Accelerating diffusion of climate-friendly technologies: a network perspective

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Abstract

We introduce a methodology to estimate the determinants of the formation of technology diffusion networks from the patterns of technology adoption. We apply this methodology to wind energy, which is one of the key technologies in climate change mitigation. Our results emphasize that, in particular, long-term relationships as measured by economic integration are key determinants of technological diffusion. Specific support measures are less relevant, at least to explain the extensive margin of diffusion. Our results also highlight that the scope of technological diffusion is much broader than what is suggested by the consideration of CDM projects alone, which are particularly focused on China and India. Finally, the network of technological diffusion inferred from our approach highlights the central role of European countries in the diffusion process and the absence of large hubs among developing countries.

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

1 Introduction

The role of technology diffusion has been strongly emphasized as a necessary condition for efficient mitigation and, more recently, as a key element in the design of climate clubs. Such clubs would bring together countries willing to implement ambitious climate policies if associated with technological, trade or financial advantages and are seen as a potential game-changer in climate policy (Nordhaus, 2015; Grubb et al., 2015; Hovi et al., 2016; Keohane and Victor, 2016).

In this perspective, two main issues relate specifically to technological diffusion. First, technological diffusion is not a simple bilateral process but might involve strong network effects and thus relates to the global structure of a potential climate club. Second, technological diffusion is eventually a firm-level decision and can only be indirectly influenced by policy. Thus, assessing the potential impact of policy on technological diffusion amounts to estimating the impact of policy on a network formation process. This is clearly beyond the realm of conventional integrated assessment models, which do not account for complex network interactions and cannot be estimated.

In this paper, we propose an innovative approach to the problem, which consists in representing technology diffusion as a stochastic epidemic process on a network of countries and to estimate the determinants of network formation by relating observed patterns of technology adoption and policy measures implemented domestically, bilaterally or multilaterally. This approach relates to recent contributions in computer science that have built on information transmission data to infer the structure of social networks (Gomez Rodriguez et al., 2010). It can also be seen as a methodology to estimate the network distance between countries in models of international trade à la Chaney (2014).

We then use this methodology to infer the wind technology diffusion network and its policy determinants. Therefore, we build on a comprehensive dataset of all wind turbines installed globally since 1983 and a unique dataset of wind policy support measures that we have built through a comprehensive analysis of the International Renewable Energy Agency (IRENA) data. The focus on wind is motivated by the fact that it is one of the fastest growing renewable energy sources, both in terms of volume and technological progress. At the end of 2017, installed capacity of wind energy reached almost 540 GW, with the largest capacities installed in China, the US, Germany, India, Spain, UK, France, Brazil and Canada (Global Wind Energy Council, 2018). Most of the growth in installed capacity currently occurs in countries outside of the OECD. It is thus particularly important in view of climate change mitigation that the latest vintage of wind turbines diffuses rapidly at the global scale.

Hence the paper provides both a methodological and an empirical contribution. From the methodological perspective, it partly bridges the literature on technological diffusion and the econometrics of network formation and thus allows to account for both the role of interrelations and of country-specific factors (as source or as target) in technology diffusion processes. From the empirical perspective, wind is representative of the technologies whose diffusion ought to be fostered by a climate club. Analyzing the policy determinants of this diffusion provides interesting insights on the potential design of the club. In this respect, our results emphasize that long-term economic and trade relationships, as measured in particular by economic integration, are key determinants of technological diffusion. Specific support measures for certain technologies seem less relevant for the diffusion per se, although they might play a crucial role from an industrial perspective, i.e., in the scaling up of a technology to reach relevant market size.

The remainder of the paper is organized as follows. Section 2 surveys the related literature. Section 3 introduces the methodology. Section 4 describes the application to wind energy and highlights the structure of the wind diffusion network and the policy determinants of its formation. Section 5 concludes.

2 Related literature

This paper relates and contributes to the growing literature on the adoption and diffusion of climate-friendly technologies, as well as the network literature on technological diffusion. Although complex system models have been employed to study various climate change related areas (see e.g., Balint et al., 2017, for a recent survey), diffusion dynamics and the role of networks has received less attention in the literature on green innovation. In this respect, since the diffusion process involves the spread of an innovation among agents which can depend on their interactions and various socio-economic determinants, it is extremely relevant to take a network perspective (cf. ibid; Rogers, 2010; Allan et al., 2014). The main objective of this paper is precisely to further bridge these areas.

The existing literature on technological diffusion mainly adresses the issue of adoption from the host country perspective, i.e, it focuses on adoption (cf. Popp et al., 2011; Narbel, 2013, and references therein). In particular, Popp et al. (2011) study the investment in renewable energy capacity (measured as kW per thousand inhabitants) for wind, solar photovoltaic, geothermal and electricity produced from waste and biomass in 26 OECD countries from 1991 to 2004. Using feasible generalized least squares, they estimate the effect of innovative activity (knowledge stock proxied by patents), policy measures (the main one being a binary variable for whether a country has ratified the Kyoto Protocol), and other control variables (e.g. GDP per capita) on the investment per capita in capacity of renewable energy installed. In general, the previous literature has emphasized the role of regulation and policy as the primary driver of the adoption of green technologies. In fact, it is found that environmental policy has a much larger impact on renewable energy investment than other country characteristics such as GDP per capita and the knowledge stock.

In addition, data from the Clean Development Mechanism (under which developed countries can contribute to GHG emission reduction through projects implemented in developing countries) have been used in a number of studies focusing on developing countries. For example, Lema and Lema (2013) analyze 14 developing countries that were by April 2009 hosts to almost 200 individual CDM wind projects, where India and China are the major host countries (as is the case more generally), going more in-depth into the underlying adoption mechanisms. It is found that a greater variety of mechanisms exist than those commonly assumed, which are imports (trade) and foreign direct investment. Although these latter dominate for the other countries among which were Argentina and Brazil, they are not the most important for China and India. For example, only China has wind CDM projects supplied by local companies using licensing arrangements, and this mechanism accounts for almost a quarter of the wind projects in all countries (ibid, p. 8).

More recently, the literature has approached the notion of technology transfer by focusing on bilateral relations between countries (e.g., see Dechezleprêtre et al., 2008; Glachant et al., 2013; De Coninck and Sagar, 2015, and references therein). In this perspective, it builds on a range of proxy measures to characterize transfers (Johnstone et al., 2011). A first range of contribution relies on patent data. Specifically related to wind energy, Dechezleprêtre and Glachant (2014) investigate the influence of domestic and foreign demand-pull policies across 28 OECD countries from 1991 to 2008 on wind technology transfer using a Poisson model. In particular, the dependent variable specified as the number of patents granted in wind power technology in country i that are filed in country j in year t proxies cross-border technology transfer/diffusion. As in Popp et al. (2011), they also emphasize that wind energy deployment is largely driven by public policy support. Nevertheless, they do not estimate the specific impact of one component of the policy mix (e.g. feed-in tariffs or renewable portfolio standards), but rather use annual wind power generation in each country as a proxy measure of the stringency of the portfolio of demand-pull policies.

Relatedly, using CDM data, Dolšak and Crandall (2013) employ logistic regression to investigate the influence of host-country characteristics (e.g., institutions) and dyadic characteristics (e.g., former colonial ties) on CDM location decisions during 2004 to 2006. Among key findings is that bilateral familiarity determinants (e.g., bilateral trade and colonial relationship) have a significant impact on CDM location decisions. In fact, these prior and current interactions with the host country appear to be much more important than the overall quality of institutions, though UNFCCC specific domestic institutions (e.g., whether the host country has submitted a National Communication to the Secretariat of the UNFCCC) seem to be influential to CDM location decisions. Similarly, but in addition to host-country characteristics including those of investor (home) countries, Dinar et al. (2011) find that strong trade relations positively influence the level of cooperation between hosts and investors.

Two caveats of the CDM approach is the sole focus on the relationship between developed and developing countries and the fact, emphasized by (Dechezleprêtre et al., 2008), that not all CDM projects encompass actual technology transfers. More broadly, the existing literature adopts a bilateral rather than a network-based perspective and thus discards the role of indirect connections in the diffusion process. A first contribution including a network perspective is Halleck Vega and Mandel (2018), which uses wind installation data to infer the network of technological diffusion. However, this latter contribution remains silent about the policy determinants of network formation.

The present paper aims to overcome this shortcoming and thus bridge to frontier research on the network structure of international trade and the econometrics of network formation (e.g. Hidalgo and Hausmann, 2009; Chaney, 2014; De Paula, 2015; Bramoullé et al., 2016; Chandrasekhar, 2016). In fact, the micro-foundations of our approach are related to the role of exporting firms in the diffusion of technologies. In this respect, a recent contribution by Chaney (2014) proposes a model of the formation of international trade relationships in which firms sequentially enter new markets following their geographical proximity. This model is a particular case of the model of network formation introduced by Jackson and Rogers (2007) in which agents on a social network meet preferentially the connections of their existing connections (friends of friends). In Chaney (2014), the underlying notion of connection between countries is based purely on geographical distance. Moreover, the diffusion process is mainly supply driven as the firm is the only agent involved in the decision to enter a new market, and, as in the case of the bilateral CDM framework, the decisions are not influenced by others' decisions (i.e., there are no explicit inter-firm interactions).

However, in network-based models of technology diffusion, such interactions and their topology have been shown to be a core aspect of the technological diffusion process. Geroski (2000) provides a general overview of models including the epidemic and probit type models, which serve as an empirical basis to model the typical S-shaped diffusion process. Initially, adoption of a new technology can rise slowly, but eventually, as more agents adopt, information accumulates and uncertainty about its usage is resolved so that the number of users flattens out. In this way, technology can spread like an epidemic. In theoretical contributions, Acemoglu et al. (2011) make a distinction between epidemics (denoted as simple contagion) and complex contagion, where each agent requires multiple adoption in their neighborhood before adopting the innovation focusing on the linear threshold model, while Montanari and Saberi (2010) make a distinction between epidemic and game-theoretic models based more on strategic decision-making. Namely, when adopting a new technology, each agent makes a rational choice to maximize their payoff in a coordination game where players obtain a higher payoff from adopting the same strategy as their opponents. In this sense, the adoption and diffusion process is viewed more in terms of utility maximization than exposure. Most existing econometric network-formation models are based on this utilitarian perspective (see Chandrasekhar, 2016, for details).

The characteristics of the diffusion process also interact with the topological properties of the network. From an empirical perspective, Chang et al. (2009) show how the analysis of patent citation networks, in particular through cluster analysis, can help recover the dynamics of knowledge and technology diffusion. From a more behavioral perspective, Cowan and Jonard (2004), Delre et al. (2007), and Midgley et al. (1992) develop micro-founded models of knowledge and technology diffusion. In particular, Cowan and Jonard (2004) and Delre et al. (2007) show that (i) the efficiency of a diffusion network depends on the relationship between the micro-economic properties of the diffusion process and the structure of the network and that (ii) small-world networks exhibit a form of generic efficiency. Delre et al. (2007) further emphasize that heterogeneity of the population can accelerate the speed of diffusion.

Accordingly, our contribution aims to account for the interactions between the diffusion process and the network structure in the estimation of the determinants of technological diffusion.

3 The model

In order to assess the potential impact of policy on the global patterns of technological diffusion, we propose a methodology to estimate from data about installation of a given technology, the determinants of the diffusion of this technology in a network of countries. Two caveats apply à priori to this approach. First, the main agents of technological diffusion at the micro-level are firms, not countries (see e.g. Chaney, 2014). This raises the issue of aggregation and in particular of the possibility for a country to be taken as representative of its domestic firms. Second, as emphasized in the recent trade literature (in particular Hidalgo and Hausmann, 2009), there are major interactions and interdependencies between the diffusion of different products; one is actually concerned by two networks: a network of countries and a network of products.

With respect to the latter issue, we try to proxy the interactions between products by considering among the determinants of technological diffusion the characteristics of the global trade network (measured using the NSF-Kellogg Institute Economic Integration Agreement Database). With respect to the issue of aggregation at the country-level, two specific features of our approach help mitigate the problem. First, the underlying model of diffusion we use is of an "epidemic" rather than of a utilitarian nature. Thus countries do not decide to adopt a technology. Rather, the technology diffuses between countries. Second, our estimation procedure is based on data about actual, physical, installations. Thus, the spatial dimension is hard-wired to our approach. A country is then considered as the set of locations in which a technology is actually employed. Choosing the country-level is really a matter of scale. In particular, there are no issues about the domiciliation of firms and/or their headquarters that could render data interpretation problematic (as for CDM data, see below). Last, but not least, the country-level is the right scale to address policy issues. In this respect, we are interested in the structural properties of the network and how these are influenced by both domestic and international policy. This opens a potential channel for policy to foster the diffusion of technology, and also a rationale for implementing the model at the country level. In the context of climate policy, enhancing the diffusion of low-carbon technology is one of the key measures put forward in the COP21 Paris agreement. In particular, a better understanding of the structural impacts of both national and international policy on technological diffusion can help linking international trade and environmental agreements in the context of climate clubs formed by subset of UNFCCC member countries (see e.g. Nordhaus, 2015; Hovi et al., 2016; Keohane and Victor, 2016).

More formally, we use a representation of the technological diffusion network inspired by the epidemiological literature (see e.g., Hufnagel et al., 2004) and recent contributions focusing on the diffusion of information in social networks (in particular Gomez Rodriguez et al., 2010). Namely, we represent the space of technological diffusion as a set of countries N linked through a weighted network $A = (a_{i,j})_{i,j=1 \cdots N} \in [0, 1]^{N \times N}$ where $a_{i,j}$ represents the probability for a technology to diffuse from country i to country j. At the micro-level, this corresponds to the probability for a firm offering a technology on the market in country i to expand its operations to country j. A similar measure is introduced in the trade network formation model of Chaney (2014), but it is assumed to be a simple function of GDP and distance.[1] We rather argue that this probability, which measures the rate at which embodied technologies diffuse between countries, depends on a range of characteristics about the source country, the target country and their relationship. For example, it might depend on the size of the market in the source country, the level of human capital in the target country and on the existence of a trade agreement between the two countries. The choice of these explanatory variables might depend on the type of technology considered, hence, in the application to wind energy considered below we account specifically for environmental agreements (ratification of the Kyoto Protocol) and domestic regulation on renewable energy, such as feed-in tariffs or mandatory requirements (see section 4.1 below for a detailed description of these policy measures). Now, in all generality, one can consider three main types of variables: a first set of variables $x_i := (x_i^1, \cdots, x_i^{n_1}) \in \mathbb{R}^{n_1}$ characterizing the source country, a second set of variables $y_j := (y_j^1, \cdots, y_j^{n_1}) \in \mathbb{R}^{n_2}$ characterizing the target country, and a third set of dyadic variables $z_{(i,j)} = (z_{(i,j)}^1, \cdots, z_{(i,j)}^{n_1}) \in \mathbb{R}^{n_3}$ characterizing the relationship between the two countries ($z_{(i,j)}$ shall in general be a multi-dimensional variable accounting for the range of bilateral features discussed above). A natural approach would then be to try to estimate the diffusion probability between country i and j using a logistic model of the form:

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

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 country, the target country, and their relationship.

The estimation of this model would require the observation of diffusion events between pairs of countries. Such phenomena are however hardly observable. In practice, one rather observes the country of origin of the product/technology and its progressive adoption in a set of countries but without specific information

[1] See equation 7 in Chaney (2014).

about the diffusion routes. A range of countries can however play a role in the diffusion thanks to complementary features such as their capacity to adapt technologies to regional market conditions, their central position on commercial routes or the structure of international trade or environmental agreements.

Formally, the diffusion of a technological vintage in the discrete time-frame $\{0, \cdots, T\}$ is captured by a "cascade," i.e. a series of dates $(t_1, \cdots, t_N)$ where $t_i \in \mathcal{T} := \{0, \cdots, T\} \cup \{+\infty\}$ is the date at which the technological vintage was adopted in country i (with $t_i := +\infty$ if the vintage was never adopted). Such a cascade can also be represented by a boolean matrix of adoption status $S_v \in \{0,1\}^{N\times T}$ where $S_v(i,t) = 1$ if the vintage v is present in country i at time t and $S_v(i,t) = 0$ otherwise.

Then, given observations of a set of cascades $S = (S_v)_{v\in V}$ corresponding to V different technological vintages, we can estimate the determinants of bilateral diffusion by maximum likelihood, i.e., determine the coefficients in equation (1) for which the likelihood of the observed diffusion patterns is maximal. Indeed, given panel data about source countries $X = (x_{i,t})_{i=1\cdots N, t=1\cdots T}$, target countries $Y = (y_{j,t})_{j=1\cdots N, t=1\cdots T}$, and relationship characteristics $Z = (z_{(i,j),t})_{i=1,\cdots,N, j=1\cdots N, t=1\cdots T}$, one can compute the likelihood of a cascade S_v as follows under the assumption that the diffusion process is Markovian.

- Given the adoption status in period t, the probability for a non-adopting country j to remain non-adopting in period $t+1$ is

$$\prod_{\{i|S_v(i,t)=1\}} (1 - P_{(\alpha,\beta,\gamma)}(x_i^t, y_j^t, z_{i,j}^t)) \tag{2}$$

  while the probability that it adopts is

$$1 - \prod_{\{i|S_v(i,t)=1\}} (1 - P_{(\alpha,\beta,\gamma)}(x_i^t, y_j^t, z_{i,j}^t)) \tag{3}$$

  .

- Thus the probability of the transition from the adoption vector $S_v(\cdot, t)$ to the adoption vector $S_v(\cdot, t+1)$ is given by:

$$\prod_{\{j|S_v(j,t+1)=0\}} \prod_{\{i|S_v(i,t)=1\}} (1 - P_{(\alpha,\beta,\gamma)}(x_i^t, y_j^t, z_{i,j}^t))\times$$
$$\prod_{\{j|S_v(j,t+1)=1\}} \left(1 - \prod_{\{i|S_v(i,t)=1\}} (1 - P_{(\alpha,\beta,\gamma)}(x_i^t, y_j^t, z_{i,j}^t))\right) \quad (4)$$

- Therefrom, using the assumption that the diffusion process is Markovian, one deduces the likelihood of cascade S_v as:

$$\mathcal{P}^v_{(\alpha,\beta,\gamma)}(X, Y, Z) = \prod_{t=0}^{T-1} \prod_{\{j|S_v(j,t+1)=0\}} \prod_{\{i|S_v(i,t)=1\}} (1 - P_{(\alpha,\beta,\gamma)}(x_i^t, y_j^t, z_{i,j}^t))\times$$
$$\prod_{t=0}^{T-1} \prod_{\{j|S_v(j,t+1)=1\}} \left(1 - \prod_{\{i|S_v(i,t)=1\}} (1 - P_{(\alpha,\beta,\gamma)}(x_i^t, y_j^t, z_{i,j}^t))\right) \quad (5)$$

This approach for the computation of the likelihood of a cascade was introduced in Wu et al. (2013) (although their formulation is less general and incomplete). The default approach to then compute the likelihood of a set of cascades is to use the independent cascade model of Gomez Rodriguez et al. (2010), that is to assume that the diffusion of each technology is an independent process. This yields the following equation for the likelihood of the set of observed cascades $S = (S_v)_{v\in V}$.

$$\mathcal{L}_{\alpha,\beta,\gamma}(S) = \prod_{v\in V} \mathcal{P}^v_{(\alpha,\beta,\gamma)}(X, Y, Z) \quad (6)$$

One can then estimate the determinants of diffusion, (α, β, γ), by maximum likelihood. This allows in particular to investigate, through the coefficient γ associated with link characteristics, the impact of the participation in bilateral or multilateral trade or environmental agreements on the diffusion of technologies between countries. In particular, it shall allow to investigate which designs for climate clubs might be conductive to enhanced technological diffusion in line with the commitments of the Paris Agreement.

Nevertheless a number of caveats apply to the model. First the choice of a logit specification for the bilateral probability of diffusion is not necessary. It corresponds to a Poisson diffusion process and hence to the assumption that the rate of diffusion from a country to its neighbor is constant over time. Alternatives can be considered in which the diffusion rate decays over time (see e.g. the power-law model in Gomez Rodriguez et al., 2010), which amounts to consider that the probability of diffusion is maximal at the time of adoption and decreases from then on. Second, the assumption that the cascades are independent is a major simplification, in particular in the context of technological diffusion where one could rather consider that adoption of previous technological vintages has increased technological capability and therefore is likely to enhance adoption of new technological vintages. However, as emphasized below, this can be partly overcome by using alternative measures of the technological level of the countries.

4 Data description and estimation results

4.1 Description of variables and data

We shall use the methodology introduced above to analyze the determinants of the formation of the wind technology diffusion network. Wind is indeed one of the fastest growing forms of renewable energy and exhibits rapid technological progress. It is thus expected to play a key role in climate change mitigation (see e.g. Edenhofer et al., 2011). Furthermore, there exists a very complete database, the "Wind Power",[2] providing detailed technological and industrial information

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

and almost comprehensive coverage on wind turbines installed from 1983 to 2016 at the global scale.

We have thus extracted from the wind power dataset observations of 223 wind technology diffusion cascades. A technology is identified with a pair (manufacturer, turbine size) given that the turbine size is the main determinant of its capacity and a representative carrier of technological progress. We have then defined the diffusion process of each technology, i.e., the cascades per se, by associating to each country the first date at which a turbine corresponding to that particular technology has been installed in the country. In this sense, our analysis focuses purely on the technological dimension, i.e., the presence of a technology or not, but discards completely the industrial perspective, i.e., the scale of deployment of the technology. With respect to time-scales, the speed of diffusion is reasonably fast with respect to the lifetime of the technology. The length of cascades in our sample ranges between 4 and 20 years. The average life of a wind power turbine is 20 years (16-24 years). The amortization period of a wind plant is of the same order of magnitude, since the turbine cost has varied historically from 64-84% of the total production costs, with later estimates towards the upper end (IRENA, 2018).

There are 94 countries that have installed at least one wind turbine according to our dataset. They form a sub-sample of countries to which we have added the set of countries that are members of the United Nations to form a full sample of 195 countries.[3] In order to proceed with the analysis of the determinants of technological diffusion in this network of countries, we enrich this dataset with characteristics that can be associated to a country as a source (of the type x_i in equation (1)) and as a target (of the type y_j in equation (1)) of technological diffusion, as well as characteristics of the relationship between pairs of countries (of the type $z_{i,j}$ in equation (1)).

[3]Since the original turbine dataset includes the Faroe Islands and Puerto Rico, these are also included in the full sample.

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 country, which generally coincides with the manufacturer source country (although the exact place of production is impossible to ascertain unambiguously given the global nature of value chains in production and the fact that each wind turbine assembles hundreds of different components).

With respect to policy drivers, key variables are included to capture the impact on technological diffusion of international trade and environmental agreements, as well as domestic support policy. For international trade, we include a measure of the level of economic integration of bilateral country pairings i and j at time t from the NSF-Kellogg Institute Economic Integration Agreements (EIA) Database.[4] Compared to trade openness measures commonly used in both the trade and technology diffusion literature (e.g., see Ferrier et al., 2010; Comin and Hobijn, 2010),[5] it allows for a richer evaluation of trade relationships. In addition, since this variable is dyadic by nature, it is included as one of our $z_{i,j}$ features, with the expectation that the impact will be positive and significant, as increased trade openness should facilitate technological flows (Lovely and Popp, 2011).

For environmental policy, we focus on policy directed at combatting climate change, both nationally and internationally. As regards international institutions and mechanisms, we control for whether the country has ratified the Kyoto Protocol or not. For Annex 1 countries it implied binding emission reduction targets over the treaty period[6] and for non-Annex 1 countries it opened for participation

[4] Depending on the integration level, 0= No Agreement, 1= Non Reciprocal Preferential Trade Arrangement, 2= Preferential Trade Arrangement, 3= Free Trade Areas, 4= Customs Union, 5= Common Market, 6= Economic Union. For most of the cells where the EIA status of the country pair changes, there even exists a hyperlink to a copy of the original treaty.

[5] Generally, this is defined as the sum of exports and imports of goods and services measured as a share of GDP, or the ratio of imports per worker (Caselli and Coleman, 2001).

[6] The Kyoto Protocol, adopted in December 1997, entered into force in February 2005 after the ratification requirements had been fulfilled, with a first commitment period running from 2008 to 2012.

in the Clean Development Mechanism. In our estimations following equation (1), we define it as a dyadic variable $z_{i,j}$ taking the values 0 if no country in the pair has ratified, 1 if at least one country in the pair has ratified and 2 if both countries have ratified.[7] As noted in Section 2, public policy and regulation in general has been shown to be a major driver behind renewable energy investment. However, results on the impact of the Kyoto Protocol on renewable energy adoption have been mixed (Pfeiffer and Mulder, 2013), which may be a signal that policy efforts predating the Kyoto Protocol (although less of a coordinated effort) were in part responsible for early adopters (cf. Popp et al., 2011). Despite the Kyoto Protocol occurring after the enactment of specific renewable support policies in some countries, it is a notable breakthrough in international climate policy and as pointed out by Popp et al. (2011, p. 657), can serve as a signal of a country's commitment and future carbon prices even though it does not require countries to make specific investments in renewables. Grubb et al. (2015) also note that measures such as feed-in tariffs can be considered as encompassing an indirect form of carbon pricing, relating to the domestic dimension of climate policy.

For domestic support policy, a unique aspect of our data is that we have constructed it especially for this paper with a focus on wind energy. The sources are the IEA/IRENA Global Renewable Energy Policies and Measures Database[8] combined with IRENA policy briefs for some individual countries and regions (IRENA, 2015). We created two measures based on the data: first, a binary variable taking the value of 1 (and zero otherwise) if a country has in place a direct support policy of wind energy for each year.[9] General policy support and policies aimed at funding R & D are not included, but rather, economic and regulatory

[7] To control for the effect of the Kyoto Protocol, unilateral analyses of the adoption of renewable energy typically use either a dummy variable from 1998 onwards (Brunnschweiler, 2010; Pfeiffer and Mulder, 2013) or a dummy variable indicating whether the country has ratified the Protocol in a given year (Popp et al., 2011).

[8] This database contains information on energy-related policies, among which are policies to support renewable energy development and deployment: https://www.iea.org/policiesandmeasures/renewableenergy/

[9] Implementation after 1 August is counted as the following year.

incentives aimed at the actual installation of wind power: fiscal incentives such as subsidies, corporate tax breaks, green certificates and feed-in tariffs, as well as regulatory instruments such as mandatory requirements and obligation schemes. This is important because direct economic incentives have been shown to be effective in inducing adoption from a unilateral perspective (Söderholm and Klaassen, 2007), with some evidence of the type of support differing according to the type of renewable energy (Polzin et al., 2015). The second measure of policy encouraging adoption of wind energy is a binary variable set equal to one (and zero otherwise) if a country has enacted reductions in import tariffs for wind equipment for a given year. Following equation (1), the first measure is introduced into the equation as both x_i and y_j, while the second measure is introduced only for the target country y_j. Intuitively, the first measure is primarily meant to stimulate demand thus inducing more development/adoption of renewables within a country or imports of the technology, while for the second measure a target perspective is more reasonable as the policy is aimed at lowering trade barriers for imports of wind energy.

In addition, we control for other standard determinants from the literature on technology diffusion. Since GDP per capita and human capital measures are strongly correlated with a measure of technological capability (r>0.70; also see Caselli and Coleman, 2001; Comin and Hobijn, 2010), we include only the latter as it has more intuitive appeal in this context. Several studies highlight the importance of capacity building as a means to accelerate technology diffusion. In this respect, although trade can provide elements of technology, in order for the technology transfer to be successful, there needs to be a foundation. For this purpose, we use the composite ArCo technology index, covering three main dimensions of technological change: innovative activity (number of patents and scientific publications), infrastructures (diffusion of old and new technologies), and the quality of human capital (Archibugi and Coco, 2004).[10] As noted in

[10]This measure is widely used in many areas including (green) technology adoption and diffusion, and economic development.

Dechezleprêtre et al. (2008), the expected effect of this factor is not clear-cut. At first, it seems that new technologies are more likely to be diffused to countries with higher technical competence. However, higher technical competence can signify that many technologies are already locally available, thus reducing transmission probabilities. In this case, it is interesting to consider both source and target perspectives, and hence we introduce this variable in the estimations as both x_i and y_j. Another main country-level characteristic included in the technology adoption and diffusion literature is institutions (cf. Comin and Hobijn, 2009). We use the rule of law measure, which is an index ranging from -2.5 (weak) to 2.5 (strong) governance performance for each country over time from the World Bank's Worldwide Governance Indicators. This indicator was particularly chosen because it is meant to capture the extent to which agents have confidence in and abide by the rules of society, especially the quality of contract enforcement, property rights, police, and courts (Kaufmann et al., 2011).

In addition, we include the log of annual added wind power generation (GWh) for each source country over time x_i in our estimations. As discussed in Section 2, Dechezleprêtre and Glachant (2014) actually use this measure as a proxy for domestic policy. Here, we include it as a measure of market share or ability of a country to diffuse to other potential countries since production is found to be only weakly correlated with the policy measures used in the analysis (r<0.12). Finally, we also include geographical proximity, measured as the inverse of bilateral distances (in km) between countries i and j (Mayer and Zignago, 2011).

4.2 Empirical results

From a policy point of view, the results presented in Table 1 provide interesting insights on accelerating the diffusion of wind energy, which forms a key component in the energy transition as highlighted in the introduction.[11] First, one of

[11] In terms of evaluating model adequacy, we report the McFadden-R^2 which is a useful pseudo R^2 measure and find that it is quite high, representing good model fit for all specifications

the most important factors driving technology diffusion is economic integration. This corroborates previous studies (e.g., Dinar et al., 2011; Dolšak and Crandall, 2013), that the strength of international relations (e.g. trade and prior interactions such as colonial ties) are key in facilitating flows. As can be seen in the first and third columns (Models A and B, respectively), trade policies fostering increased economic cooperation between countries induce a positive impact on global deployment with the EIA point estimate being positive and highly significant for both model specifications. In particular, ceteris paribus, a one unit increase in the level of integration multiplies the initial odds ratio by 1.231.[12] A distinguishing factor of this measure is that even though it has a dyadic format, it not only represents bilateral trade flows and agreements, but also multilateral ones such as trade blocs thus going more into the direction of climate clubs fostering cooperation. In this context, it can be envisioned that agreed treatment of international trade extended to for example renewable technologies such as wind power can be a vital element in the formation of such a club based more on benefits accrued to its members (cf. Grubb et al., 2015). As EIA can be seen as a continuous variable with level 6 representing the strongest economic integration (see previous subsection) and there is overlap between the different levels, we first treat it as such. Nevertheless, it is also interesting to examine if the types of EIA have different effects. We have thus also estimated the impact of EIAs with treatment coding (with the reference group being EIA=0, i.e., No Agreement). These results are shown in the second and last columns. Due to few observations on deeper EIAs - customs unions, common markets and economic unions - these are combined into one variable as in Baier et al. (2014). The odds of transmission occurring in a country-pair having a preferential trade agreement (EIA_{PTA}) are $\exp(0.023) \approx 1.023$ times higher than the odds of having no trade agreement. A country-pair that has in place a free trade agreement (EIA_{FTA}) where trade barriers are eliminated (or at least substantially) among members, the odds of

(McFadden, 1973; Cameron and Trivedi, 2005).

[12]Model B is more parsimonious as will be explained below. Since results are similar, the discussion refers to Model A unless stated otherwise.

transmission are around 1.071 times higher than the odds of transmission between a country-pair without this type of trade agreement. This corroborates that a higher level of economic integration between countries facilitates technological flows. Furthermore, the deeper EIAs ($EIA_{CUCMEUN}$) have an even larger effect, where the odds are around 2.515 times higher than the odds of transmission if no agreement is in place between countries.

In addition to the strength of international trade relationships, it is also expected that international and domestic environmental initiatives positively influence the acceleration of climate-friendly technologies. However, in terms of the international dimension an unexpected result is found for the Kyoto ratification variable. In this respect, it is relevant to mention two main points. First, these types of measures are usually explored in terms of their impact on domestic adoption rather than from a cross-border transfer perspective as is the case here. Although overall Kyoto ratification is found to have a positive impact on investment decisions, it is interesting to note in this context that Popp et al. (2011) find that for wind, the effect of Kyoto falls when wind related country variables are controlled for that we have included (e.g., wind-specific domestic policies to be discussed shortly).[13] For this reason, we have also included the results of Model B to explore whether taking out these latter variables affect the Kyoto estimate. It turns out, however, that the results across all models are quite similar. This leads us to the second main point. Since our cascade dataset starts 15-20 years before Kyoto ratification (which entered into force in 2005), the diffusion patterns we observe occur too early for the policy to show its impact. For this reason, it is also relevant to introduce specific domestic policies in the specification that predated this international agreement. Indeed, the earliest years for ratification of the Kyoto Protocol are between 1998 and 2000 but ratification can occur as late as in 2009 and 2010 whereas economic and regulatory incentives for wind power are observed as early as in 1989-2002 for several European countries, and some

[13]As mentioned in Section 2, for the specific study on wind, Dechezleprêtre and Glachant (2014) do not include the Kyoto Protocol or specific domestic policy instruments.

countries in South America.

Regarding domestic environmental policies, as for the international measures, they are also generally analyzed in terms of own-country effects in contrast to a network perspective. In our case, as described in the previous subsection they are customized especially for wind energy. In particular, in addition to economic integration, we find that whether a country has in place a direct support policy for wind energy has a positive and significant impact on the probability that a country diffuses a technology. This suggests that such policies contribute to the development of an industrial base, which fosters further diffusion. The impact of support policy in target countries is, at first glance, unexpected. It is found to be negative rather than positive, although statistically insignificant. The most likely explanation for this finding is that what is measured in the cascades is the first time a technology was introduced rather than the volume (in terms of number of turbines or their capacity). Indeed, the introduction of a technology is likely to predate the support policy. Moreover, since domestic support policies are created primarily to stimulate investments to promote increased use of renewables, the impact is accordingly much more on the volume than the existence of a diffusion event as reflected in the current conceptualization of cascades.[14] Since these two effects can be confounding, we also estimated Model A without the direct policy measure from the source perspective and find that all estimates remain similar (see the results of Model B in columns 3 and 4). Another likely explanation for these results relate to those discussed above on the Kyoto Protocol. From the support policy data, it can be observed that in many countries the policy was introduced relatively recently (mostly in the 2000s) and thus possibly after the first diffusion event for most technologies, which is what is captured in a cascade. Yet, it might also be the case (and it is definitely not ruled out by our results) that domestic environmental policies have no effect whatsoever on technological transfers.

[14] As an extension, it would be relevant to modify the definition of a cascade in the modeling approach so as to account for each installation (not only the first one) in order to better account for the intensive margin.

	Model A	Model A_EIAs	Model B	Model B_EIAs
Intercept	-8.923**	-8.194**	-8.952**	-8.251**
	(-37.356)	(-21.387)	(-39.925)	(-35.171)
Geographical proximity	0.051	0.032	0.038	0.037
	(0.002)	(0.001)	(0.001)	(0.002)
Kyoto ratification	-0.725**	-0.670**	-0.687**	-0.638**
	(-16.987)	(-9.904)	(-17.227)	(-15.627)
Rule of law_target	0.354*	0.330*	0.267*	0.339*
	(2.407)	(2.246)	(2.034)	(2.509)
ln Windgen_source	0.282**	0.259**	0.312**	0.287**
	(23.581)	(19.931)	(28.314)	(24.673)
EIA	0.208**		0.222**	
	(13.566)		(14.375)	
EIA_PTA		0.023**		0.061**
		(2.564)		(3.921)
EIA_FTA		0.067**		0.115**
		(4.144)		(5.940)
EIA_CUCMEUN		0.922**		0.983**
		(5.679)		(11.405)
ArCo_source	2.747**	2.071**	3.129**	2.376**
	(14.531)	(10.033)	(17.279)	(11.807)
ArCo_target	-0.727	-0.547	-0.617	-0.624
	(-1.325)	(-0.591)	(-1.192)	(-1.146)
RE direct policy wind_source	0.628**	0.588**		
	(6.404)	(5.105)		
RE direct policy wind_target	-0.097	-0.061		
	(-0.599)	(-0.313)		
RE tariff exemptions wind_target	0.254	0.381		
	(0.782)	(0.951)		
McFadden R^2	0.226	0.232	0.223	0.229
Log-Likelihood	-5815.22	-5774.12	-5837.17	-5793.07

Table 1: Estimation results of the diffusion network approach

Notes: For country-specific explanatory variables, the number of observations is 195×34, with 195 nodes and 34 time periods. For dyadic variables, there are $195 \times 194 \times 34$ observations; for geographic proximity this is symmetric, but this is not necessarily the case, as in the case of the EIA variable where the values of (i, j) and (j, i) can differ. t-values are reported in parentheses. **Significant at the 1 percent level. *Significant at the 5 percent level.

In relation to the level of technological development, a striking pattern emerges concerning technological capability as measured by the ArCo index. This factor has a highly positive and significant impact from the source perspective, but is different in sign and insignificant from the target perspective for all specifications. This relates back to the point made in the previous subsection on the contrasting effects of technological capability on technology transfers; from an importer stance higher capability can mean that since technologies are already available, this reduces the probability of transfers. In fact, it has been shown in recent CDM related literature that in countries such as China and India with stronger domestic bases, technology transfer is less prevalent (cf. De Coninck and Sagar, 2015).[15] The significant impact from the exporter viewpoint for the ArCo measure, nonetheless, indicates that factors such as skilled technical personnel, information on available technologies, and production capabilities are crucial for accelerating diffusion at a global scale. Moreover, the point estimate of annual wind power generation is highly significant across all models, with cross-border technology diffusion positively influenced; in particular, ceteris paribus, a one percent increase in wind power generation in country i induces a 0.28 (0.31) percent increase in the odds of a transmission. In relation to technological development and capacity building, it is also found that the quality of institutions is an influential determinant, suggesting that the overall governance level of countries enhances the likelihood of technology flows between countries.[16]

Finally, we find a positive estimate for the impact of geographical proximity on diffusion probability as one can expect that flows increase as the distance between countries decreases. However, this effect is statistically insignificant. This highlights the preponderance of socio-economic factors over physical ones in the diffusion process. This is a positive policy result in the sense that countries more

[15]Though more from a developed to developing transfer perspective, Foucart and Garsous (2017) theoretically show that larger absorptive capacities in developing countries may deter investment by developed countries to invest in clean technology resulting in less transfers.

[16]Note that the Rule of law measure has been introduced from the target perspective as intuitively it can be expected that it promotes inflows. We also checked a specification including the same measure in the source country and it has a positive influence as well.

at the periphery (further from the most important actors in the wind diffusion network) can still potentially receive new technologies through other relevant factors such as strengthened cooperation through trade and/or environmental agreements. This also suggests potential extensions of the model of trade network formation of Chaney (2014) where the probability of diffusion is mainly based on geographical distance. In sum, the results reinforce that capacity building, domestic environmental policy initiatives and long-term relationships existing between countries, especially as measured by the deeper EIAs, can help accelerate deployment of wind energy (and potentially other climate-friendly technologies) at the global scale.

4.3 The structure of the technological diffusion network

To further explore the network dimension, it is possible to reconstruct the wind diffusion network based on the estimated coefficient values from Model A (parameterization) of the transmission probabilities according to equation (1). Taking the values of the features for the most recent year and setting a threshold value of $a_{i,j} > 0.01$, different visualizations of the reconstructed networks are provided in Figures 1 to 6.[17] In Figures 1 and 2 the node size is based on the betweenness, a centrality measure capturing the notion of hubs facilitating technology flows.[18] A visualization based on degree (Figure 3) also shows that among top key players are the USA, Canada, Sweden, Germany, the UK, Denmark, Spain, France, the Netherlands, Finland, Norway, and Taiwan. Interestingly, this has some overlap with the findings in Halleck Vega and Mandel (2018) on key players in the network, though they use a different framework. Despite being one of

[17] All figures have been realized using the Gephi software (Bastian et al., 2009). Figure 1 provides a symbolic representation of the network using a force-layout algorithm and aggregated countries outside of the most important into geographical clusters. Figures 2 to 6 use a geographical layout and should be explored online using the zoom functionality of the file viewer.

[18] Since potentially all nodes can be connected, we set a threshold as most $a_{i,j}$ values are almost nil; overall, conclusions with smaller and larger values are similar.

the largest countries with installed wind energy capacity, China does not appear prominently. This is most likely a reflection of the prioritization on national demand rather than participation both in global exports and imports relative to other countries such as the USA and Germany, where the latter build more of a global position in the supply chain (Lacerda and van den Bergh, 2014). However, China's growing position in the global wind energy market, as well as for solar power, are more recent phenomena.

On this note, it is important to keep in mind that the reconstructed network is a conceptualization of potential paths of diffusion of new technologies rather than actual exports and imports. In fact, the most influential players in this setting are due to their higher transmission probabilities and thus in their potential of accelerating technology diffusion. Another useful measure in this sense is closeness centrality (Figure 4), providing an indication of how fast a technology seeded in one country would, on average, reach another country in the network. In this case, in addition to aforementioned key players, Poland, Greece, Japan, Switzerland, and Austria are also highly ranked. We also checked these conclusions based on Model B and as expected, they are similar. To add a different perspective, the reconstructed network in Figure 5 is based on eigenvector centrality, which can be seen as a measure of the total diffusion range of a technology as a function of the seed country. In this case, a European core is more clearly visible, although the US and other countries elsewhere are still very prominent in the network. An interesting further exploration, in this case, is to take an earlier time such as the start of the turn of the 21st century when global wind power capacity started taking off to a greater extent. This is represented in Figure 6 (same as Figure 3 except for the point in time), and here it can be seen that centrality is more evenly spread out in this earlier diffusion period.

This absence of large hubs in the technological diffusion network is particularly salient in developing countries. This is in line with the results of Halleck Vega and Mandel (2018), which emphasize the lack of south-south transfers in the global diffusion process and hence that most technological diffusion occur through north-

Source/Target	Arg	Brz	Chn	Ind	Mex	Mor	Pak	Serb	SA	SK	Urg	Viet	**Total**
Australia			4	2									6
Austria			45										45
Belgium			2						1				3
Denmark			2										2
Finland			28										28
France			75	1		2							78
Germany			18	5	4				1		1		29
Italy		2	8	1								1	12
Japan	1		26	6						3			36
Liechtenstein								4					4
Netherlands		6	80	9					1		1		97
Norway			8										8
Spain		4	10	5	9					1	1		30
Sweden			74	12	2						1		89
Switzerland		8	168	37					1	1		3	218
U.K.	5	9	595	36	5	2	7		1			1	661
Total	6	29	1143	114	20	4	7	4	5	5	4	5	1346

Table 2: Registered CDM projects for wind as of January 2018.

Notes: The source is the country of the CDM buyer, the target the host of the CDM project. Target countries with less than 3 CDMs have been omitted. Remaining target countries are Argentina (Arg), Brazil (Brz), China (Chn), India (Ind), Mexico (Mex), Morocco (Mor), Pakistan (Pak), Serbia (Serb), South Africa (SA), South Korea (SK), Uruguay (Urg), Vietnam (Viet).

south transfers. These findings and the fact that a relatively large numbers of developing countries are nevertheless part of the wind diffusion network (because they have indeed adopted some of the technologies) are in strong contrast with the picture that emerges from CDM data. Indeed, as illustrated in Table 2, the diffusion of wind technology through CDM is extremely concentrated on China and India whereas actual diffusion is much more evenly spread. Furthermore, most of the CDM projects originate from Switzerland and the United Kingdom and are initiated by financial rather than industrial actors. This comparison suggests that CDM projects account for a very small share of actual technological diffusion processes and that the focus on CDM data provides a somehow distorted view of the global technological diffusion network. This provides additional explanation for the negative impact of the Kyoto ratification in our estimation above and reinforce our conclusions about the dominance of long-term economic and trade relationships as significant drivers of technological diffusion.

5 Conclusions

We have developed a methodology to estimate the determinants of the formation of a technological diffusion network from adoption data. We assume that bilateral diffusion can be explained by a logit model taking into account the characteristics of source and target countries as well as that of their bilateral relationship. On this logit model we superimpose an epidemic-like model of network diffusion. We then estimate, via maximum likelihood, the parameters that best explain the observed patterns of technological diffusion at the global scale. This approach allows to overcome the issue that bilateral diffusion events are generically not observed.

We have applied this methodology to wind energy, which is one of the key technologies in climate change mitigation. Therefore, we have first inferred wind technology diffusion patterns from a comprehensive dataset about wind turbines installed globally since the beginning of the 1980s. We have then constructed a database of wind support policy measures through an in-depth analysis of the IEA/IRENA Global Renewable Energy Policies and Measures Database. Finally, we have combined these with detailed data about trade integration, technological and economic development, environmental policy and geographical characteristics in order to estimate the determinants of technological diffusion. Our approach treats each type of wind turbine produced by each manufacturer as a different technological vintage, but does not use information about the volume of adoption. In this sense, our focus is much more on the extensive than on the intensive margin of technological diffusion.

Our results emphasize that long-term relationships as measured by economic integration, in particular being part of a customs union, common market or economic union, are key determinants of technological diffusion. It is also found that the level of technological development, as in the knowledge/skills base, as well as whether a country has a direct support policy for wind energy contributes to the deployment of this renewable energy source. Nevertheless, other specific support measures for certain technologies seem less relevant for the diffusion per se, although they might play a crucial role in industrial policy, i.e., in the scaling up of a technology to reach relevant market size. Our results also highlight that the scope of technological diffusion is much broader than what is suggested by the consideration of CDM projects alone, which are particularly focused on China and India.

Finally, the network of technological diffusion inferred from our approach highlights the central role of European countries in the diffusion process and the absence of large hubs among developing countries. From an empirical perspective, these findings are in line with our focus on the extensive margin of technological diffusion. Indeed, European countries are producing and installing a wide variety of turbines while the performance of large developing countries like China is more related to the volume installed. From a theoretical perspective, these findings are reminiscent of the large literature emphasizing the presence of core-periphery structures in socio-economic networks (see e.g. Hidalgo et al. (2007) for the global trade network or Vitali et al. (2011) for the global shareholding network).

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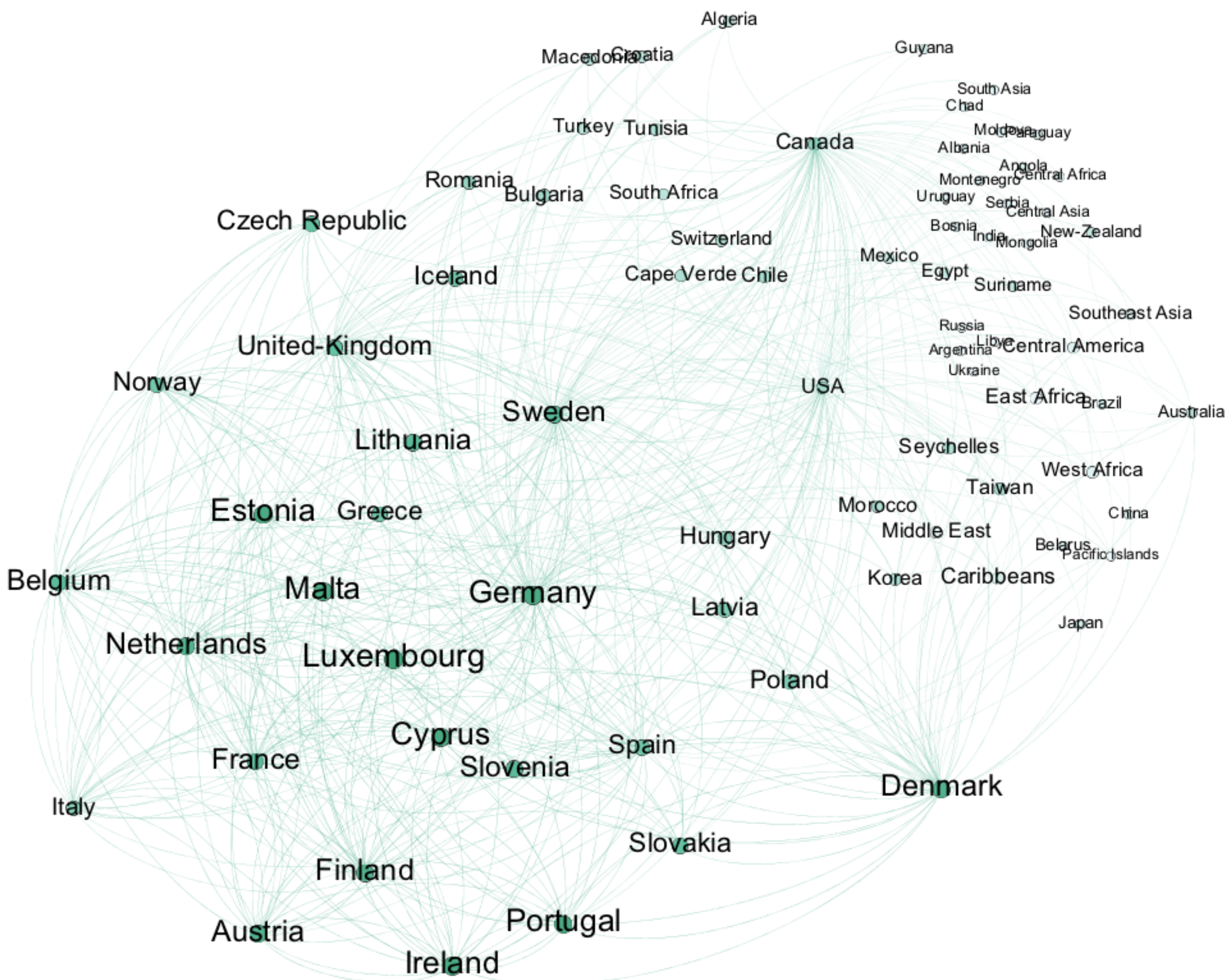

Figure 1: Reconstructed network using force-atlas algorithm. The node size is proportional to betweenness centrality, a centrality measure capturing the notion of hubs facilitating technology flows.

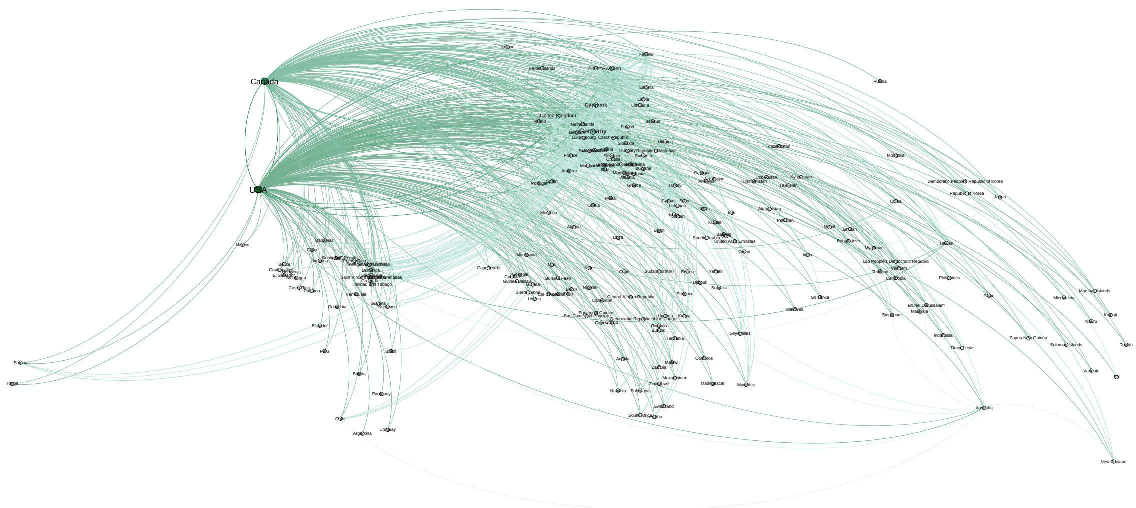

Figure 2: Reconstructed network using geographical layout. The node size is proportional to betweenness centrality, a centrality measure capturing the notion of hubs facilitating technology flows.

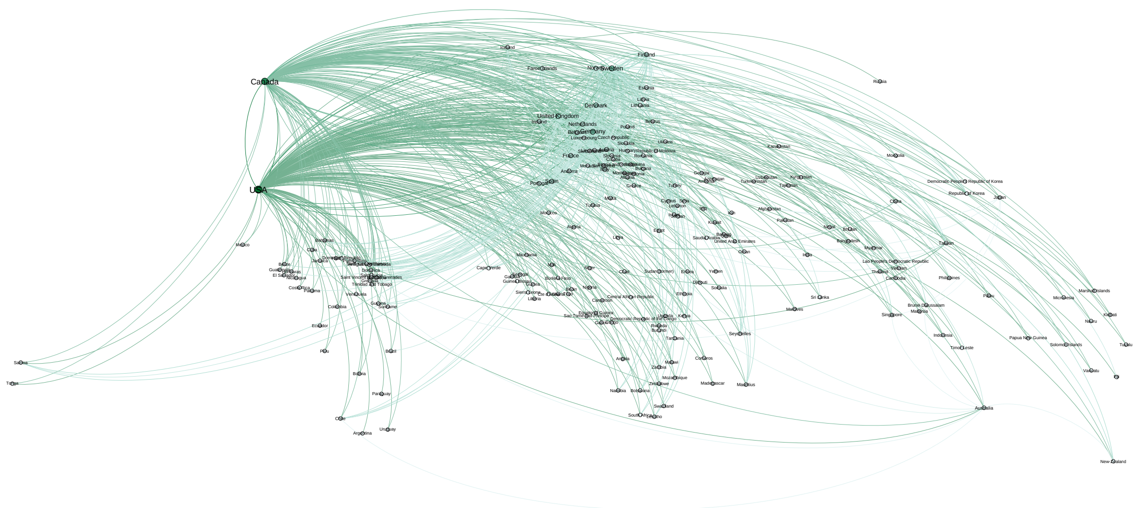

Figure 3: Reconstructed network using geographical layout. The node size is proportional to degree centrality.

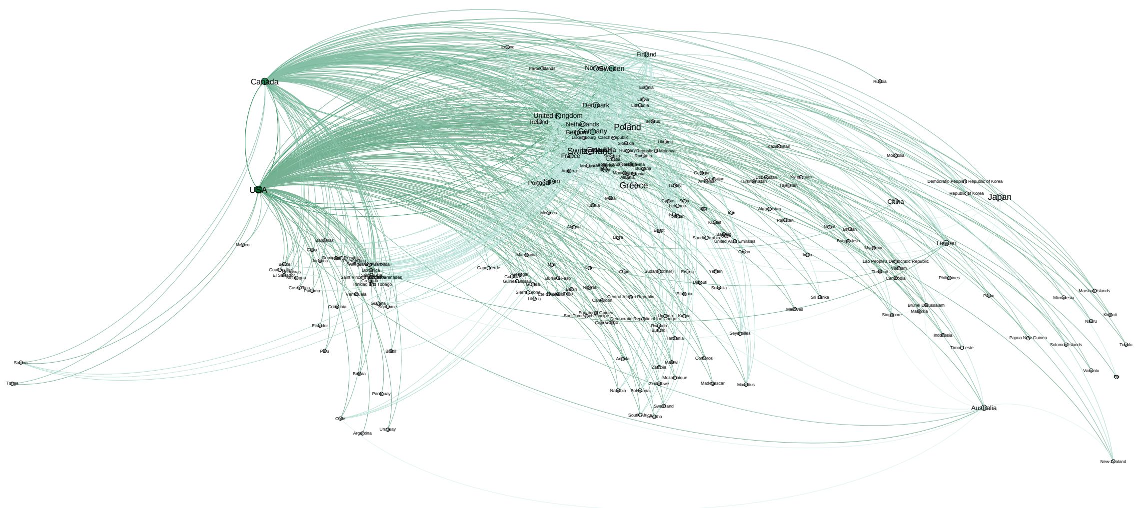

Figure 4: Reconstructed network using geographical layout. The node size is proportional to closeness centrality, which provides an indication of how fast a technology seeded in one country would, on average, reach another country in the network.

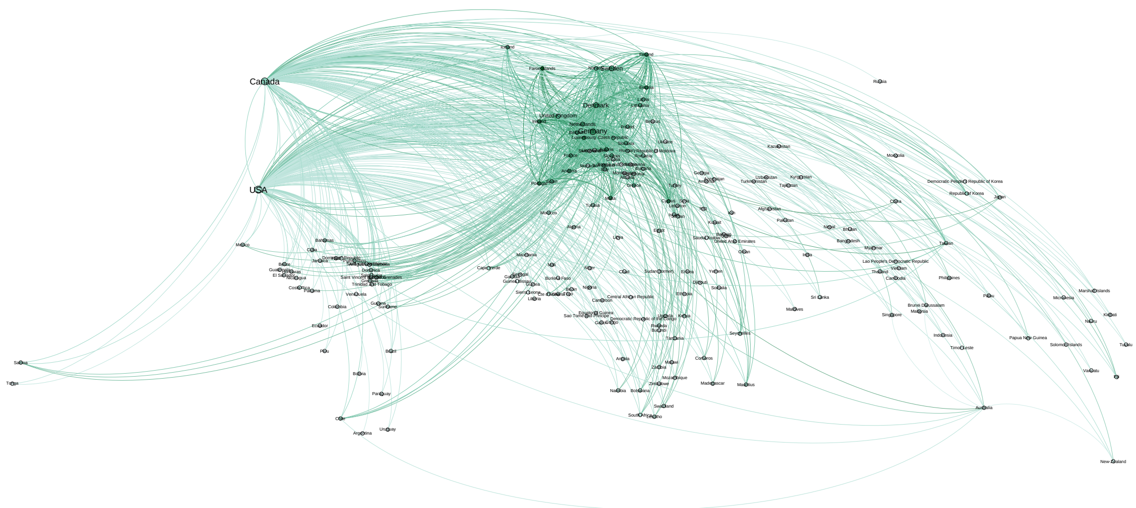

Figure 5: Reconstructed network using geographical layout. The node size is proportional to eigenvector centrality, which can be seen as a measure of the total diffusion range of a technology as a function of the seed country.

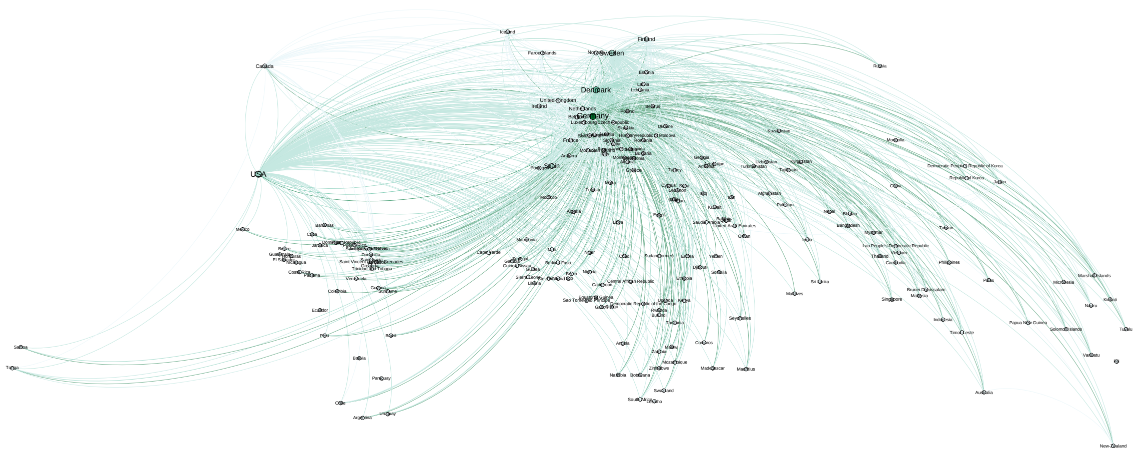

Figure 6: Reconstructed network using geographical layout. The node size proportional to degree centrality.

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