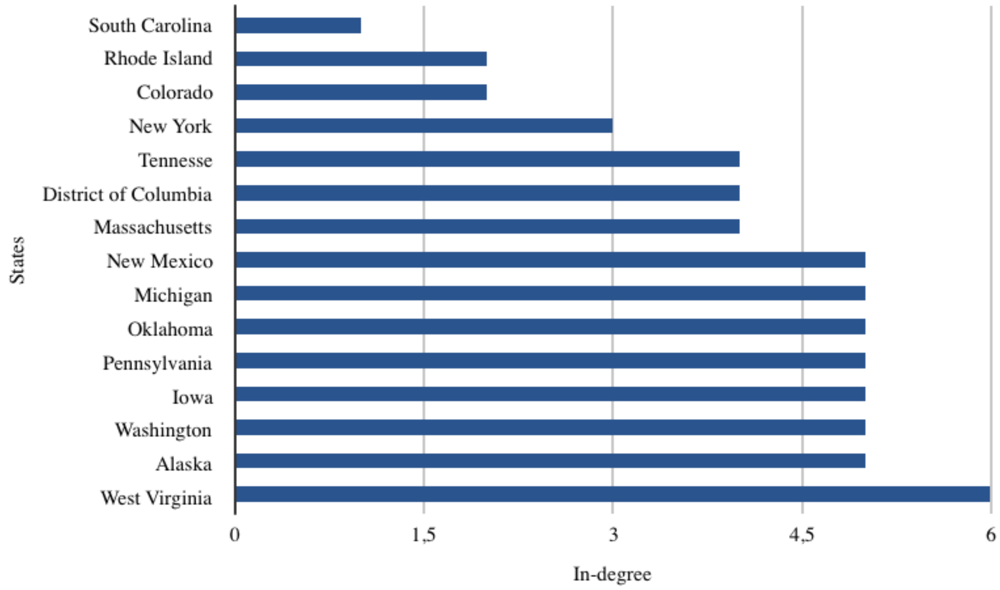


Table 5.d. Ranked last according to centrality indicators (4/6).

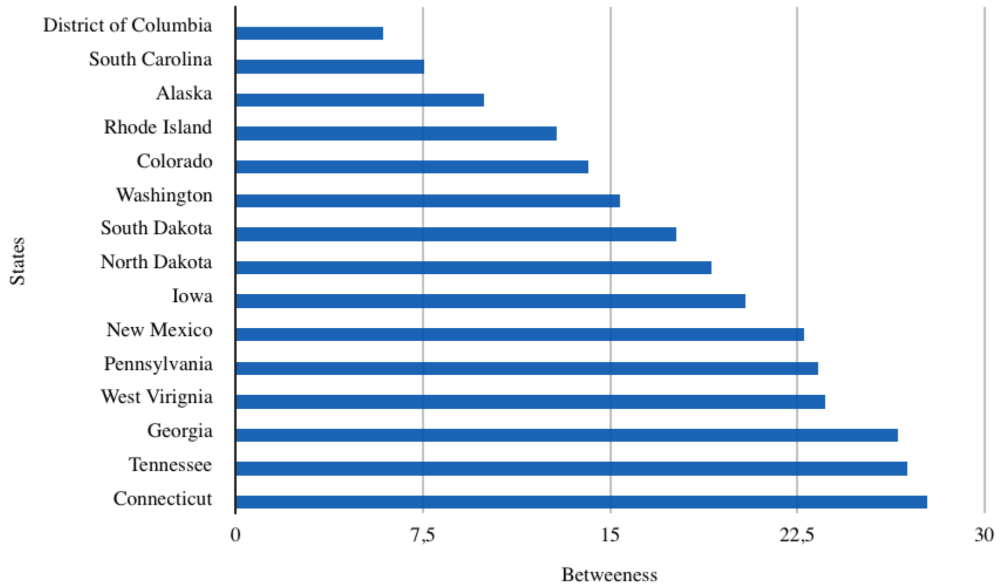


Table 5.d. Ranked last according to centrality indicators (5/6).

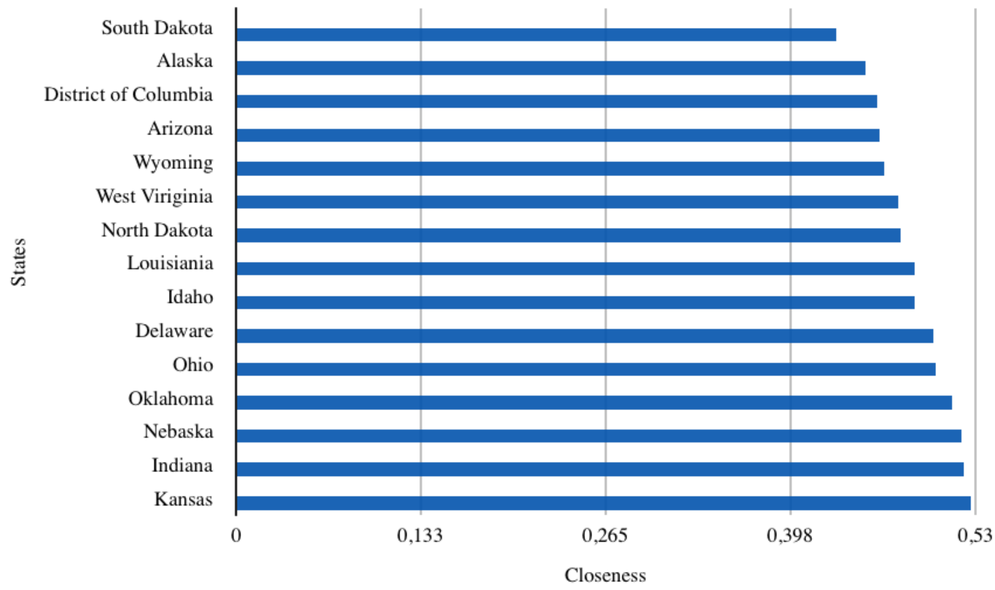
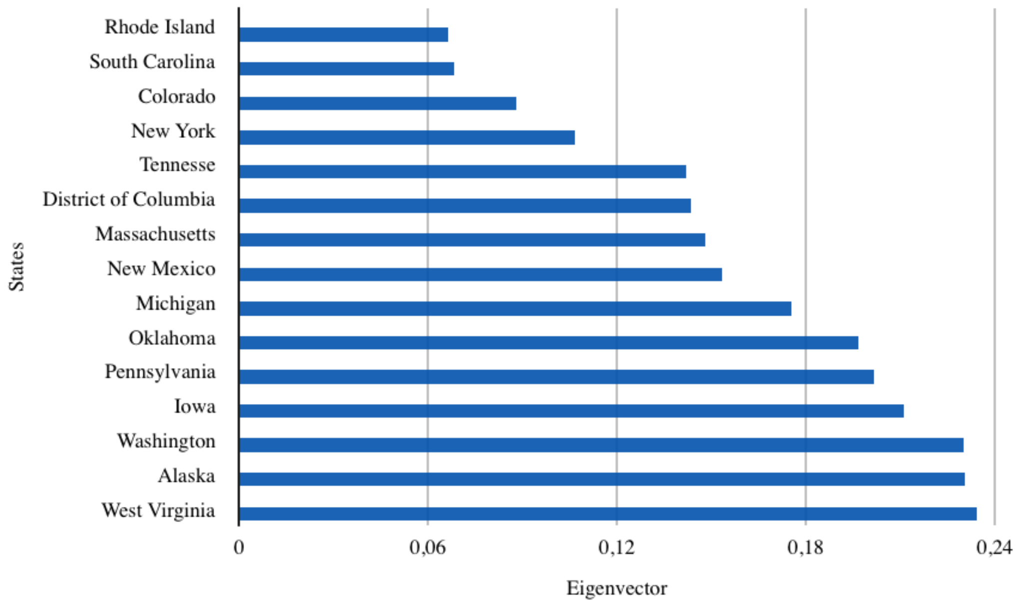


Table 5.d. Ranked last according to centrality indicators (6/6).



6. Figures A - Networks

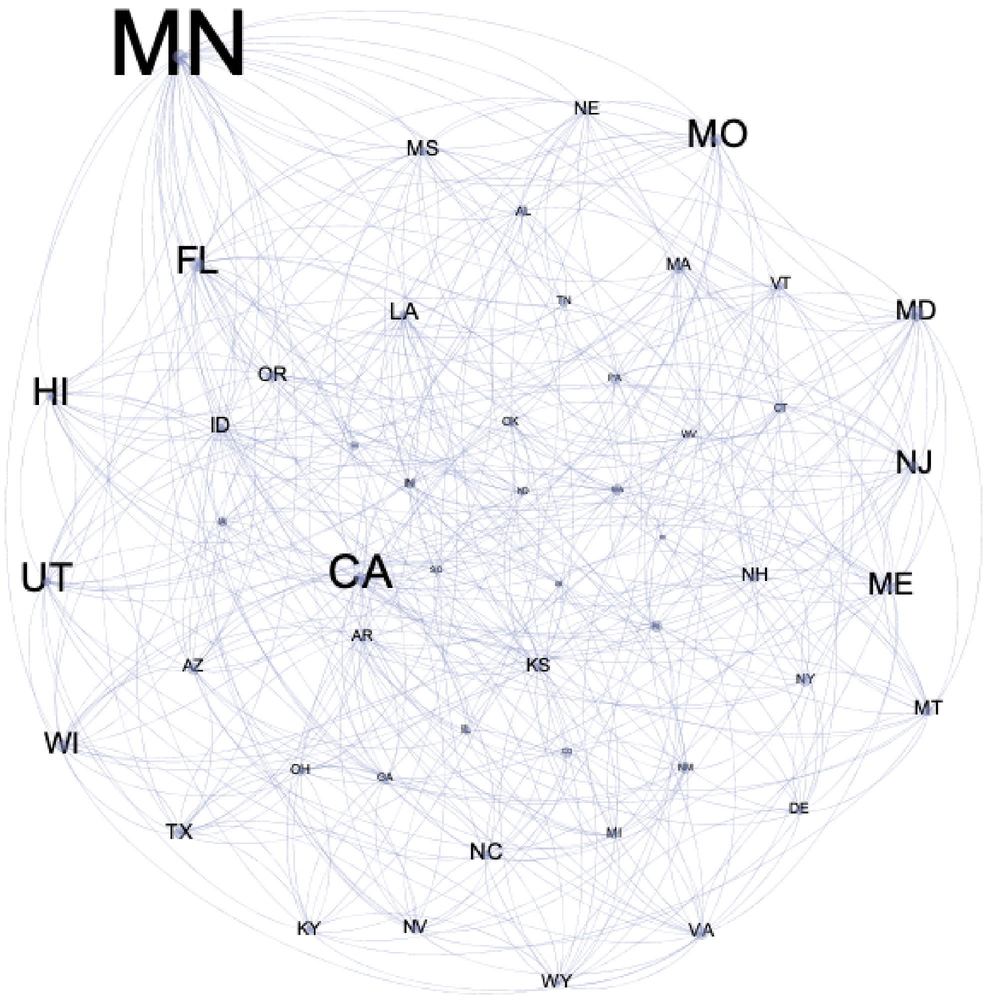


Fig.4. Reconstructed network using Force Atlas layout. The node size in proportional to betweenness centrality, a centrality measure capturing the notion of hubs facilitating policy flows.

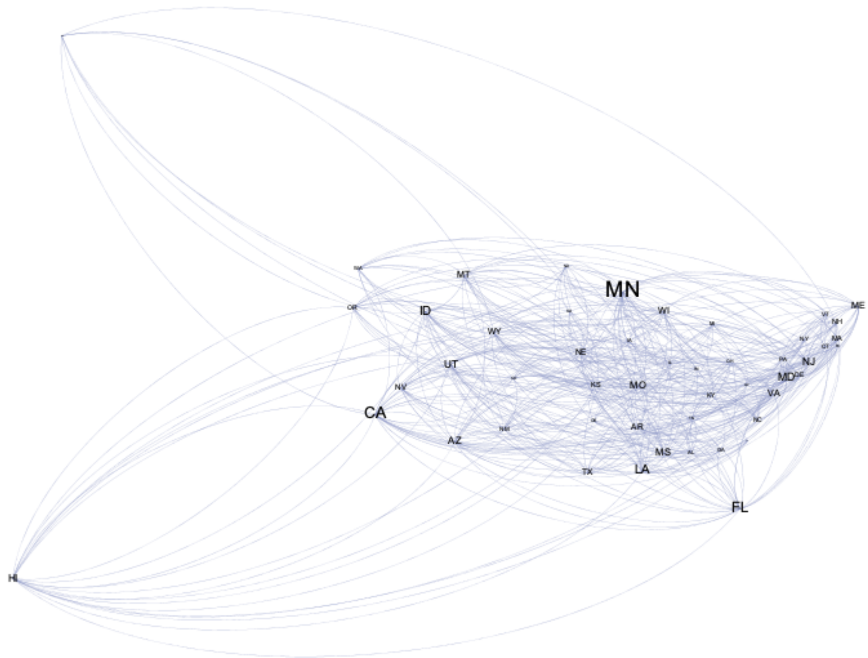


Fig.5. Reconstructed network using geographical layout. The node size in proportional to the degree centrality.

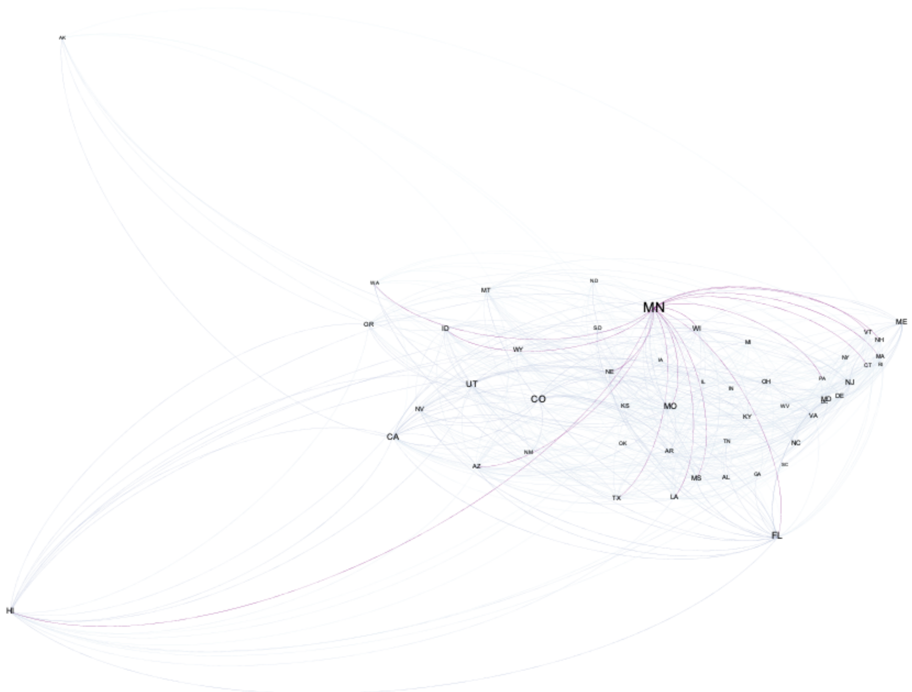


Fig.6. Reconstructed network using geographical layout. The node size in proportional to the betweenness centrality.

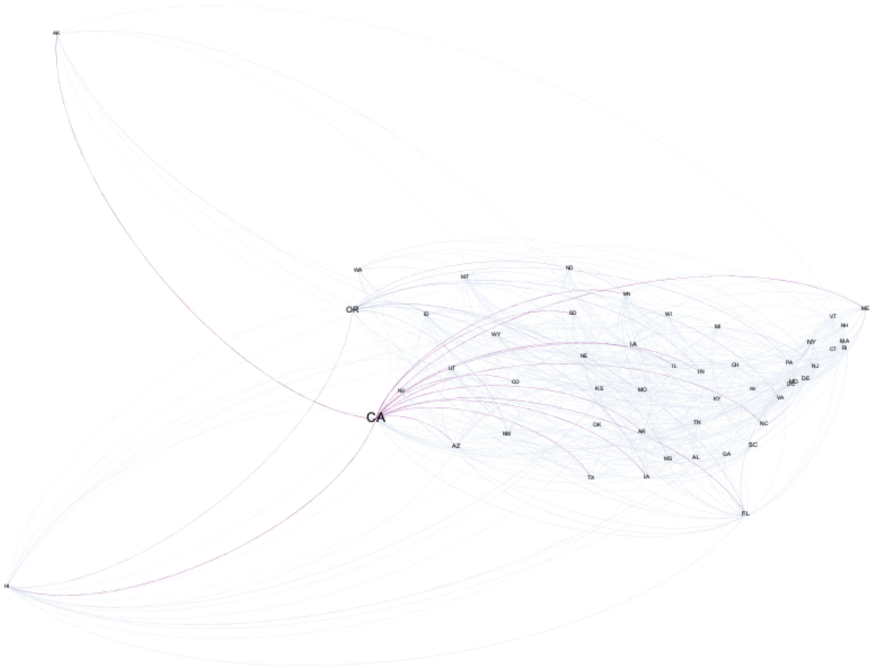


Fig.7. Reconstructed network using geographical layout. The node size in proportional to the weighted out-degree ranking.

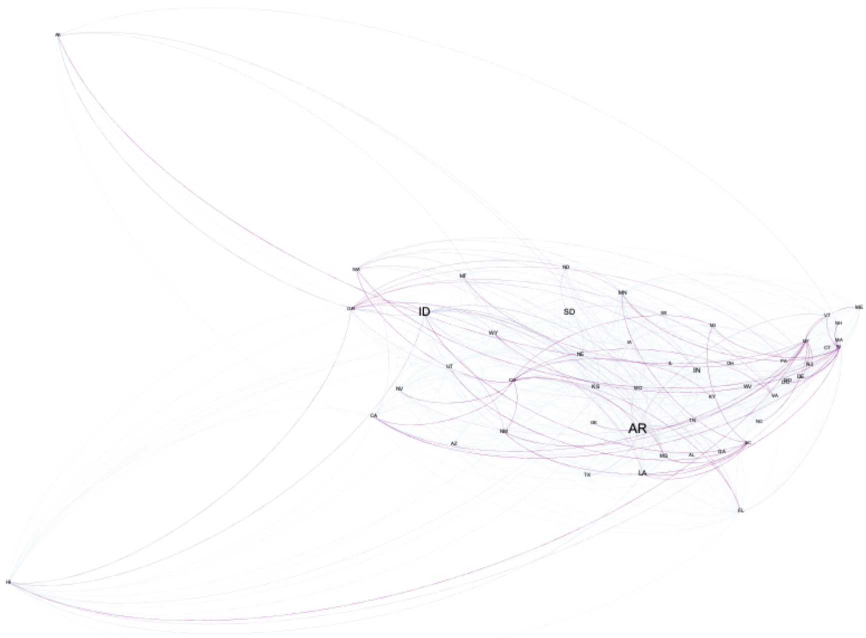
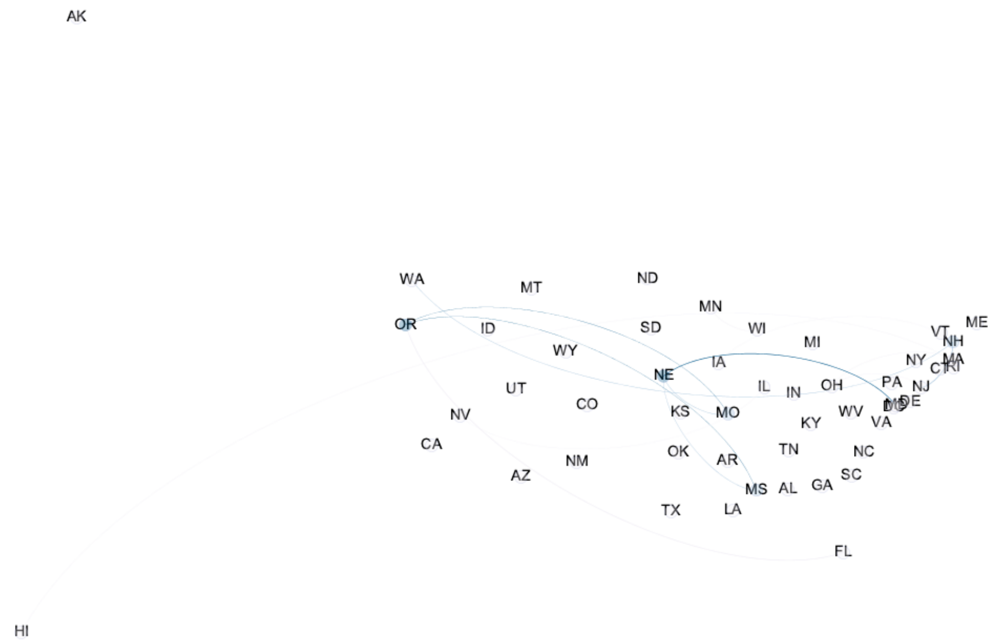


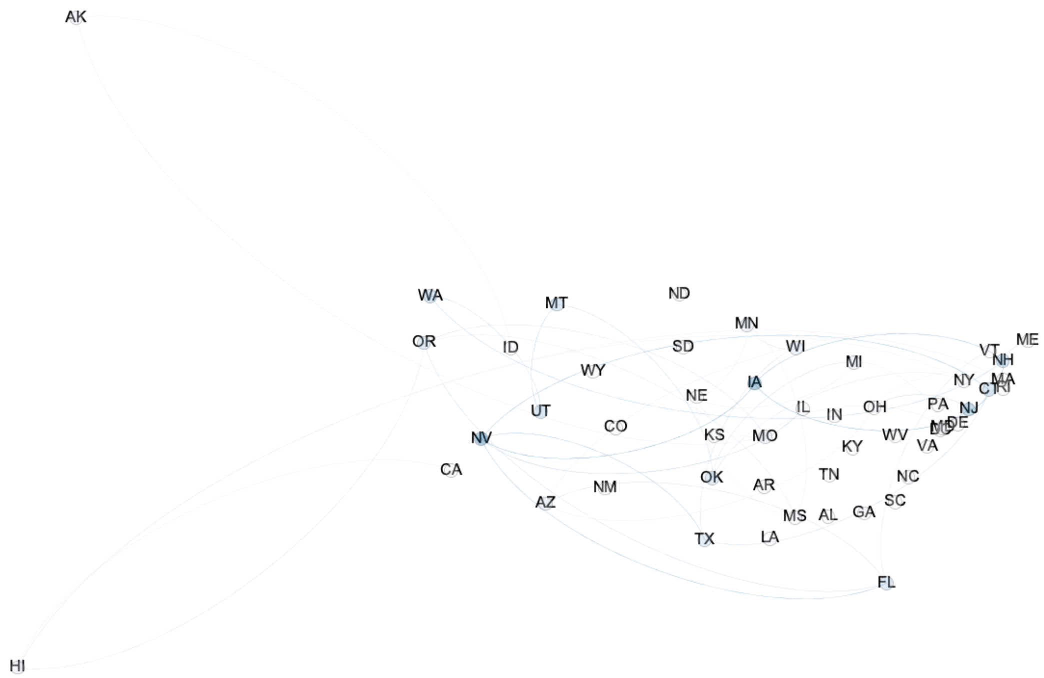
Fig.8. Reconstructed network using geographical layout. The node size in proportional to the weighted in-degree ranking.

7. Figures B - Evolution of network

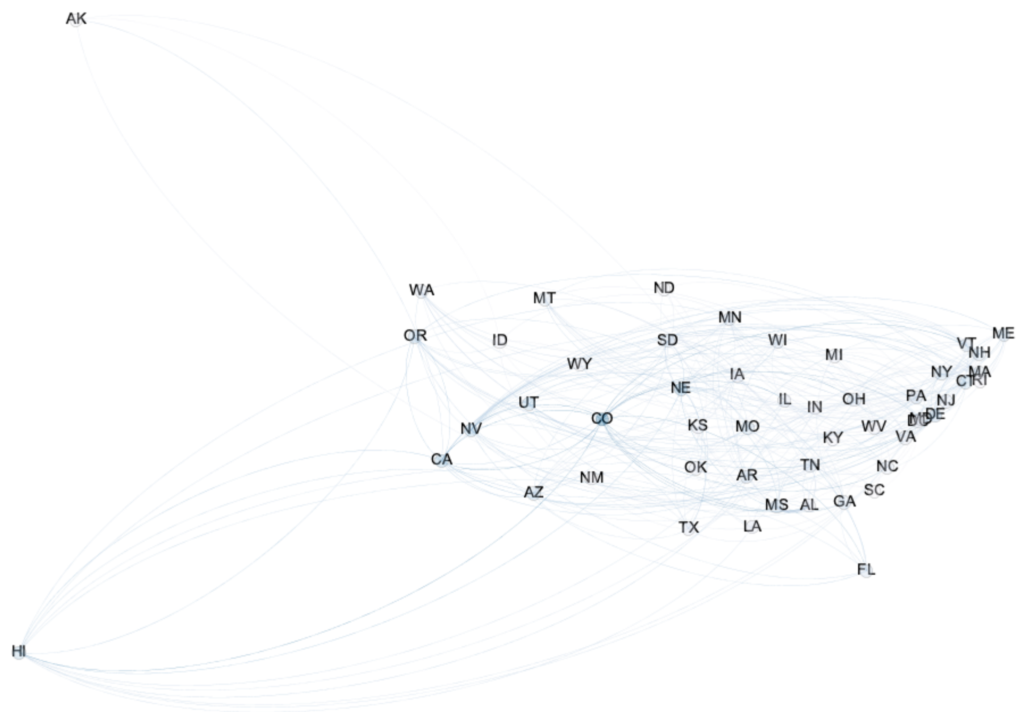
a)1974-1992



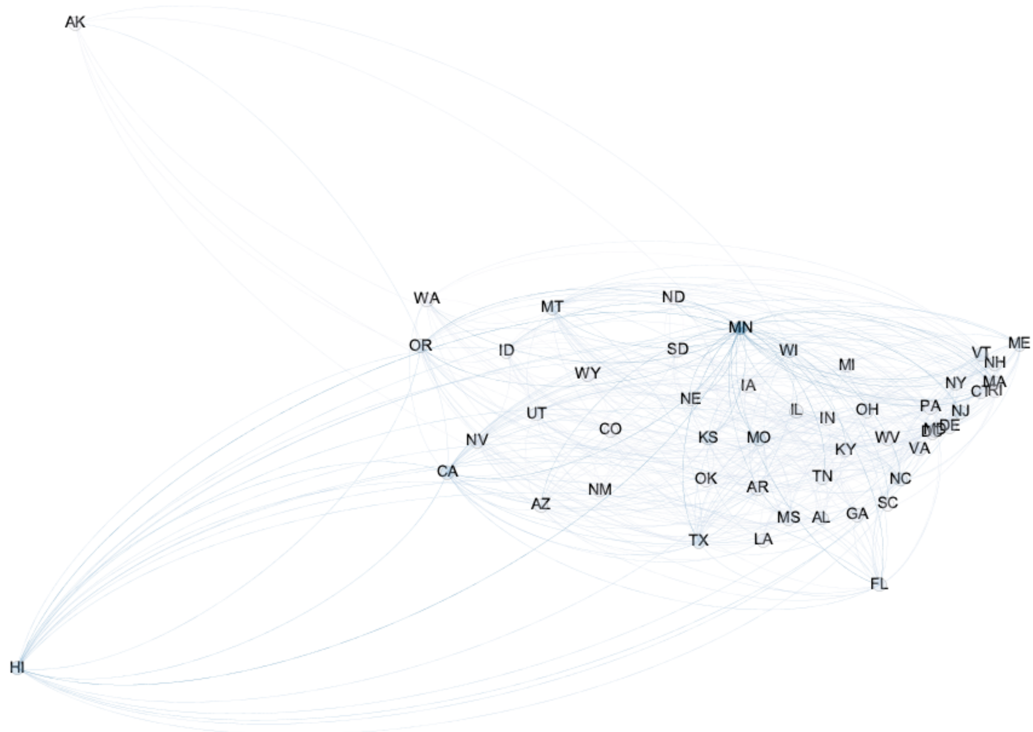
b)1974-2000



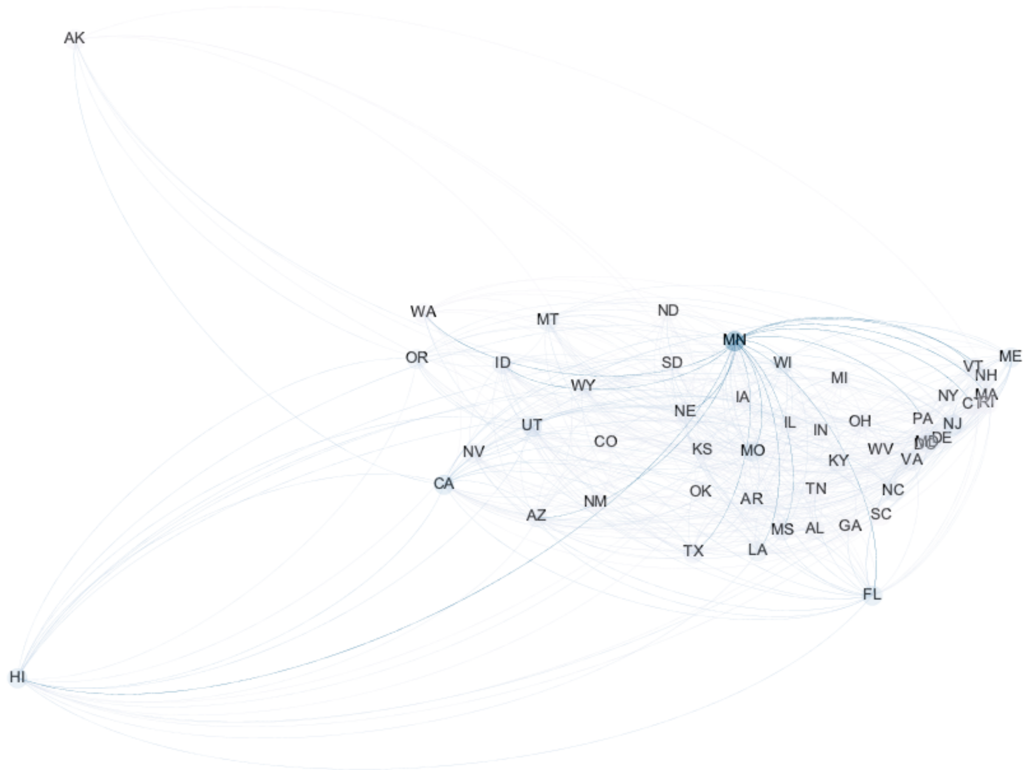
c)1974-2008



d)1974-2016



e)1974-2018



8. Determinants of Network Formation

Description of variables collected - 1974/2018

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) :

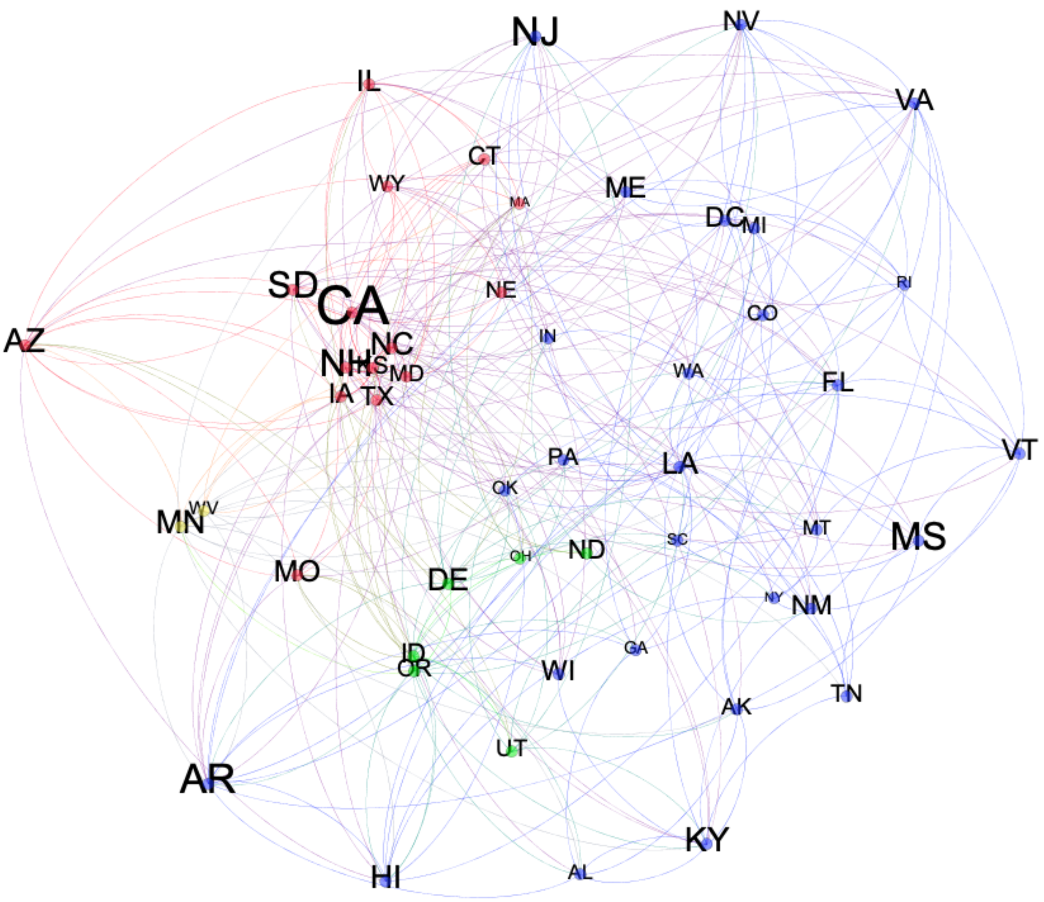
http://www.globalpolicy.science/econ-damage-climate-change-usa.

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).

9. Additional Networks

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



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