Technology transfers in the context of climate policy: A network-based approach and insights on wind energy diffusion

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Abstract

In light of the urgency of climate change, there is a substantial and growing literature on the role of technology transfers and how policy can promote diffusion of climate-mitigation technologies. A key issue is that the diffusion network is generally not observed. To address this issue, this paper proposes a systemic method building on the network inference literature. We apply this approach using detailed data on the adoption of wind turbines at the global scale since the 1980s to infer the network of diffusion of wind energy technologies. The substantial growth of wind power makes it an interesting case to investigate structural properties of the diffusion process at the global, regional, and country-level. Moreover, the inferred network can be used to gain further insights on strategies to achieve efficient technology diffusion.

Key words: Technology transfers, climate policy, diffusion networks, wind energy

JEL codes: O33, Q54, Q55, C61, C63

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1 Introduction

Technology transfers are put forward prominently, both in the Intended Nationally Determined Contributions (INDCs) and in the text of the COP21 Paris Agreement, as necessary conditions for the implementation of an effective mitigation policy at the global scale. Explicitly, the preamble of the agreement *"recognizes the urgent need to enhance the provision of finance, technology*[1] *and capacity-building support by developed country Parties, in a predictable manner, to enable enhanced pre-2020 action by developing country Parties."* The adoption of new technology can also be an important driver of economic development for adopting countries, for example, through the rise of new industries and growth of productivity or technological spillovers. Hence, technology transfers represent a key opportunity to link climate change mitigation and economic development.

The proactivity apparent in the Paris Agreement suggests that technology transfers could be heavily influenced or even controlled by national governments through bi- or multi-lateral agreements. This might be true in some very specific industries such as defense and aerospace. Yet, for most of the technologies, including "green" ones, the diffusion process is the outcome of interactions between private firms (though governments might be involved). Moreover, transfers can take many forms, e.g. machinery, human experts, property rights, and employ a variety of vehicles, e.g. foreign direct investment, purchase of equipment, license agreements, joint ventures, and government aid (see Haug, 1992 for an extensive discussion). In this complex landscape, it is much less clear what policy can do and how it can operate.

In order to shed light on these issues, this paper proposes a methodology to infer the network of technology diffusion between countries from adoption data and then investigates how this network could be used, or modified, by international climate policy in order to foster mitigation via technological diffusion. Hence, our objective is threefold: (i) to provide a map of the existing routes of technological diffusion, (ii) to characterize efficient technology transfer policies and (iii) to anticipate structural changes that could be brought about by new modes of international cooperation such as the development of climate clubs (see Nordhaus, 2015 in this respect).

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[1] Our emphasis. See also articles 66 to 71 of UNFCC (2015).

Adopting a network-based approach allows us to provide a systemic perspective that accounts for the impact of each country not only on his direct connections, but also on the global diffusion process. Indeed, a country might be quantitatively neither the most important source nor the most important adopter of a technology, but still play an important role as a hub in its diffusion. The fundamental role of such network effects has been identified in a wide range of contexts such as epidemics (see e.g., Pastor-Satorras and Vespignani, 2001), social dynamics (see e.g., Castellano et al., 2009), and the diffusion of innovations (e.g., Rogers, 1983). From the methodological point of view, an important difficulty is that technology diffusion networks cannot be directly observed. To overcome this issue, we build on 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 technology adoption using a parametric model of diffusion.

To illustrate this approach, we infer the network of diffusion of wind energy technologies using a very detailed database on wind turbines installed globally from 1983 onwards. The substantial additions to renewable energy capacity and advancements in wind power makes it an interesting case to study. We then investigate what would be efficient seeding strategies, i.e. strategies that pick up initial inception in order to maximize the diffusion of a new generation of technology in this wind network. Preliminary findings suggest that (i) the wind energy diffusion network has fat tails, i.e. there are countries which are much more connected than expected if sizes were drawn from a normal distribution; (ii) regional hubs such as Brazil for Latin America and France for Europe play an important role in the diffusion process; (iii) the network diameter is relatively large, which suggests there might be important lags between advanced and developing countries in technology adoption. Against this background, we investigate if transfer strategies tailored towards the diffusion of technologies to subgroups of developing countries can be more efficient than seeding strategies based on conventional centrality measures.

The remainder of the report is organized as follows. In section 2, we review the related literature. Section 3 provides a detailed description of our methodology and section 4 its application to the diffusion of wind energy. Section 5 then aims at characterizing policies for an efficient diffusion in view of climate change mitigation. Section 6 concludes raising ideas for further research.

2 Related literature

The importance of technological diffusion processes for the achievement of climate policy objectives has been emphasized at least since the Kyoto Protocol (see e.g., Blackman, 1999). Within the scientific community, the Intergovernmental Panel on Climate Change (IPCC) has repeatedly put forward its central role for climate policy and sustainable development (e.g., see IPCC, 2015). In the policy debate, technology transfers are strongly emphasized in the Intended Nationally Determined Contributions (INDCs) prepared for the COP21 and their key role is recognized in the Paris Agreement which puts forward in its preamble *"the urgent need to enhance the provision of finance, technology and capacity-building"* and devote a full section to its decisions on "technology development and transfer", hence putting it on an equal footing with mitigation and adaptation.

Three main market channels of technology transfer have been distinguished in the literature (see e.g. Glachant et al., 2013): (i) international trade in intermediate goods (e.g., export and import of capital goods such as machines and equipment), (ii) foreign direct investments including joint ventures, and (iii) licensing (e.g. of patents). Accordingly, the existing literature has mainly focused on the characterization of bilateral technological flows using measures such as international trade data, FDI, and patents (see e.g., Popp et al., 2011; Glachant et al., 2013, Dechezleprêtre et al., 2013). In the specific context of climate change, technology transfers through the clean development mechanism (CDM) and its determinants have been extensively analyzed (see Dechezleprêtre et al., 2008, 2009; Rahman et al., 2016; and references therein). The data from the project design documents of the CDM is detailed, but an extremely important limitation, also mentioned by the former authors, is that data of projects are usually registered during a very short period (around 2 years), thereby not allowing to analyze the *dynamic* aspects of diffusion. More generally, an important challenge for research on technological diffusion put forward in Comin et al. (2013) is the lack of comprehensive datasets that directly document the diffusion of specific technologies across countries. Consequently, most empirical studies on technology adoption and transfer have treated adoption units as independent or have taken a bilateral approach as in the CDM literature (cf. Comin and Mestieri, 2014).

This focus on bilateral transfers fails to take into account the key role of interconnections in the global diffusion of technologies. Yet, as emphasized in a recent survey on the diffusion of green technology (see Allan et al., 2014), networks play a fundamental role in the spread of technologies. In the theoretical literature, recently developed network-based models of innovation and technology diffusion (e.g. Centola et al., 2007; Montanari and Saberi, 2010; Acemoglu et al., 2011; Banerjee et al., 2013) account for the actual complexity of the diffusion process and provide insights on the influence of the network's topology on its dynamics. These models consider a wide range of possible diffusion processes ranging from epidemic-like contagion to strategic adoption (see Montanari and Saberi, 2010) through linear threshold models (see e.g. Centola et al., 2007). Conclusions on what facilitates diffusion is far from clear-cut. Nevertheless, typically the literature suggests that innovations spread further across networks with a higher degree of clustering. In principle, clusters can promote diffusion where a seed node exists inside them, but they are more difficult to penetrate when not targeted during the initial seeding phase.

In the context of green technologies, a major issue however is that the diffusion network is generally not observed. In order to address this issue, we build on the one hand on recently consolidated databases about the global deployment of green technologies (the Windpower database on wind turbines as far as this paper is concerned), and on the other hand on the growing literature on the network inference problem (Saito et al., 2009; Gomez-Rodriguez et al., 2010; Gomez-Rodriguez et al., 2011; Daneshmand et al., 2014). The latter literature has led to the development of parametric models of diffusion that can be used to reconstruct the structure of the network by maximizing the likelihood of the observed diffusion patterns. Here, we reconstruct the network of diffusion of wind energy technologies from the observed deployment of successive generations of wind turbines at the global scale. The inferred network can then be used to simulate the diffusion of new vintages of technologies. Hence, our approach allows to directly track the diffusion of a technology among countries, as well as analyze the role of the network structure in the diffusion process.

The application of network-based methods to international technology transfer has no precedent to our knowledge, though it is strongly inspired by the work of Hidalgo and Hausmann (2009) on economic development in the global network of countries and products.

3 Network inference method

The cornerstone of our approach is to use the independent cascade model of Gomez-Rodriguez et al. (2010) to infer a network of technological diffusion from a time-series of observations of the adoption/installation of subsequent generations of a technology within a country. The weights of the resulting network are interpreted as the rates at which an instance of the technology is likely to be transferred between countries. These weights summarize on the one hand (i) the effects of a number of latent variables that govern the bilateral diffusion between countries, e.g. the export strategy of firms, the flow of foreign direct investment or the existing trade and/or cooperation agreements between countries, and (ii) the systemic role that countries can play by serving as intermediaries in the global diffusion process.

More formally, we consider that we are given series of observations of the diffusion of subsequent vintages of a technology. Each vintage c is characterized by a cascade of adoptions $\boldsymbol{t}^c = (t_1^c, \ldots, t_N^c)$, 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 country i adopted the technological vintage c if finite and is infinite if the country did not adopt the technology 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 ∞ 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. Our observation data can then be represented by a set C of cascades, one cascade for every vintage, and denoted as $C \coloneqq \{\boldsymbol{t}^1, \ldots, \boldsymbol{t}^{|C|}\}$.

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 E and a set of edges V) representing the potential diffusion paths of the technology and $A = [\alpha_{j,i}]$ is a matrix of transmission rates, i.e. $\alpha_{j,i} > 0$ quantifies how likely it is that a technology spreads from node j to node i if $(i,j) \in E$ (and $\alpha_{j,i} = 0$ if $(i,j) \notin E$). 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).

More 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. In the following, we shall consider, as a benchmark, the exponential model for which $f(t_i|t_j;\ \alpha_{j,i}) = \alpha_{j,i}e^{-\alpha_{j,i}(t_i-t_j)}$ (if $t_j < t_i$ and zero otherwise). This corresponds to a setting where the rate of diffusion from an activated node to its neighbors is constant over time, i.e. the diffusion process follows a Poisson process. As an alternative, we shall also consider the power-law model for which $f(t_i|t_j;\ \alpha_{j,i}) = \alpha_{j,i}(t_i - t_j)^{-1-\alpha_{j,i}}$ (if $t_j < t_i$ and zero otherwise). As emphasized by Barabási (2005), this model can be seen as the outcome of a queuing process in which a decision-maker intervenes to set priorities. It leads to much fatter tails in the temporal distribution of events than the exponential distribution, consistently with empirical data about the timing of human-driven events. In our setting, it amounts to considering that most diffusion events are clustered near the activation time of the source node, while the remaining diffusions experience very large waiting times. A natural interpretation of this pattern is that countries generally adopt the latest vintage of a technology so that the bulk of adoptions should happen in a relatively short time-window after its inception before the technology becomes obsolete.

Now, given the conditional density $f(t_i|t_j;\ \alpha_{j,i})$, one can infer the likelihood of a set of cascades $\{\boldsymbol{t}^1, \ldots, \boldsymbol{t}^{|C|}\}$ given a network $A = [\alpha_{j,i}]$ as follows (see Gomez-Rodriguez et al., 2011 for a comprehensive discussion).

- First, given a cascade $\boldsymbol{t}^c = (t_1^c, \ldots, t_N^c)$, the likelihood of node *i* being activated by node *j* is given by: $f(t_i|t_1, \ldots t_N \setminus\ t_i; A) = \sum_{j:t_j\leq t_i} f(t_i|t_j;\ \alpha_{j,i})\times \prod_{j\neq k, t_k \leq t_i} S\left(t_i|t_k;\ \alpha_{k,i}\right)$ (1)
  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 as:
  $f(\boldsymbol{t}^c_{\leq T}\ ; A) = \prod_{t_i\leq T} \sum_{j:t_j\leq t_i} f(t_i|t_j;\ \alpha_{j,i})\times \prod_{k:t_k<t_i, k\neq j} S\left(t_i|t_k;\ \alpha_{k,i}\right)$ (2)
- Further, the likelihood of a cascade accounts for the fact that some nodes did not get activated (we actually consider that nodes not activated before time T never get activated). It is therefore given by: $f(\boldsymbol{t}^c\ ; A) =$
  $\prod_{t_i\leq T} \prod_{t_m>T} S(T|\ t_i; \alpha_{i,m}) \prod_{t_i\leq T} \sum_{j:t_j\leq t_i} f(t_i|t_j; \alpha_{j,i}) \prod_{k:t_k<t_i, k\neq j} S\left(t_i|t_k; \alpha_{k,i}\right)$ (3)

- Finally, the likelihood of a set of cascades $C = \{\boldsymbol{t}^1, \dots, \boldsymbol{t}^{|C|}\}$, assuming each cascade is independent, is the product of the likelihoods of the individual cascades given by equation (3), that is: $f(\{\boldsymbol{t}^1, \dots, \boldsymbol{t}^{|C|}\}; A) = \prod_{t^c \in C} f(\boldsymbol{t}^c; A)$ (4)

Eventually, our objective is to find the network $A = [\alpha_{j,i}]$ such that the likelihood of the observed set of cascades $C = \{\boldsymbol{t}^1, \dots, \boldsymbol{t}^{|C|}\}$ is maximized. The solution of the network inference problem can thus be stated as solving the following maximum likelihood (ML) optimization problem:

$$\begin{array}{ll} \text{minimize}_A & -\sum_{c \in C} \log f(\boldsymbol{t}^c; A) \\ \text{subject to} & \alpha_{j,i} \geq 0, i, j = 1, \dots, N, i \neq j \end{array} \quad (5)$$

Remark 1 In practice, we solve equation (5) using CVX, which is a general purpose package in MATLAB for specifying and solving convex programs (Grant and Boyd, 2015) and the algorithm NETRATE, which are publicly released open source implementations.

Remark 2 This continuous time model of diffusion has a resemblance to the additive regression model used in survival theory analysis (see e.g., Aalen et al., 2008), which has also interestingly been used for link prediction in social network data by Vu et al. (2011), relating to the network formation literature.

The inferred network provides two main types of information. First, the adjacency structure of the network indicates which routes technologies are likely to follow in their diffusion. Second, the weight of an edge gives an estimate of the speed at which diffusion is likely to occur between nodes. Note that this interpretation does not presuppose that diffusion is the outcome of a (rational) decision of countries, consistently with the epidemiological roots of the model. Similar to the reproduction and the diffusion of viruses, which are the outcome of micro-level phenomena beyond the control of the central nervous system, the diffusion of technologies is the outcome of the decisions of firms and households, which are for the most part beyond the control of the state. This does not imply that the state cannot influence the diffusion process through policy. However, in the following, we shall consider the national policy setting is fixed and rather consider policy interventions at the international level such as the exogenous inception of a technology in a country (e.g. through CDM like projects).

4 The wind energy network

4.1 Context and data

In the following, we provide a first application of this network inference approach to wind energy. Wind energy currently is the most important source of renewable energy and has been growing exponentially in the last decades (see Figure 1 as well as GWEC, 2015 and IEA, 2015). Therefore, it is expected to play a key role in mitigation policy globally. From this perspective, a prerequisite is to ensure that new generations of wind turbines can be diffused rapidly at the global scale. An important empirical macro-level observation in this respect is that the geographical pattern of deployment is changing. Whereas OECD countries led early wind development, from 2010 non-OECD countries installed more wind turbines, and using scenario-based analysis it is predicted that after 2030 this will rise to more than 50% of global installed capacity (see OECD/IEA, 2013). This further emphasizes the need of efficient technological diffusion to ensure that the newly installed turbines are as close as possible to the technological frontier. Indeed, technology improvements of wind turbines since the 1980s has largely contributed to growth in wind power capacity. The general trend has been an overall growth in size, with an increase in the height of the tower, the length of the rotor blades and greater power capacity (see the Wind Energy Technology Roadmap report in OECD/IEA, 2013 for details).

The Wind Power database provides detailed technological and industrial information, as well as almost comprehensive coverage on the wind turbines installed worldwide from 1983 onwards[2]. Hence, it can be used to reconstruct the diffusion cascades of successive technology vintages and therefrom infer the network of diffusion of wind energy according to the methodology introduced above.

Table A.1 provides details on the country, wind farm, and power capacity coverage for the 94 countries in the database. These include wind farms that have been installed and are in operation, as well as under construction, approved or planned within each country. As can be seen in the sample of the data provided in Table A.2, for wind farms with the status operating, there is information on the commissioning date. These are time series observations spanning the period from 1983 to 2016. Wind farm entries in the database under construction, approved or

[2]http://www.thewindpower.net/

planned are also essential information and are included since they reflect recent diffusion patterns, which are assigned to years 2017, 2018, and 2019, respectively.

The uniqueness of the dataset is that in addition to the space and time information coverage of the wind farms, there is also precise data on power capacity and manufacturers of the wind turbines of the wind farms. This allows us to identify 240 vintages of technologies, which are mainly characterized by the size of the turbine and the manufacturer (e.g. as shown in Table A.2, the Samsung 2500, the Vestas 2600 turbine and so forth). One can then define one cascade per technology vintage as follows. We consider countries as our nodes and set the activation time of a given technology vintage for a country as the commissioning date of the first wind farm in the country using the vintage. By convention, the activation time of a country not using the vintage is set to infinity. After excluding some countries of the dataset because of unavailable data[3], we hence reconstruct 240 cascades spanning 94 countries over an observation window of 37 years, i.e. T=37.

4.2 Statistical analysis of the network

As illustrated in Figure 2, the inferred network first provides a map of existing diffusion routes and hence a much broader view than obtained from the sole consideration of bilateral transfers. For example, in our setting, it can be the case that countries x and y are not linked by a direct transfer, but there is a very short path from x to y through z; hence diffusion shall nevertheless occur relatively rapidly from x to y. On the contrary, the path from x to w could be relatively long (going through a,b,c,d,e, and so forth), which suggests a relatively long lag in the diffusion from x to w.[4]

From a more systemic perspective, Figure 2 also puts forward the existence of a well-connected core mainly formed by the most advanced European countries surrounded by a periphery organized in geographical clusters. This is consistent with the leading role played by European firms and countries in the development of wind energy in the past decades.

[3]In particular, these are Albania, Chad, Curacao, Mozambique, Namibia, Panama, Tanzania, and Vanuatu. Also, there is no data altogether for Guyana and Indonesia.
[4]We later run a series of simulations based on the shortest path lengths.

From a more quantitative perspective, structural properties of the diffusion process can be characterized via a statistical analysis of the network. In this respect, key features of the network are reported in Table 1. 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). In the context of technological diffusion, they respectively measure the direct potential to adopt or spread a technology. The inferred network has 596 edges, i.e. 596 links among the 94 countries. In other words, the average degree is approximately 12.6 and the network density, i.e. the ratio between actual and total potential number of links is 0.07. These values are in line with those generally observed in socio-economic networks (see Chandrasekhar, 2015 or Albert and Barabási, 2002).

Then, 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 technological diffusion, the average path length can be seen as a measure of the average technological distance between two countries and in our setting, it has a value 3. This is relatively large with respect to the random graph benchmark usually satisfied by socio-economic networks (see 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). Furthermore, the diameter of the network, which is the shortest path between the two most distant nodes, has a value of 8 in our setting, which is again 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 relatively large diameters and average path lengths hint at the existence of relatively long lags in the diffusion processes. Reassuring evidence appears graphically in Figure 2, where one can observe that certain countries (e.g. Bolivia and Peru) are very loosely and indirectly connected to the core of the network and, more generally, that there are poor interconnections between the different regional clusters. Hence the current wind technology diffusion network displays a certain level of inefficiency. In particular, there might be significant delays between technology adoption in advanced and developing countries. As a complement, we also made a regional-level analysis, which further reinforces these observations (see Appendix, A.3).

To gain more insight on the origins of these inefficiencies, one can infer a systemic characterization of the network via the 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 wind network are shown in Figure 3, also in log-log scale. The distribution clearly has fatter tails than normal, consistently with the presence of highly connected nodes in the core. The middle range of the distribution even seems to follow a power law. As a matter of fact, the Kolmogorov-Smirnov statistics fail to reject the hypothesis that the data could have been drawn from the fitted power-law distribution (the KS-statistics are 0.163 (p-value=0.97) for the in-degree distribution and 0.124 (p-value=0.98) for the out-degree distribution). However, the right tail of the distribution clearly drops faster than this of a power law. This indicates the lack of very large nodes that would play the role of central hubs in the diffusion process and hence would increase its efficiency. The distance-based utility model of Jackson (2008) further suggests that in a setting where the social objective amounts to minimize distances in a network, the star would be the efficient network. A graphical comparison then suggests that the existing wind network has a much less hierarchical structure with a relatively large number of nodes with medium connectivity, but no clear center.

In order to gain deeper insights into the origins of the current structure, our methodology can be used to simulate the network formation process by running our network inference algorithm for sub-periods of increasing lengths. The results of this analysis are presented in Figure 4. They can be compared with benchmark network formation processes such as preferential attachment, according to which entering nodes should connect to existing nodes with a probability proportional to the latters' degree.

A first observation is that the growth of the network has been remarkable. It has expanded considerably, both in terms of size and of connectivity. In comparison with Figure 2, the landscape for the earliest sub-period is much less dense with only a few major countries such as Denmark, a pioneer in developing commercial wind power. In the following sub-period, 1983-2000, it can be seen that the major players are Germany in the center, Denmark, Austria, the United Kingdom, and also the Netherlands, Ireland, Spain, and Greece in Europe, which branch among themselves as well as with mainly China, Japan, and the United States. It can still be seen that are much less countries in the network, such as South Africa which reflects that large-scale wind farms did not pick up there until the later 2000s. Comparing Figure 2 with 1983-2005, three main changes come into view: the concentration in Europe is much greater (with e.g., Denmark, Sweden, Belgium, and Germany having very high betweenness), China, India, Japan, and New Zealand are also more prominent in their respective regions (than e.g. South Korea), and other areas in the world are much less represented (e.g. Latin America). For 1983-2010, the network is still less dense, and importantly there is still less of a presence of some regions such as Latin America. The United States is quite more prominent in the network, as well as India and South Korea. Finally, comparing sub-period 1983-2015 to Figure 2, as expected they are quite similar. In general, these significant topological changes reflect the vastly dynamic nature of the wind energy diffusion network.

4.3 Centrality analysis

To further investigate the role and position of hubs in the network, several centrality measures developed in the literature can be used in our framework (see Jackson, 2008 for an overview):

- The degree centrality of node i 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 technology seeded in one country would, on average, reach another country in the network.
- The betweenness centrality of node $\underline{i}$ measures the share of shortest paths in the network on which node i lies (see Appendix A.4 for a formal definition). Hence, in our context, it measures to which extent a country 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 (see Appendix A.4 for a formal definition). In the context of technological diffusion, it can be seen as a measure of the total diffusion range (direct and indirect) of a technology, as a function of the seed country.

Table 2 and Figure 5 provide an overview of the distribution of centrality in the network. It is clear that among the most predominant countries are France, Germany, Ireland, Italy, Spain, Sweden, Turkey, the United Kingdom, and the United States. In fact, many overlap across the different centrality measures. Canada, Denmark, Finland, and Hungary also appear among the top for some of the indicators. In addition, it can be observed that some emerging economies including the major BRICS, with the exception of Russia, have a strong presence, especially Brazil and China.

Although out-degree can be seen as reflecting a spreader of technology, with a higher number implying greater coverage, in-degree can also be important indicating receptiveness to the technology. Since the diffusion process involves accumulation of technology arising from adoption decisions, both the ability to spread and absorb new technologies are interrelated and important. In aggregate, main hubs are France, Germany, the United Kingdom, and the United States.

With respect to closeness centrality, which provides an indication of which countries can reach all other reachable nodes quickly, Turkey, Hungary, Spain, Germany, Italy, the United States and United Kingdom take the top positions.

Betweenness centrality is particularly insightful. As previously discussed, it determines the relative importance of a country by measuring the amount of flows through that country to other countries in the network, thus acting as a bridge. The visualization of the network based on the betweenness indicator (Figure 2) highlights the importance of both regional and global hubs in the wind energy diffusion network. For example, Brazil for Latin America, Canada and the United States in North America, France in Europe which is evidently very central in the network, Turkey for Eurasia, Australia for Oceania, and South Korea, as well as China and Japan for Asia.

Eigenvector centrality builds upon degree centrality, but also adds in a sense the quality of the connections, i.e. how connected a country is to hubs in the wind energy diffusion network. France, the United States, the United Kingdom, Germany, Sweden, Finland, and China are among the most important actors in the network according to this measure (see Figure 5). It should be noted that some of these are also hubs themselves, while some countries such as Croatia and Denmark do not overlap over these measures.

Hence, the comparison between centrality measures reinforces the conclusion of the preceding section: there is only partial overlap between the different centrality measures and the distribution of centrality among top nodes is relatively uniform. In this sense, the network is multi-polar and no single node appears as an evident center. Therefore, it is not straightforward to put forward a node, nor a region, as the optimal target for the inception and the diffusion of new vintages of wind technology.

5 Efficient diffusion strategies in the wind network

In order to gain further insights on the means to achieve efficient technology diffusion in the multi-polar world described above, we run a series of simulations in which we compare the performance of different seeding strategies, i.e. strategies that foster the inception of a technology in a certain subset of countries in view of further diffusion. The initial inception points can be seen as the initiator of the technology, but also as a partner country in which the country is proactively diffused in the context of bilateral or multi-lateral technological cooperation or development aid.

Remark 3 For the simulations, we first randomly draw (e.g., 1,000 times) the activation times from the probability density function (pdf) of the exponential distribution given the transmission rates, i.e., $f(t_{j,i};\ \alpha_{j,i}) =\ \alpha_{j,i}\times e^{-\alpha_{j,i}t_{j,i}}$ if $t_{j,i} > 0$ and zero otherwise. Then, using these activation times, we calculate the minimum costs (i.e. the minimum time it takes for country i to reach other countries j) and shortest paths using Dijkstra's algorithm.[5]

In line with the objectives put forward by the UNFCC (2015) of using technology transfers in order to foster climate change mitigation and economic development, we focus on the efficiency of technological diffusion among different groups of developing countries. Table 3 provides a ranking of groups of developing countries based on (i) the maximum time it takes for them to spread to all other countries in their region, and (ii) their ability to achieve the most technological deployment (i.e. the most coverage) in the region within two decades. Similarly, we conduct

[5]This has been implemented using Joseph Kirk's code available on the file exchange of MathWorks. The outputs are an $N\times N$ matrix of minimum cost values for the shortest paths, and an $N\times N$ cell array containing the shortest path arrays where each element shows for each country, which countries are required to reach all other countries. To be noted is that the pdf of the exponential distribution in MATLAB is defined using an alternative parameterization, namely, $1/\alpha_{j,i}\times e^{-t_{j,i}/\alpha_{j,i}}$ if $t_{j,i} > 0$ and zero otherwise; hence we take the reciprocal of the transmission rates.

similar policy experiments, presenting a ranking of Annex I Parties in their efficiency to spread new technologies to Non-Annex I Parties, as defined by the UNFCCC.

A striking result for Africa is that South Africa does not seem to be an efficient hub in terms of a spreading potential of new technology to the rest of the countries in the region, at least for wind power technological diffusion. In contrast, northern African countries such as Egypt are better able to cover more countries faster overall and in a shorter amount of time. This points to potential bottlenecks in the within-regional network, i.e. a lack of strong routes among them. For Asian countries, Thailand, Vietnam, Taiwan, and Turkey are among the top-ranked. Some also ranked highly on the centrality measures, but in general some are ranked higher such as Taiwan. It suggests that Southeast Asia and Taiwan have a more promising potential as spreaders of new technologies than implied by the centrality measures. Yet, it is important to note this pertains to the spreading potential within Asia.

For Latin America, Colombia appears to best cover Latin America as a whole, but is not the fastest in terms of covering the most countries in a shorter period. Surprisingly, although Brazil is mid to top-ranked, it is not among the top spreading forces in the region. This suggests that even though it is an important regional hub, its role as a global hub is more prevalent, which is also the case for China. Finally, for countries part of the Annex I Parties, it is notable that some of the major countries such as the United States and the United Kingdom do not seem to be so efficient in their ability to spread new technology to the Non-Annex I Parties, which are mostly developing countries. This leaves it interesting to explore more in-depth why and how the wind energy diffusion network can be upgraded. A potential reason why some of these major countries (though there are some exceptions such as Germany), do not come out to be so highly ranked in the simulation results is that the network is still concentrated among a few key players.

6 Conclusion

In view of providing a global assessment of the potential contribution of technology transfers to climate change mitigation, we aim at extending our approach to a comprehensive portfolio of technologies and have started to identify relevant databases in this respect. This includes other renewable energies such as solar power and biofuels, as well as technological improvements to make for example, steel production processes more environmentally friendly. Potential databases include the Plantfacts database from the Fédération Française de l'Acier (FFA), which is continuously updated by the Association of German Steel Manufacturers (VDEh), as well as data on biofuel refineries from for example Bioenergy 2020. From a more micro-economic perspective, our approach could be applied in an agricultural context to investigate the diffusion of new generation of biofuels.

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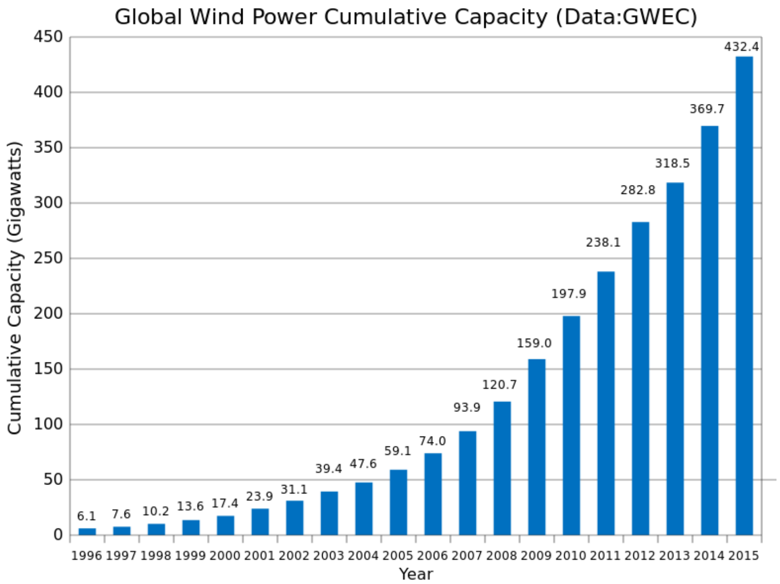
Figure 1. Wind power capacity



Source: Global Wind Energy Council statistics

Table 1. General properties

Overall network characteristics	
Number of nodes	94
Number of links	596
Network density	0.068
Mean degree	12.681
Mean path length	2.905
Network diameter	8
Mean clustering coefficient	0.146

Figure 2. Betweenness centrality for full time-period sample

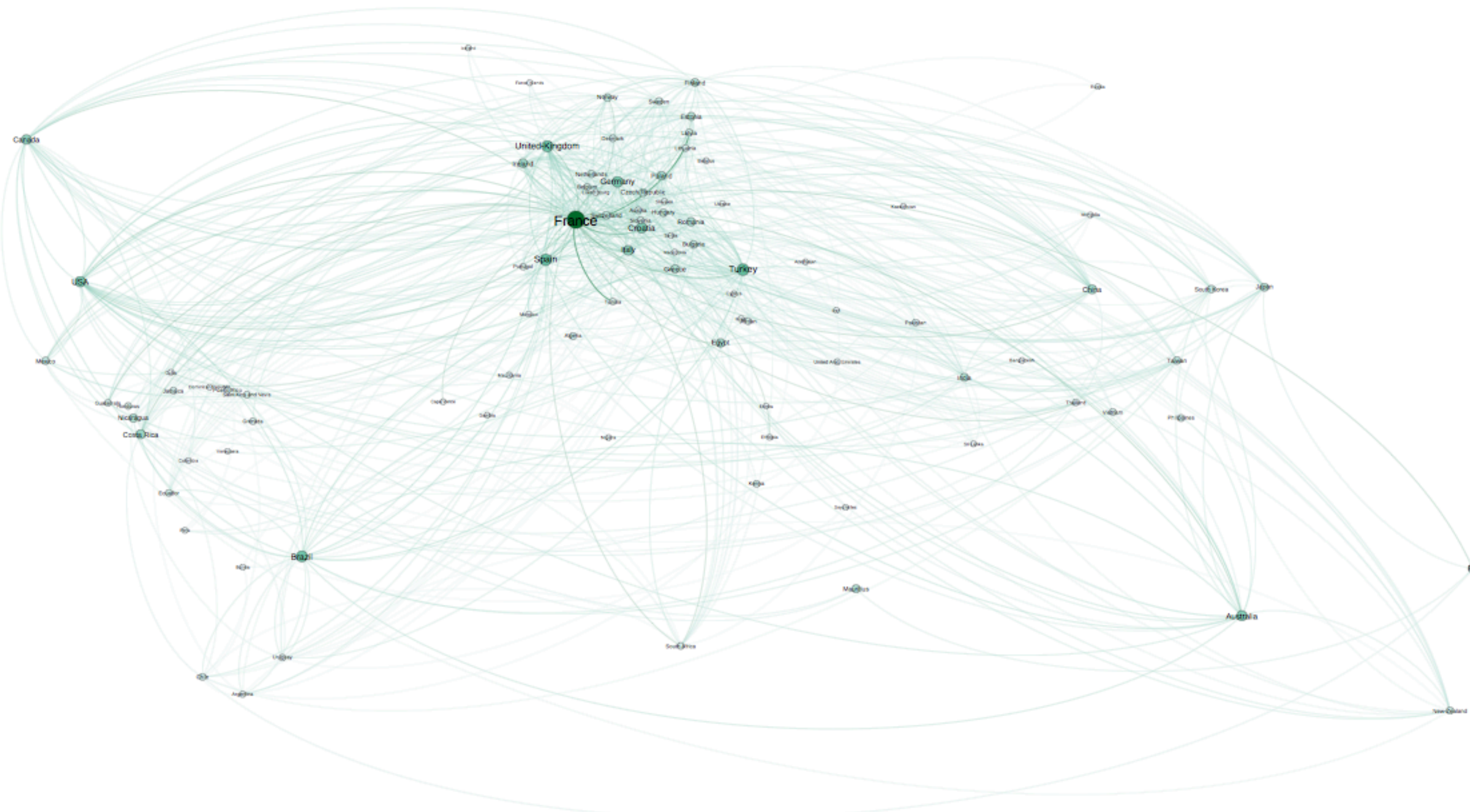
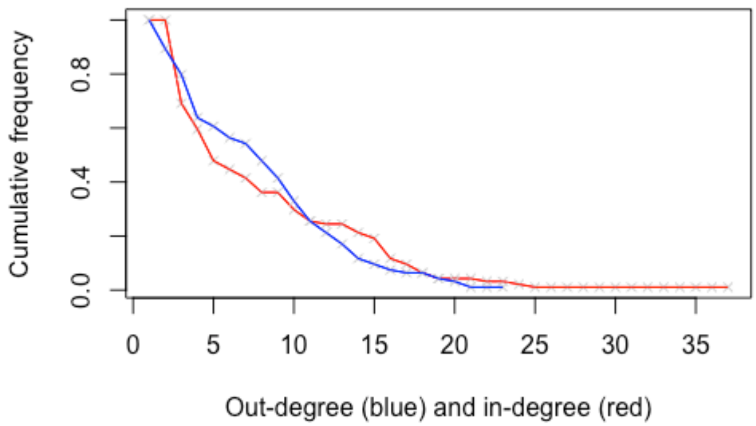


Figure 3. Cumulative distribution of countries' out-degree and in-degree



Log-log scale

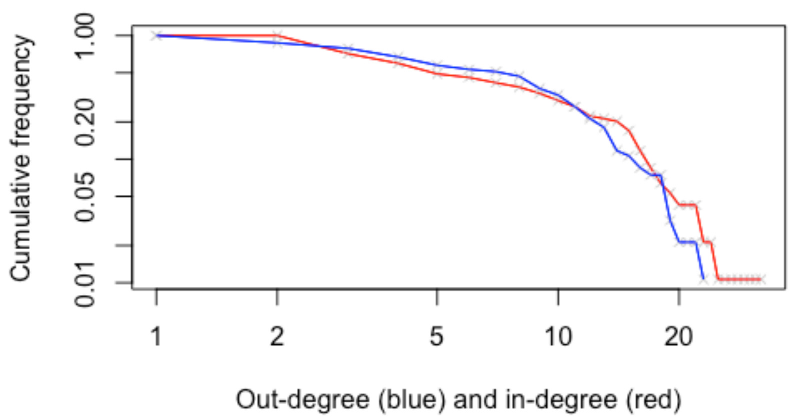
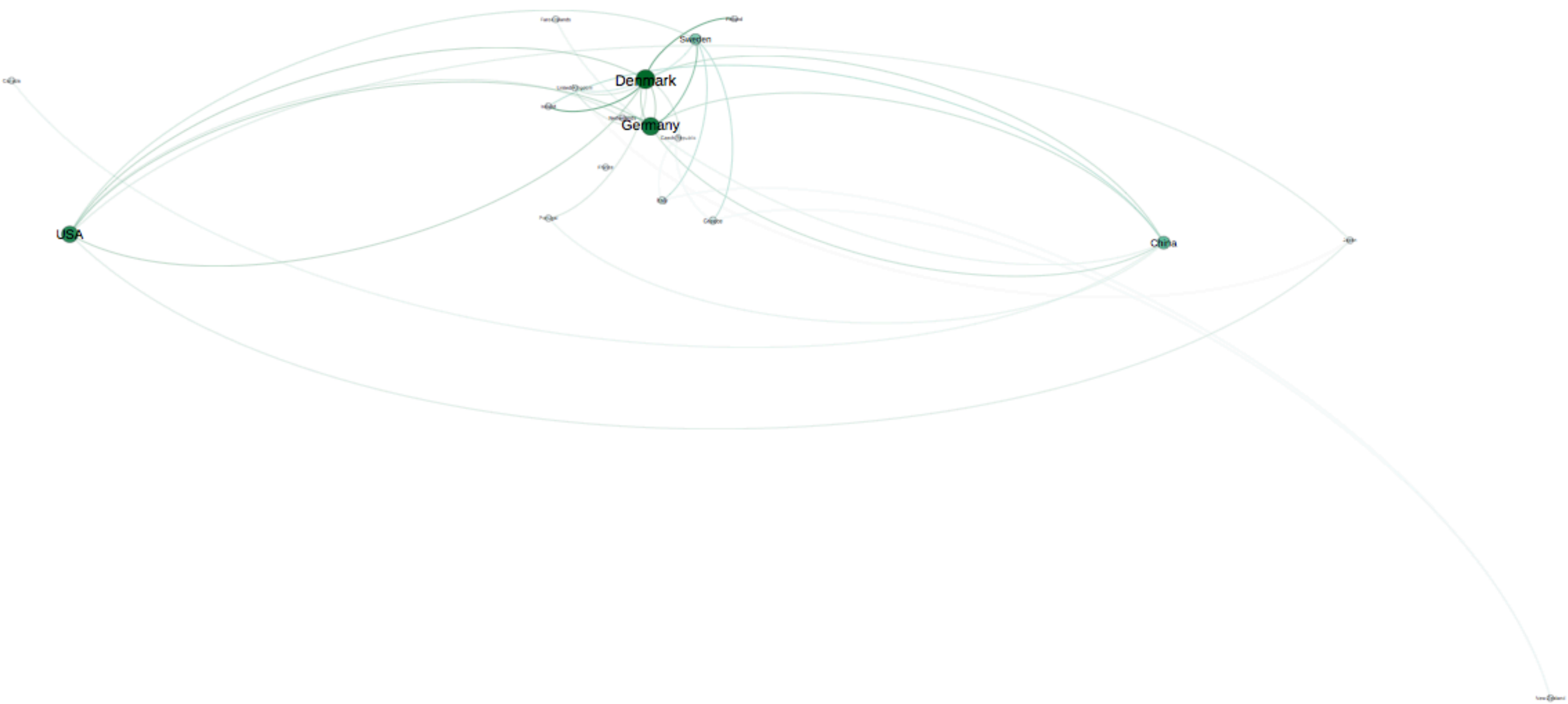
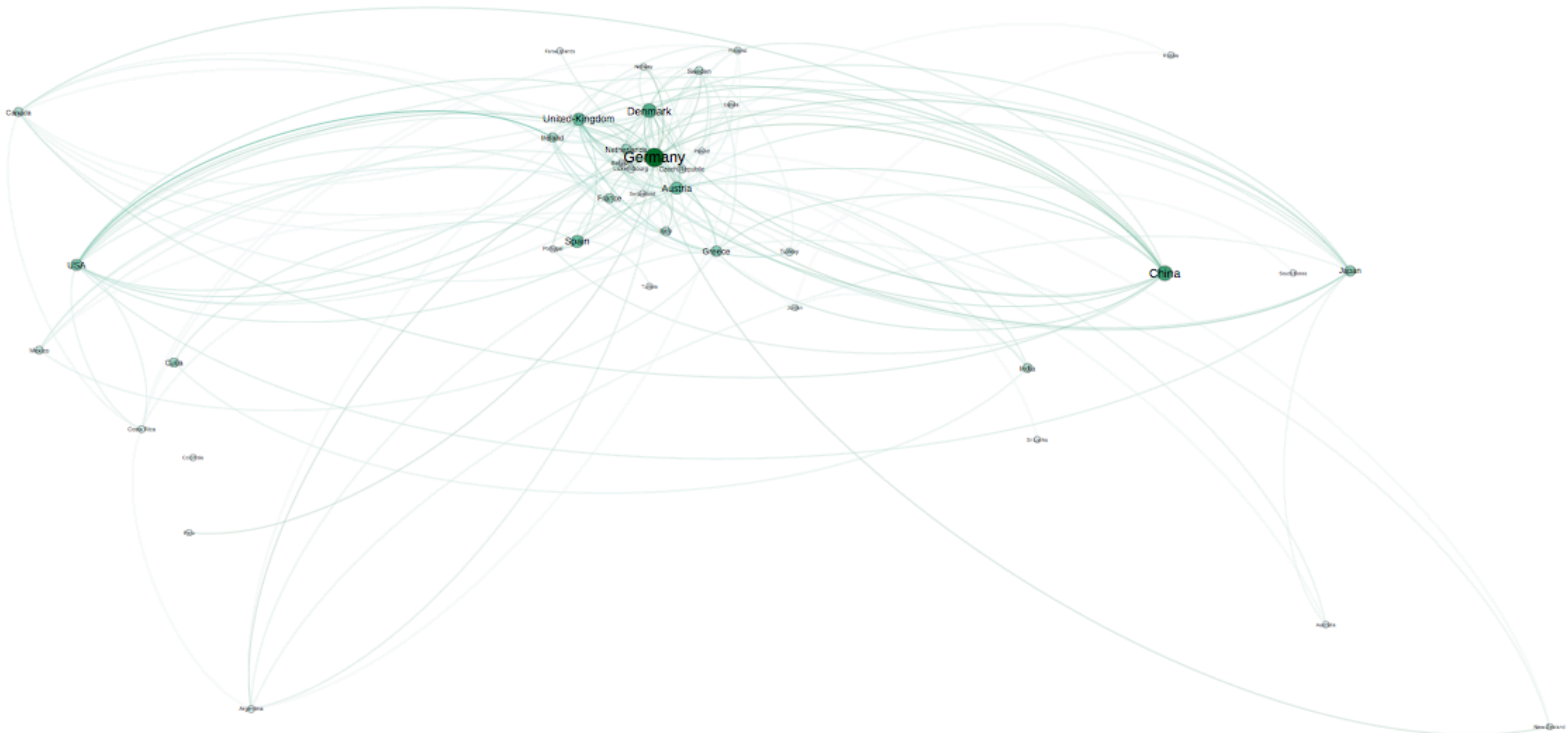


Figure 4. Evolution of network

a) 1983-1993



b) 1983-2000



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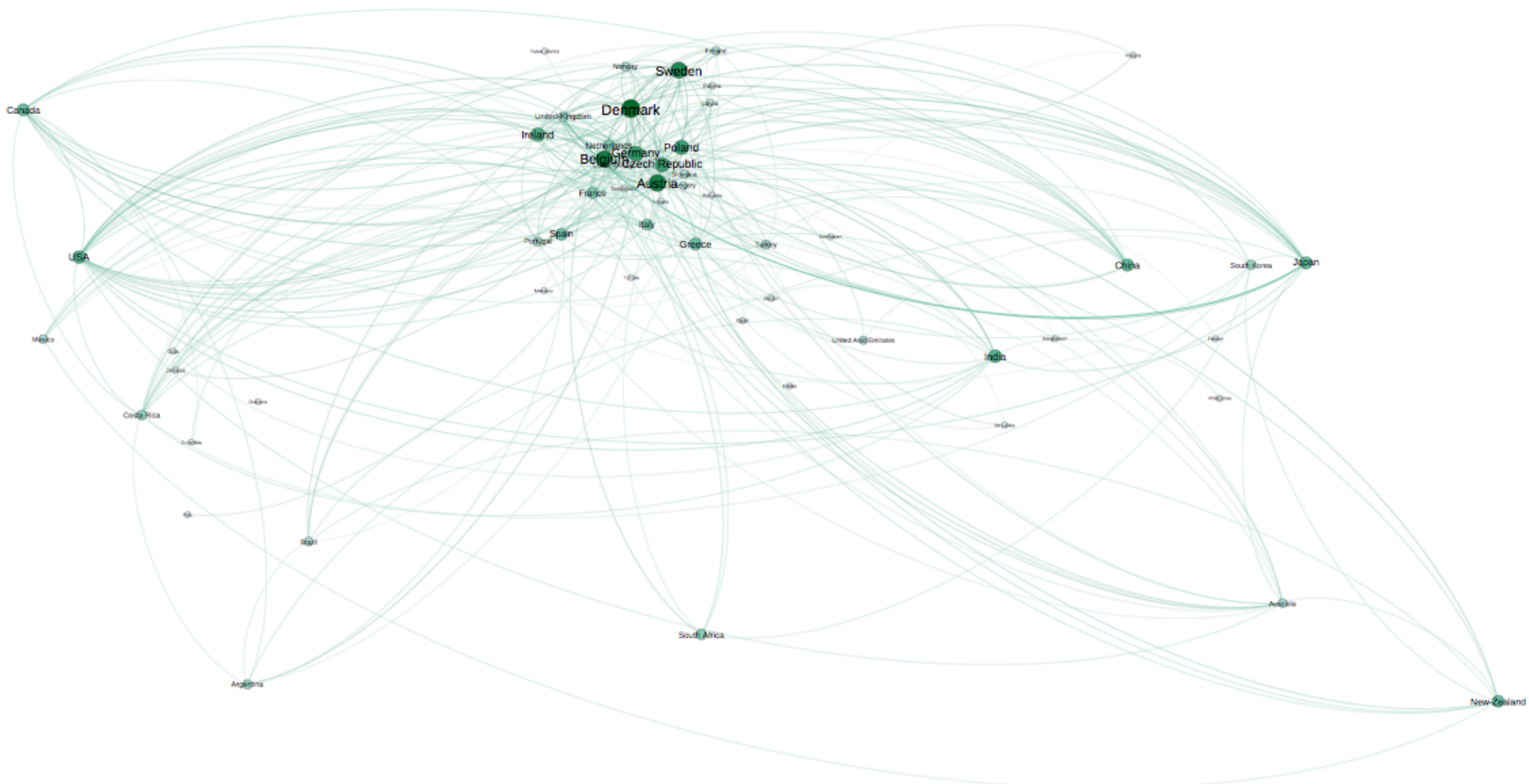
c) 1983-2005



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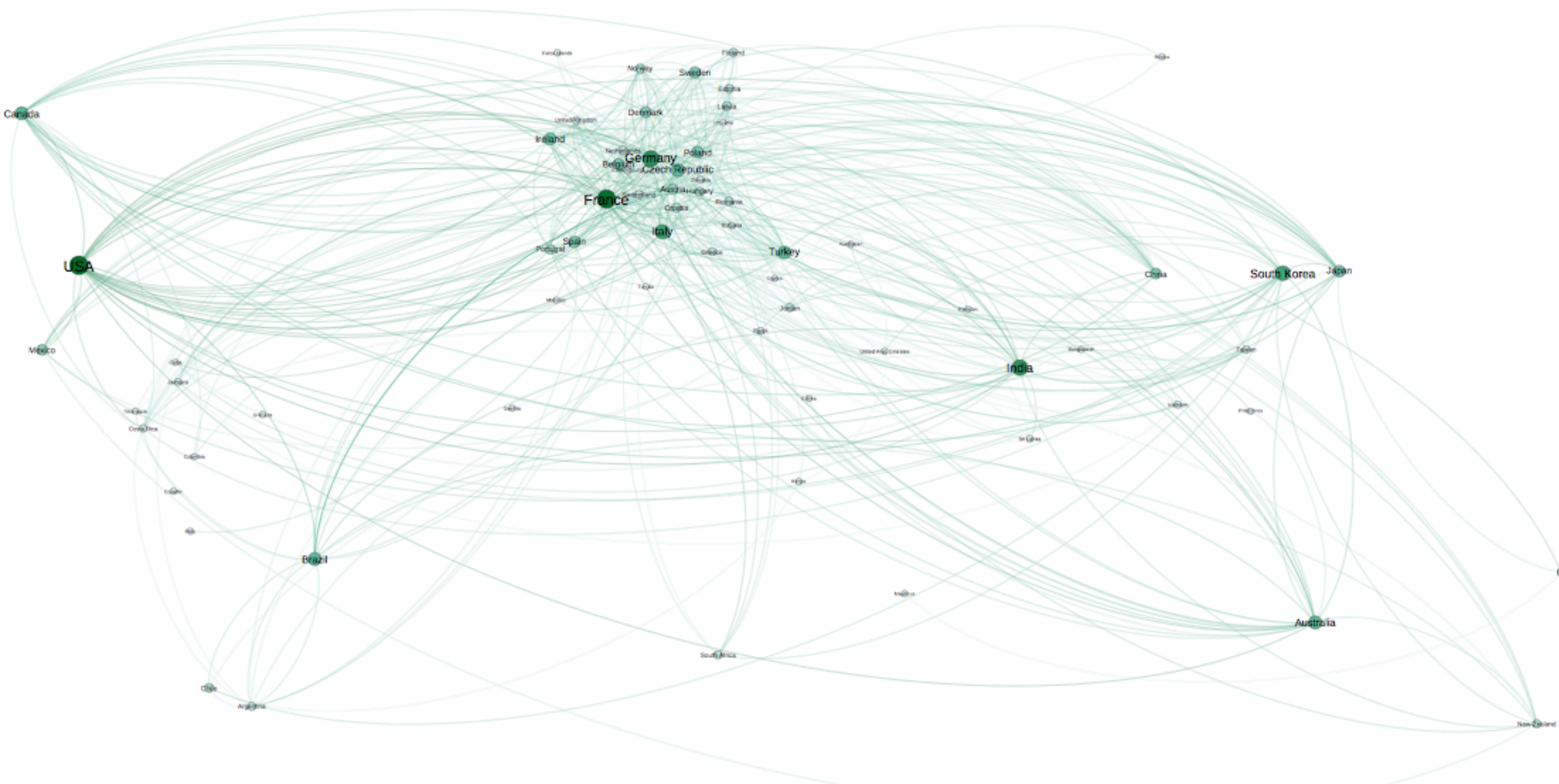
d) 1983-2010



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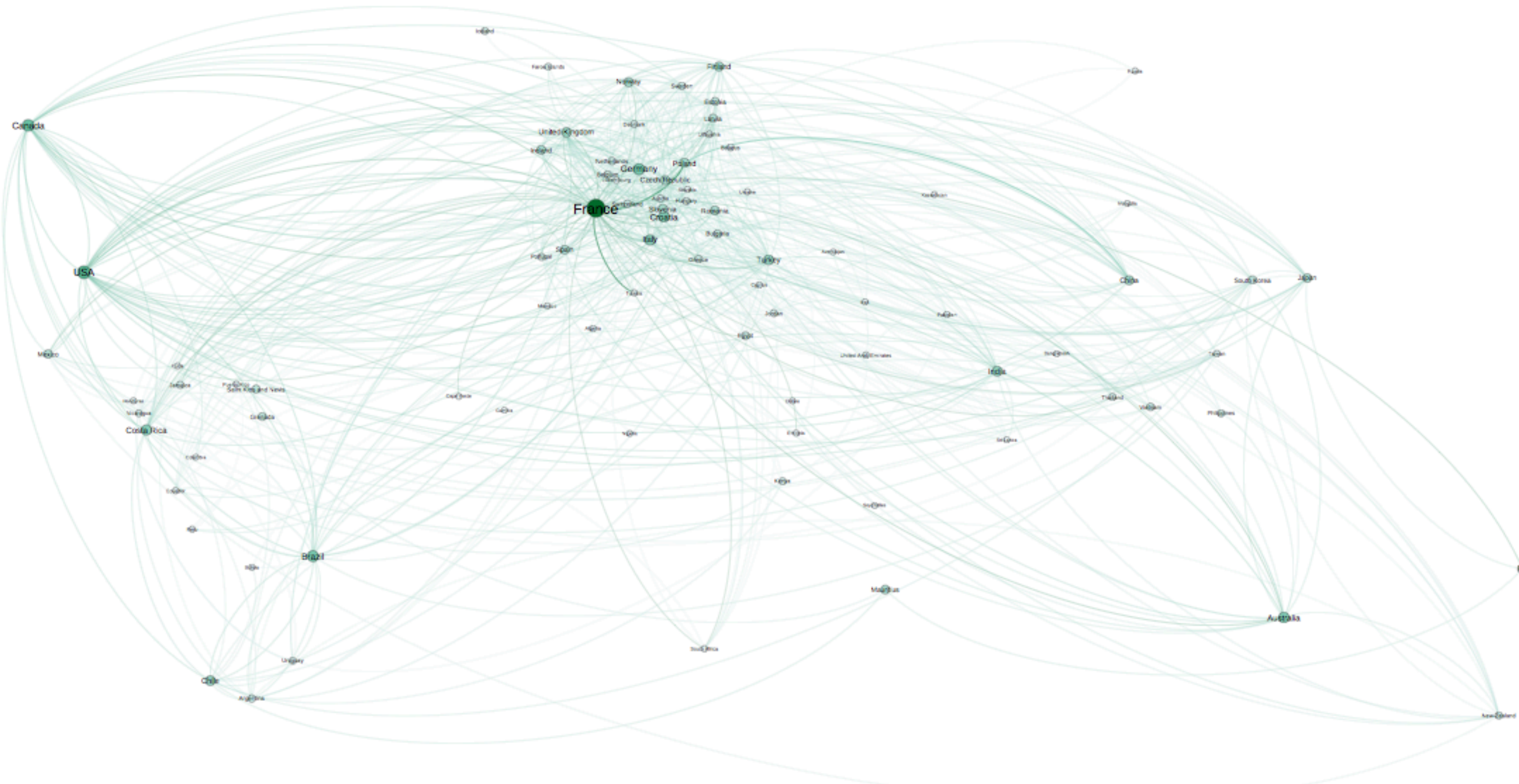
e) 1983-2015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Mauritius
Chile
Argentina

Table 2. Centrality measures

Id	Country	(1) Out-degree	(2) In-degree	(3) Total degree	(4) Closeness	(5) Eigenvector	(6) Betweenness
1	Algeria	2	1	3	0.235	0.010	121
2	Argentina	5	5	10	0.343	0.169	44
3	Australia	12	10	22	0.404	0.350	445
4	Austria	12	8	20	0.408	0.253	93
5	Azerbaijan	0	2	2	0	0.040	0
6	Bangladesh	1	1	2	0.284	0.005	1
7	Belarus	3	1	4	0.298	0.061	21
8	Belgium	11	8	19	0.413	0.407	105
9	Bolivia	2	2	4	0.263	0.024	10
10	Brazil	10	14	24	0.404	0.377	532
11	Bulgaria	11	8	19	0.394	0.179	191
12	Canada	12	16	28	0.413	0.512	382
13	Cape Verde	1	1	2	0.296	0.065	0
14	Chile	3	10	13	0.317	0.148	119
15	China	10	17	27	0.388	0.611	323
16	Colombia	2	1	3	0.307	0.051	1
17	Costa Rica	10	8	18	0.388	0.205	339
18	Croatia	15	7	22	0.415	0.198	467
19	Cuba	2	3	5	0.333	0.198	14
20	Cyprus	9	2	11	0.384	0.013	45
21	Czech Republic	10	15	25	0.371	0.409	213
22	Denmark	17	7	24	0.408	0.374	114
23	Dominican Republic	0	2	2	0	0.046	0
24	Ecuador	9	2	11	0.383	0.007	105
25	Egypt	7	4	11	0.356	0.088	282
26	Eritrea	0	1	1	0	0.035	0
27	Estonia	8	12	20	0.386	0.327	224
28	Ethiopia	0	3	3	0	0.147	0
29	Faroe Islands	0	4	4	0	0.137	0
30	Fiji	3	1	4	0.298	0.100	322
31	Finland	9	18	27	0.386	0.646	217
32	France	12	31	43	0.417	1.000	1179
33	Gambia	0	1	1	0	0.018	0
34	Germany	22	16	38	0.437	0.664	491
35	Greece	4	14	18	0.346	0.401	246
36	Grenada	3	1	4	0.325	0.002	85
37	Guatemala	7	1	8	0.363	0.047	90
38	Honduras	2	1	3	0.284	0.010	90
39	Hungary	21	5	26	0.441	0.112	180
40	Iceland	1	2	3	0.218	0.035	10
41	India	8	13	21	0.342	0.369	229

Table 2. Centrality measures (continued)

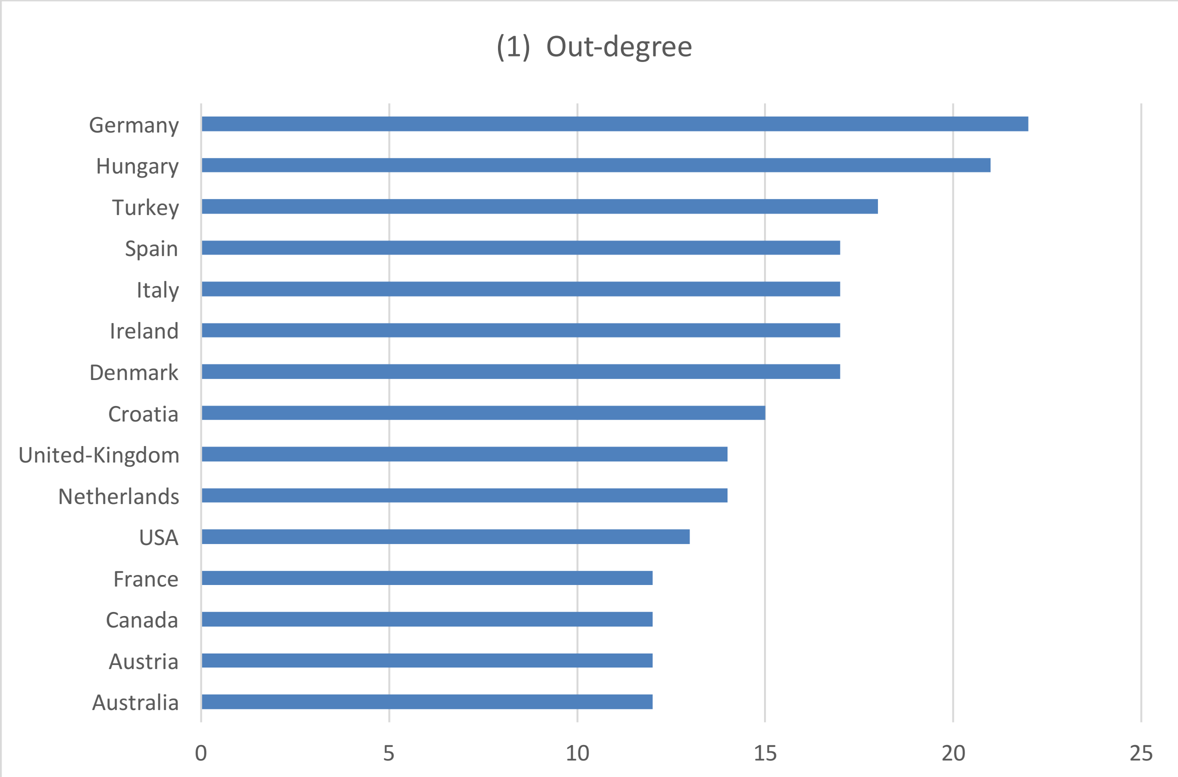
Id	Country	(1) Out-degree	(2) In-degree	(3) Total degree	(4) Closeness	(5) Eigenvector	(6) Betweenness
42	Iran	0	1	1	0.000	0.064	0
43	Ireland	17	15	32	0.421	0.505	313
44	Israel	0	1	1	0	0.002	0
45	Italy	17	14	31	0.429	0.529	386
46	Jamaica	3	3	6	0.323	0.063	102
47	Japan	7	14	21	0.365	0.455	220
48	Jordan	6	2	8	0.350	0.038	94
49	Kazakhstan	0	1	1	0	0.042	0
50	Kenya	3	2	5	0.298	0.005	96
51	Latvia	11	3	14	0.401	0.126	142
52	Lithuania	3	3	6	0.312	0.147	86
53	Luxembourg	7	5	12	0.363	0.178	36
54	Macedonia	0	1	1	0	0.003	0
55	Mauritania	2	1	3	0.313	0.002	31
56	Mauritius	2	1	3	0.251	0.010	239
57	Mexico	7	7	14	0.394	0.246	170
58	Mongolia	5	1	6	0.358	0.039	5
59	Morocco	3	3	6	0.323	0.061	22
60	Netherlands	14	13	27	0.404	0.501	155
61	New-Zealand	7	9	16	0.371	0.311	139
62	Nicaragua	11	4	15	0.378	0.087	254
63	Nigeria	0	2	2	0	0.003	0
64	Norway	9	10	19	0.391	0.242	188
65	Pakistan	4	6	10	0.326	0.137	105
66	Peru	1	3	4	0.235	0.089	11
67	Philippines	2	3	5	0.305	0.067	96
68	Poland	6	15	21	0.365	0.408	287
69	Portugal	8	11	19	0.386	0.409	58
70	Puerto Rico	8	1	9	0.341	0.021	96
71	Romania	7	9	16	0.375	0.140	261
72	Russia	1	2	3	0.234	0.047	0
73	Saint Kitts and Nevis	3	1	4	0.325	0.002	85
74	Serbia	7	1	8	0.358	0.006	11
75	Seychelles	1	1	2	0.280	0.007	12
76	Slovakia	6	1	7	0.380	0.022	18
77	Slovenia	1	2	3	0.275	0.020	93
78	South Africa	2	13	15	0.331	0.498	92
79	South Korea	9	9	18	0.368	0.351	179
80	Spain	17	10	27	0.437	0.409	571
81	Sri Lanka	2	6	8	0.271	0.081	7
82	Sweden	2	21	23	0.303	0.659	141

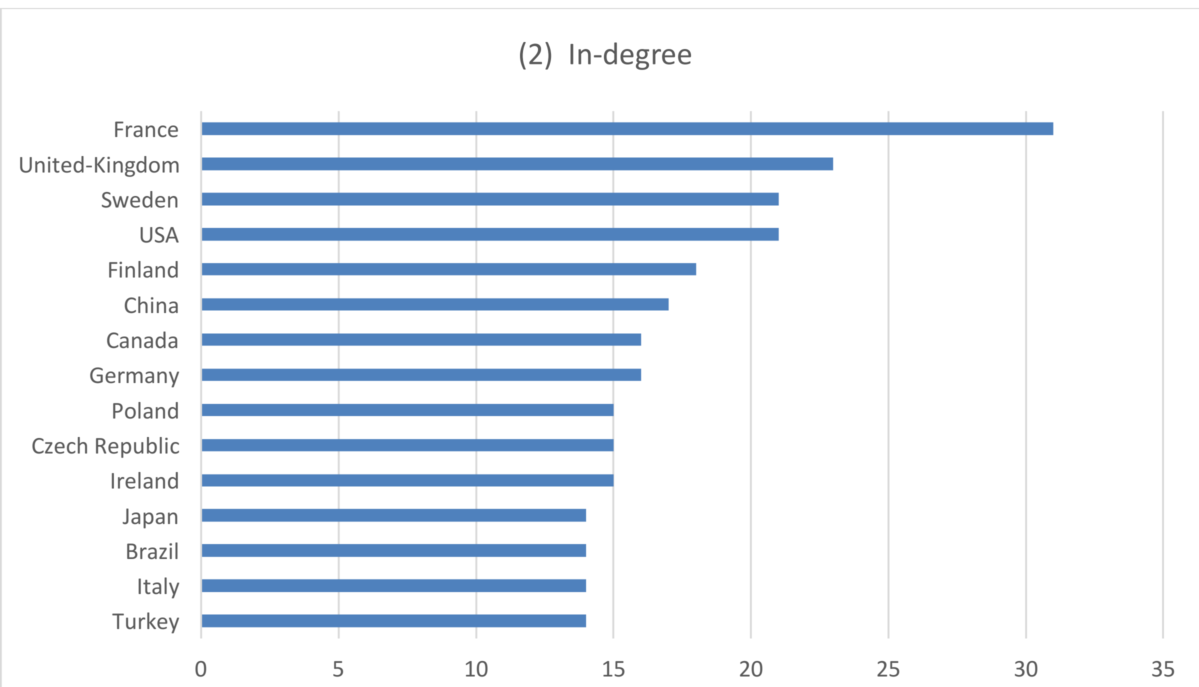
Table 2. Centrality measures (continued)

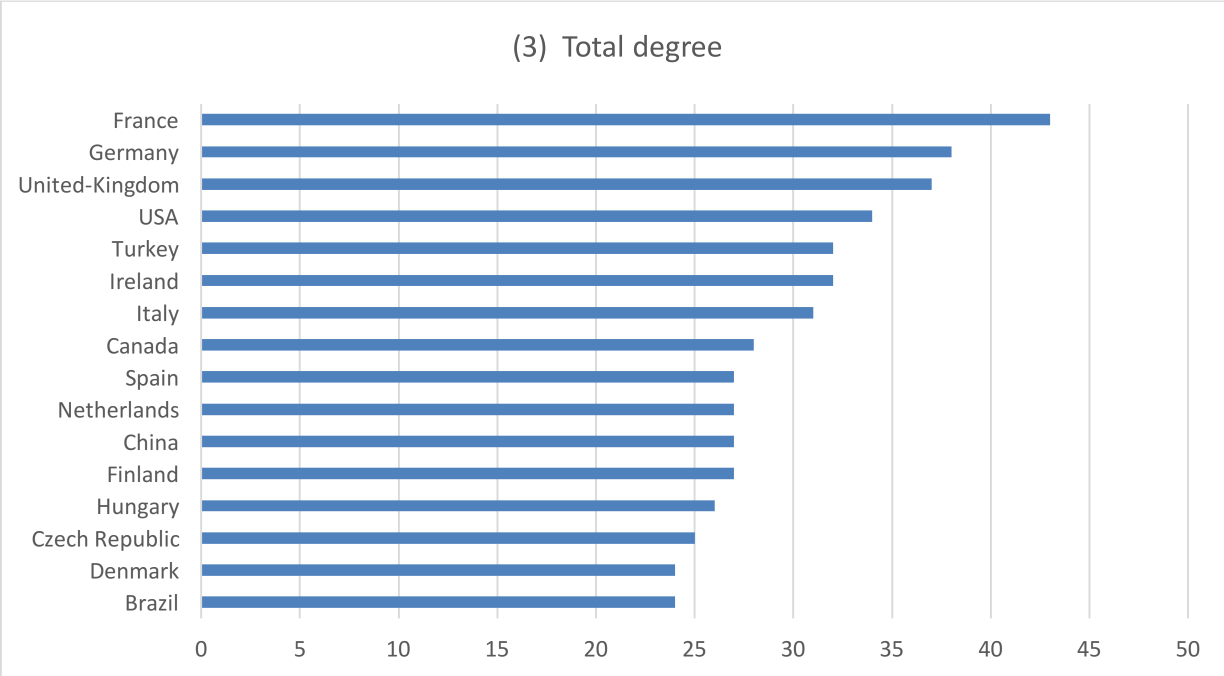
Id	Country	(1) Out-degree	(2) In-degree	(3) Total degree	(4) Closeness	(5) Eigenvector	(6) Betweenness
83	Switzerland	7	6	13	0.363	0.165	195
84	Taiwan	12	5	17	0.404	0.124	180
85	Thailand	9	3	12	0.394	0.104	90
86	Tunisia	10	1	11	0.406	0.041	79
87	Turkey	18	14	32	0.443	0.470	592
88	Ukraine	1	1	2	0.296	0.019	7
89	United Arab Emirates	6	1	7	0.384	0.013	48
90	United-Kingdom	14	23	37	0.429	0.684	540
91	Uruguay	4	7	11	0.342	0.198	83
92	USA	13	21	34	0.429	0.771	468
93	Venezuela	0	1	1	0	0.065	0
94	Vietnam	4	3	7	0.331	0.094	111

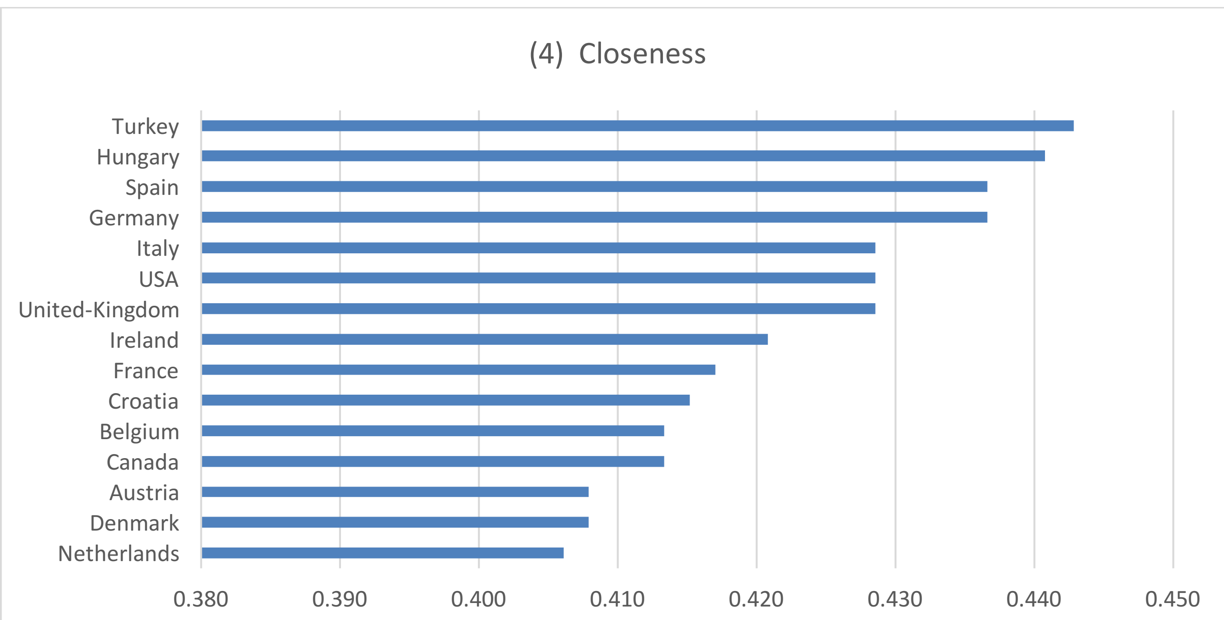
Notes: Calculations based on the estimated network from the wind energy diffusion data described earlier. The fourth column contains the normalized closeness measures.

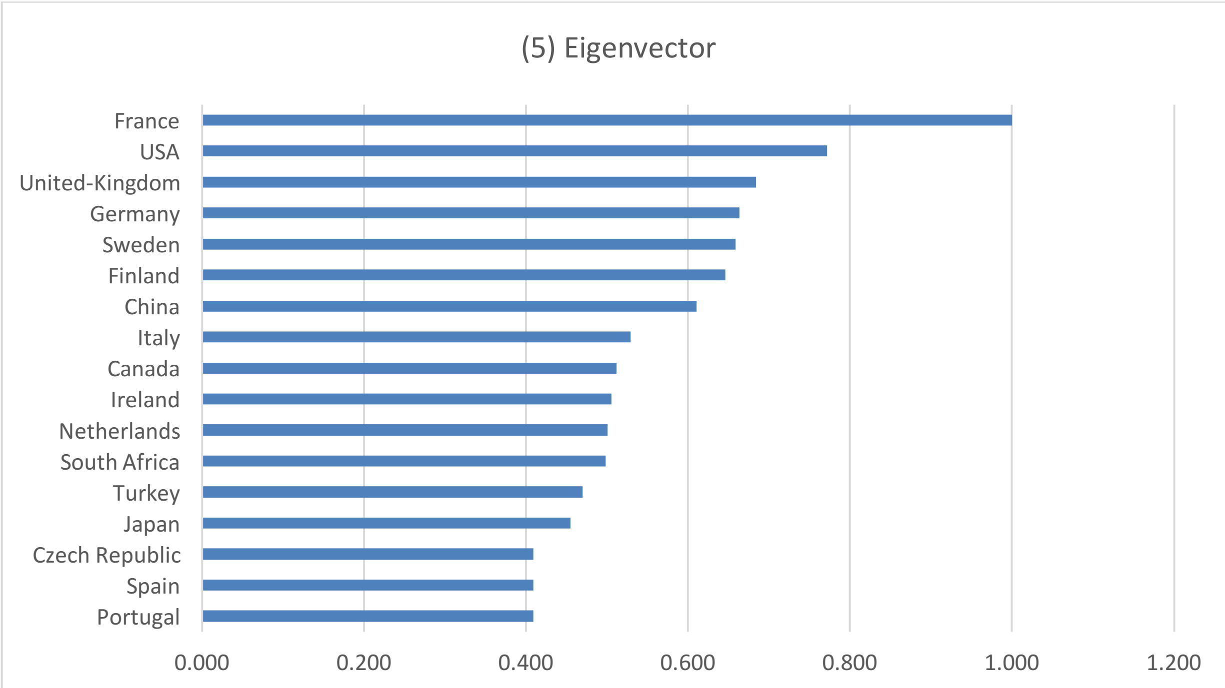
Figure 4. Top rankings according to centrality indicators






(3) Total degree
France
Germany
United-Kingdom
USA
Turkey
Ireland
Italy
Canada
Spain
Netherlands
China
Finland
Hungary
Czech Republic
Denmark
Brazil
0
5
10
15
20
25
30
35
40
45
50


(4) Closeness
Turkey
Hungary
Spain
Germany
Italy
USA
United-Kingdom
Ireland
France
Croatia
Belgium
Canada
Austria
Denmark
Netherlands
0.380
0.390
0.400
0.410
0.420
0.430
0.440
0.450


(5) Eigenvector
France
USA
United-Kingdom
Germany
Sweden
Finland
China
Italy
Canada
Ireland
Netherlands
South Africa
Turkey
Japan
Czech Republic
Spain
Portugal
0.000
0.200
0.400
0.600
0.800
1.000
1.200

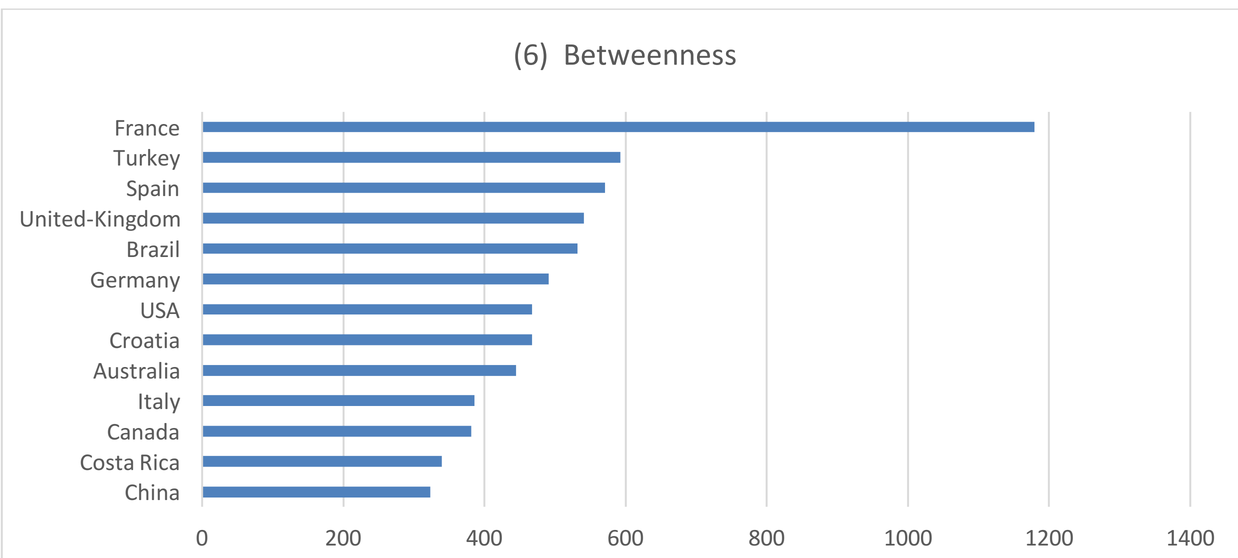

(6) Betweenness
France
Turkey
Spain
United-Kingdom
Brazil
Germany
USA
Croatia
Australia
Italy
Canada
Costa Rica
China
0
200
400
600
800
1000
1200
1400

Table 3. Rakings based on simulations

Africa		Asia		Latin America		Annex I Parties	
(i)	(ii)	(i)	(ii)	(i)	(ii)	(i)	(ii)
Cape Verde	Algeria	Thailand	Thailand	Colombia	Puerto Rico	Hungary	Croatia
Mauritius	Egypt	Taiwan	Vietnam	Guatemala	Guatemala	Slovakia	Hungary
Seychelles	Mauritius	Vietnam	Taiwan	Ecuador	Nicaragua	Croatia	Slovakia
Tunisia	Tunisia	Turkey	Pakistan	Puerto Rico	Bolivia	Luxembourg	Ukraine
Morocco	Kenya	Russia	Philippines	Nicaragua	Ecuador	Italy	Spain
Egypt	Seychelles	Pakistan	Russia	Honduras	Honduras	Belgium	Latvia
Mauritania	Mauritania	Bangladesh	Turkey	Mexico	Brazil	Germany	Turkey
Kenya	Morocco	South Korea	South Korea	Costa Rica	Uruguay	Turkey	Lithuania
Algeria	Cape Verde	Philippines	India	Brazil	Chile	Ireland	Belarus
South Africa	South Africa	India	Bangladesh	Bolivia	Mexico	Ukraine	Bulgaria
Eritrea	Eritrea	China	China	Uruguay	Cuba	Latvia	Poland
Ethiopia	Ethiopia	Japan	Japan	Cuba	Argentina	Belarus	Switzerland
Gambia	Gambia	Sri Lanka	Sri Lanka	Argentina	Colombia	Denmark	Romania
Nigeria	Nigeria	UAE	Mongolia	Peru	Costa Rica	Spain	Luxembourg
		Mongolia	UAE	Chile	Peru	Bulgaria	Italy
		Jordan	Jordan	DR	DR	New-Zealand	Estonia
		Azerbaijan	Azerbaijan	Venezuela	Venezuela	Lithuania	Canada
		Iran	Iran			Romania	Belgium
		Israel	Israel			Estonia	Ireland
		Kazakhstan	Kazakhstan			Canada	New-Zealand
						Austria	Australia
						Australia	Slovenia
						Netherlands	Denmark
						Slovenia	Iceland
						Switzerland	UK
						Iceland	Norway
						France	USA
						Poland	Germany
						Norway	Netherlands
						Finland	Greece
						UK	France
						USA	Portugal
						Czech R.	Cyprus
						Greece	Czech R.
						Cyprus	Austria
						Japan	Finland
						Sweden	Japan
						Russia	Sweden
						Portugal	Russia
						Israel	Israel

Appendix

Table A.1 Database coverage

Country	Wind farms	Capacity (MW)
Algeria	1	10.2
Argentina	27	434.66
Australia	74	4086.32
Austria	249	2335.53
Azerbaijan	4	55.8
Bangladesh	2	1.9
Belarus	3	3.43
Belgium	212	2178
Bolivia	2	27
Brazil	362	9694.51
Bulgaria	76	637.55
Canada	267	11598.14
Cape Verde	5	30.4
Chile	33	1417.85
China	1134	61264.11
Colombia	1	19.5
Costa Rica	13	326.4
Croatia	21	431.8
Cuba	4	11.7
Cyprus	6	153.9
Czech Republic	87	323.41
Denmark	2418	5266.88
Dominican Republic	4	242,00
Ecuador	3	25.15
Egypt	9	744.82
Eritrea	1	0.83
Estonia	29	294.21
Ethiopia	4	324.18
Faroe Islands	5	18.55
Fiji	1	10.18
Finland	140	1104.23
France	1090	11426.28
Gambia	1	0.15
Germany	7518	43140.99
Greece	185	2110.54
Grenada	3	1.28
Guatemala	1	52.8
Honduras	3	155.9
Hungary	46	512.58
Iceland	2	4.2
India	597	17859.93

Table A.1 Database coverage (continued)

Country	Wind farms	Capacity (MW)
Iran	10	150.72
Ireland	202	2478.78
Israel	3	27.25
Italy	565	9536.57
Jamaica	5	78.23
Japan	292	2620.86
Jordan	3	115.45
Kazakhstan	1	45.1
Kenya	4	342.55
Latvia	10	52.5
Lithuania	68	379.91
Luxembourg	17	64.15
Macedonia	2	36.9
Mauritania	2	34.4
Mauritius	2	10.45
Mexico	47	3874.83
Mongolia	5	50.11
Morocco	15	884.95
Netherlands	561	4314.56
New-Zealand	26	691.06
Nicaragua	5	186.2
Nigeria	1	10.18
Norway	36	984.43
Pakistan	7	308.2
Peru	8	240.35
Philippines	9	389.75
Poland	225	3997.98
Portugal	396	4936.3
Puerto Rico	4	125.03
Romania	79	3177
Russia	11	49.3
Saint Kitts and Nevis	1	2.2
Serbia	1	9.9
Seychelles	1	6
Slovakia	2	3.14
Slovenia	2	5.5
South Africa	28	1931.66
South Korea	77	698.64
Spain	1142	23323.28
Sri Lanka	19	135.65
Sweden	988	4902.32
Switzerland	18	68
Taiwan	32	586.08

Table A.1 Database coverage (continued)

Country	Wind farms	Capacity (MW)
Thailand	11	296.7
Tunisia	9	242.36
Turkey	179	5339.25
Ukraine	28	634.88
United Arab Emirates	1	0.85
United-Kingdom	909	18064.19
Uruguay	36	1279.95
USA	1274	76937.2
Venezuela	1	100.32
Vietnam	11	239

Note: From data as of 11/04/2016 from the Wind Power World Wind Farms Database.

Table A.2 Database sample

Windfarm ID	Country	Manufacturer	Power (kW)	Commissioning date	Status
5306	Germany	Fuhrländer	2500	2006	Production
4389	USA	Fuhrländer	2500	2008	Production
7148	Belgium	Fuhrländer	2500	2009	Production
16282	France	Fuhrländer	2500	2009	Production
7061	Bulgaria	Fuhrländer	2500	2011	Production
17828	Sweden	Fuhrländer	2500	2011	Production
15968	Ukraine	Fuhrländer	2500	2011	Production
17617	China	Goldwind	2500	2009	Production
21644	USA	Goldwind	2500	2012	Production
21161	Thailand	Goldwind	2500	2013	Production
1884	Netherlands	Lagerwey	2500	2012	Production
21362	Finland	Lagerwey	2500	2013	Production
6872	Denmark	Neg Micon	2500	2002	Production
1439	United-Kingdom	Neg Micon	2500	2004	Production
10731	Germany	Nordex	2500	2000	Production
16092	United-Kingdom	Nordex	2500	2001	Production
7342	Denmark	Nordex	2500	2002	Production
6289	Netherlands	Nordex	2500	2002	Production
754	Norway	Nordex	2500	2002	Production
2	France	Nordex	2500	2003	Production
6650	Germany	Nordex	2500	2003	Production
1738	Ireland	Nordex	2500	2003	Production
16048	Japan	Nordex	2500	2003	Production
1215	Czech Republic	Nordex	2500	2006	Production
21452	Portugal	Nordex	2500	2008	Production

4817	Sweden	Nordex	2500	2008	Production
10227	Italy	Nordex	2500	2009	Production
10936	Poland	Nordex	2500	2009	Production
7210	Romania	Nordex	2500	2009	Production
4394	USA	Nordex	2500	2009	Production
20197	Greece	Nordex	2500	2011	Production
21075	Belgium	Nordex	2500	2012	Production
21733	South Africa	Nordex	2500	2015	Production
21750	Uruguay	Nordex	2500	2015	Production
17078	South Korea	Samsung	2500	2010	Production
15485	USA	Samsung	2500	2011	Production
21926	Canada	Samsung	2500	2012	Production
16239	Sweden	Vestas	2600	2012	Production
20271	France	Vestas	2600	2013	Production
20643	Italy	Vestas	2600	2013	Production
22131	United-Kingdom	Alstom Power	2700	2013	Production
21740	Brazil	Alstom Power	2700	2014	Production

A.3 Regional analysis

Table A.3.1 Regional-level statistics

Id	Region	No. of countries	In-degree	Out-degree	Source region (%)	Target region (%)	Total degree
1	Africa	14	35	33	5.53	5.87	68
2	America	22	113	118	19.8	19.13	231
3	Asia	20	106	104	17.45	17.79	210
4	Europe	35	322	319	53.52	54.03	641
5	Oceania	3	20	22	3.69	3.36	42

Table A.3.2 Matrix of intra- and interregional connections

	Africa	America	Asia	Europe	Oceania
Africa	3	5	10	14	1
America	9	36	22	48	3
Asia	3	21	17	60	3
Europe	18	47	52	190	12
Oceania	2	4	5	10	1

As comes to view from both Table A.3.1 and the diagonal elements of the matrix in Table A.3.2, Europe has by far the greatest amount of total and intraregional connections, indicating that activity is highly concentrated. Europe also has the largest off-diagonal elements, reflecting it is the most integrated area in the diffusion network. Though this region also has the most country coverage, still, its presence is clearly prominent. The most interregional flows are between Europe and Asia, followed by Europe-America.

It is also informative to evaluate these figures following the United Nations Framework Convention on Climate Change (UNFCCC), where Parties are organized into five regional groups:

- African Group,
- Asia-Pacific Group,
- Eastern European Group,
- Latin American and Caribbean Group (GRULAC), and
- Western European and Others Group (WEOG).

These groupings are based on the tradition of the UN, and the others in WEOG include Australia, Canada, Israel, New Zealand, Turkey, and the United States.

Table A.3.3 UN regional grouping statistics

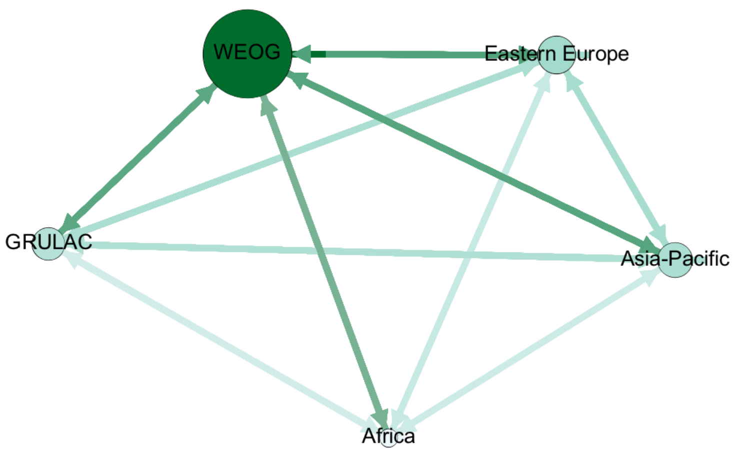
Id	Region	No. of countries	In-degree	Out-degree	Source region (%)	Target region (%)	Total degree
1	Africa	14	35	33	5.53	5.87	68
2	Asia-Pacific	18	89	97	16.28	14.93	186
3	Eastern Europe	17	93	111	18.62	15.60	204
4	GRULAC	20	77	93	15.60	12.92	170
5	WEOG	25	302	262	44.00	50.67	564

Table A.3.4 Matrix of intra- and interregional connections for UN regional grouping

	Africa	Asia-Pacific	Eastern Europe	GRULAC	WEOG
Africa	3	6	4	6	14
Asia-Pacific	3	17	21	14	42
Eastern Europe	5	15	21	10	60
GRULAC	9	15	13	23	33
WEOG	15	36	34	24	153

This subdivision reveals complementary insights. It is even more apparent that especially the WEOG countries are the most important regional hub, both in terms of links among themselves, as well as links with the other regional groups. In fact, compared to all the others, the diagonal elements far exceed the off-diagonal elements. In contrast, for example, the Asia-Pacific region has much more connections with WEOG countries than countries within the own region. As an illustration of this aggregated network, we show the interconnections among the regions with size of nodes corresponding to the total degree, as well as darker color for the arrows.

Figure #. Network connections at regional level



A.4 Centrality analysis

- The betweenness centrality measure for node k is defined as $\sum_{ij:i\neq j,k\notin ij} P_{ij}(k)/P_{ij}$, where P_{ij} denotes the number of shortest paths from node i to j, and $P_{ij}(k)$ denotes the number of shortest paths from node i to j that node k lies on.
- Eigenvector centrality is formally defined by the eigenvector corresponding to the dominant eigenvalue, and can be expressed as $x_i = \lambda^{-1}\sum_j G_{ij}\, x_j$, and rewritten as $\lambda x = Gx$, where x_i is the centrality of node i. To define an absolute score, it is necessary to normalize the eigenvector, which is usually done by summing over all vertices to one.