Journal of Cleaner Production 263 (2020) 121287

Contents lists available at ScienceDirect

Journal of Cleaner Production

journal homepage: www.elsevier.com/locate/jclepro

Inter-sector network and clean energy innovation: Evidence from the wind power sector

Fang Zhang [a, b], Tian Tang [c], Jun Su [a], Keman Huang [d, *]

[a] School of Public Policy and Management, Tsinghua University, Beijing, 10086, China
[b] Fletcher School of Law and Diplomacy, Tufts University, MA, 02143, United States
[c] Askew School of Public Administration and Policy, Florida State University, FL, 32306, United States
[d] Sloan School of Management, MIT, MA, 02142, United States

ARTICLE INFO

Article history:
Received 14 September 2019
Received in revised form
4 March 2020
Accepted 22 March 2020
Available online 29 March 2020

Handling editor: Panos Seferlis

Keywords:
Clean energy technology innovation
Inter-sector network
Wind power sector
Policy incentives

ABSTRACT

Clean energy technology innovation is never an isolated process within the energy sector. The influence of related industrial sectors on clean energy innovation has, however, not been extensively studied. In this paper, we examine how the structure of existing related industrial sectors, which we name as the inter-sector network, affects clean energy technology innovation. We present a novel approach to measuring various characteristics of the inter-sector network. Using panel data of 61 countries from 1997 to 2012, we test the impacts of three key structural attributes of the inter-sector network—size, strength, and proximity—on innovation performance in the wind power sector. We have three major findings: 1) A country with more industries related to the wind industry is likely to have higher knowledge generation and market deployment in the wind power sector; 2) A country with more globally competitive industries related to wind power is likely to have higher market deployment of wind technologies, but it does not significantly affect knowledge generation; 3) A inter-sector network that is more closely related to the wind industry facilitates knowledge generation but may hinder wind technology deployment. These findings highlight the double-sided impacts of the inter-sector network on clean energy innovation. Our findings also suggest the need for industrial policies to foster interactions between clean energy sectors and their related manufacturing sectors.

1. Introduction

Clean energy innovation plays essential roles in efforts to combat climate change, promote economic competitiveness, and achieve global energy security. Countries around the world have increasingly adopted policies to accelerate clean energy innovation. By the end of 2015, 165 countries had implemented various renewable energy policies, including 82% of high-income countries, 80% of high-middle countries, 67% of middle-low income countries, and 62% of low-income countries (REN21, 2016). While these policy initiatives have contributed to the rapid progress in renewable energy development in many countries (Lewis, 2007; Nemet, 2009), success in transitioning to clean energy sources varies. For example, China, India, Brazil, and many developed countries have witnessed robust growth in renewable energy innovation. On the contrary, some developing countries which implemented similar policies still lag in clean energy technology development and adoption. Consequently, identifying additional factors that influence the pace of a country's clean energy innovation is important for accelerating the transition to clean energy systems in developing countries and ultimately promoting global energy technological change.

Among non-policy factors, existing research has identified that knowledge base (Murphy, 2001), technological paradigms (Geels, 2004), economic development (Grossman and Krueger, 1991) and actor interactions (Lacasa and Shubbak, 2018) influence the pace of clean energy innovation. Clean energy innovation is built on multidisciplinary knowledge. Thus, it is not an independent process, but rather a systematic process depending on various supporting sectors (Porter, 1990; Adner, 2006). However, minimal research has been devoted to exploring the impacts of other related industrial sectors on clean energy innovation. A few qualitative case studies suggest that the rapid development of China's solar photovoltaic

* Corresponding author.
E-mail addresses: Fang.Zhang@tufts.edu (F. Zhang), ttang4@fsu.edu (T. Tang), sujun@tsinghua.edu.cn (J. Su), keman@mit.edu (K. Huang).

https://doi.org/10.1016/j.jclepro.2020.121287
0959-6526/

(PV) industry benefit from the country's strength in electronics manufacturing and its investment in the semiconductor industry (Quitzow et al., 2017). Similarly, China's capacity for heavy industry and generator manufacturing has supported the exponential growth of its wind power sector (Lewis, 2013). In addition, the prices of certain strategic raw materials used for wind power can have substantial impacts on the generation costs of wind projects (Blanco, 2009). To the best of our knowledge, there has been one study that empirically examines the impacts of related industrial sectors on clean energy innovation and it only tests the impacts of one complementary sector, the semiconductor industry, on solar PV innovation (Choi and Anadon, 2014). Little research has been conducted to identify all supporting sectors for a specific clean energy technology and how these related industrial sectors affect the development and adoption of the emerging clean energy technology.

To fill this intellectual gap, this paper provides an in-depth investigation of the related industrial sectors and examines their impacts on clean energy innovation. Following the systemic perspective (Gallagher et al., 2012), we define clean energy innovation as a process that starts from the research and development (R&D) of new clean energy technology and proceeds to demonstration and large-scale deployment. We draw on the product space theory (Hidalgo et al., 2007; Mendonça, 2009; Heimeriks and Boschma, 2013; Colombelli et al., 2014; Tanner, 2015) and introduce a comprehensive approach to measuring the structure of a country's industrial sectors that are related to the clean energy sector, referred to as the "inter-sector network", hereinafter. The inter-sector network consists of manufacturing sectors that are related to a specific clean energy sector, such as wind power, solar PV, or energy efficiency. The related manufacturing industries can promote clean energy innovation by providing knowledge spillovers, offering supplementary assets, and establishing the legitimacy of emerging technologies.

In this paper, we use the wind power sector to conduct an empirical analysis regarding whether inter-sector networks can shape clean energy innovation performance and, if so, what structural characteristics prompt better innovation performance on a national scale. The wind power sector is ideal for exploring the impacts of inter-sector networks on energy innovation. Wind power relies on extensive multi-disciplinary cooperation between related industries as a wind turbine has more than 8,000 components which require a high level of precision and compatibility among different components to ensure reliable operation. As a result, the improvement of wind turbine manufacturing is dependent on the productivity of the networked enterprises which specialize in each wind turbine component. While there are technological differences between wind power and other clean energy technologies, they share some commonalities regarding technological complexity and the rigorous component compatibility required for successful operation. Even the highly modularized solar PV industry relies on cooperation between different product segments to facilitate continuous innovation (Zhang and Gallagher, 2016). Hence, the findings of this research are applicable beyond the scope of the wind power sector.

This research provides three major contributions to the existing literature on clean energy innovation and has important policy implications. First, this study extends the existing literature on clean energy innovation system by introducing the inter-sector network factor to the innovation system and highlighting the importance of a country's existing industrial structure to clean energy innovation. Second, it presents a novel approach to measuring various structural characteristics of the inter-sector network for the wind power sector, including size, strength, and proximity, which can be applied to many other clean energy sectors in future research. Third, this paper is the first of its kind to empirically test the influence of inter-sector network on energy innovation by using a large sample at the country level, which overcomes the limited generalizability of previous case studies. Our empirical findings on the double-sided impacts of the inter-sector network on clean energy innovation have important implications for energy technology policymakers. In addition to existing energy policies that promote the development and deployment of clean energy technologies, our findings suggest the necessity of industrial policies that foster interactions between the emerging clean energy sector and its related industrial sectors. This is particularly important for countries that are struggling with clean energy transition.

This paper is organized as follows. Section 2 provides the theoretical framework and proposes the key hypotheses. Section 3 describes the data and major variables. Section 4 presents the empirical models and results. We discuss our findings and conclude the paper in Section 5.

2. Theoretical framework

2.1. Main drivers of clean energy innovation

Clean energy innovation faces various economic, technological, and political barriers. First, unpriced negative environmental externalities of fossil fuels and knowledge spillovers often lead to underinvestment in clean energy development and deployment from the private sector (Jaffe et al., 2005; Tang and Popp, 2016). Second, the adoption of renewable energy technologies suffers from the intermittency of these energy sources, which imposes greater challenges to grid reliability than fossil fuel technologies. Additionally, existing infrastructure and institutional systems that support the incumbent fossil fuel energy system create political resistance during attempts to transition to clean energy (Jennie and Wilson, 2016). Hence, identifying the key drivers for clean energy innovation is crucial to overcoming barriers and accelerating the pace of clean energy innovation.

The existing literature emphasizes the role of policy incentives in addressing barriers to clean energy innovation (Lewis, 2007; Nemet, 2009; Campisi et al., 2015, 2016). Clean energy technology innovation policies are often classified into two major categories: 1) technology-push policies that subsidize the clean energy R&D activities, and 2) demand-pull policies that stimulate market demand for clean energy technologies (Nemet, 2009). Technology-push policies, such as public R&D funding, can incentivize more R&D activities to generate new knowledge, and improve absorptive capacity (Johnstone et al., 2010; Lindman and Söderholm, 2016). Demand-pull policies, such as feed-in tariffs (FITs), renewable portfolio standards (RPS), and tax credits, subsidize market deployment, which can provide feedback to improve emerging technologies, and in turn, drive new knowledge generation (Johnstone et al., 2010; Lindman and Söderholm, 2016). The RPS is widely adopted at the state level in the United States while most European countries use FITs to accelerate the innovation and deployment of clean energy technologies. Existing studies have indicated their high effectiveness in promoting clean energy innovation (Green and Vasikakos, 2011; Kim and Tang, 2020; Sarasa-Maestro et al., 2013).

Another stream of literature emphasizes multiple learning mechanisms that can contribute to the creation and diffusion of new technologies. New knowledge can be generated from R&D activities to reduce production costs of an energy system, which is referred to as learning-by-searching (Junginger et al., 2005; Qiu and Anadon, 2012; Tang, 2018). Less codified or tacit knowledge (know-how) can also be acquired through learning-by-doing. Empirical studies have shown that installation and operational experience accumulated through the deployment of wind and solar energy technologies facilitates cost reduction, and in turn, accelerates large-scale deployment (Qiu and Anadon, 2012; Nemet, 2012; Grafstrom and Lindman, 2017). Furthermore, interaction between actors across different innovation phases in the national innovation system, or across countries can facilitate new knowledge spillovers and technology transfer and induce technological progress (Binz and Anadon, 2018; Grafstrom and Lindman, 2017; Junginger et al., 2005; Lewis, 2007; Tang and Popp, 2016; Tang, 2018).

While existing empirical research on clean energy innovation has acknowledged the influence of cross-actor, cross-stage, and cross-country interactions, the horizontal interaction among different industrial sectors in the energy innovation system has not yet been extensively investigated. The importance of inter-sector interaction has been increasingly discussed in innovation ecosystem theory (Adner, 2006), industry synergy theory (Mendonça, 2009) and product space theory (Colombelli et al., 2014; Hidalgo et al., 2007; Heimeriks and Boschma, 2013; Tanner, 2015). These new theories emphasize that most breakthrough innovations do not occur in isolation, but rather depend on their external innovation ecosystem – which refers to the collaborative arrangements through which innovators combine their individual offerings with external providers of complementary resources and supportive infrastructure to form a coherent solution (Adner, 2006). As clean energy innovation often involves interdisciplinary knowledge and expertise, cross-sector interaction plays an even more vital role. There is, however, only a handful of qualitative case studies that recognize that technological innovation in wind energy and solar PV relies on one or more supportive sectors (Lewis, 2013; Quitzow et al., 2017). Quantitative analysis is also rare and has only examined one key input sector, the semiconductor sector, on solar innovation (Choi and Anadon, 2014). Thus, this paper extends existing clean energy innovation studies by introducing a comprehensive approach to measuring cross-sector interactions and investigating to what extent the inter-sector network shapes a country's trajectory of clean energy innovation.

Notably, besides the factors discussed above, existing research also identifies socio-economic factors that affect a country's clean energy innovation and technological change, such as energy prices (Popp, 2002), natural resource endowments (Huenteler et al., 2018), social-technology regime (Geels, 2004), economic growth (Grossman and Krueger, 1991), market signals from the electricity market (Hiroux and Saguan, 2010) and innovative financial tools (Morea and Poggi, 2017; Campisi et al., 2018). We control most of them in our empirical models when we examine the impacts of the inter-sector network.

2.2. Hypotheses: inter-sector network and clean energy innovation

In this paper, we mainly draw on the product space theory to develop our theoretical framework. Originating from the development economics and economic geography, the product space theory argues that technology, capital, institutes, and skills needed to develop newer technological sectors are more easily adapted from some sector than from others (Colombelli et al., 2014; Heimeriks and Boschma, 2013; Tanner, 2015). New technology development is not only path-dependent but also place-dependent as well (Heimeriks and Boschma, 2013). Countries are more likely to expand into new industries, such as the green industries, that are closely related to those they currently produce (Hidalgo, 2007; Hamwey et al., 2013; Fraccascia et al., 2018).

Considerable research indicates that the related industrial sectors can facilitate clean energy innovation through multiple mechanisms as shown in Fig. 1. For example, knowledge spillovers from established industries to the emerging sector can occur through the flow of talents, intermediaries or capital assets (Hippel, 2007). Related sectors can provide a clean energy sector with crucial assets, such as specialized manufacturing capabilities, distribution channels, service networks, and complementary technologies which are closely related to the engineering and commercialization of the emerging technologies (Rothaermel, 2001; Rothaermel and Hill, 2005). For example, as steel accounts for 89% of all materials used in a typical wind turbine (Bolinger and Wiser, 2012), the wind power sector can benefit from the iron and steel industry's pre-established manufacturing expertise, infrastructure, and products. Furthermore, during the process of technology adoption and development, related sectors can help facilitate social acceptance and legitimacy for the emerging industries through their pre-existing institutional systems (Baum et al., 2000; Jacobsson and Bergek, 2004).

In this paper, we define the inter-sector network as the existing industrial sectors that are related to the clean energy sector in a country. Specifically, we investigate the inter-sector network for the wind power sector in this study. Integrating the product space theory and the network analysis literature, we investigate the impacts of three structural features of the inter-sector network, namely the number of related sectors in the inter-sector network (Rodan and Galunic, 2004; Hidalgo et al., 2007; Chiu, 2009), the average competitiveness of these related sectors in the inter-sector network (Choi and Anadon, 2014; Porter, 1990; Rigby, 2015), and the average proximity between these related sectors and the wind power sector (Chiu, 2009; Boschma et al., 2013). We propose the following three hypotheses to test the impacts of the inter-sector network on wind energy innovation.

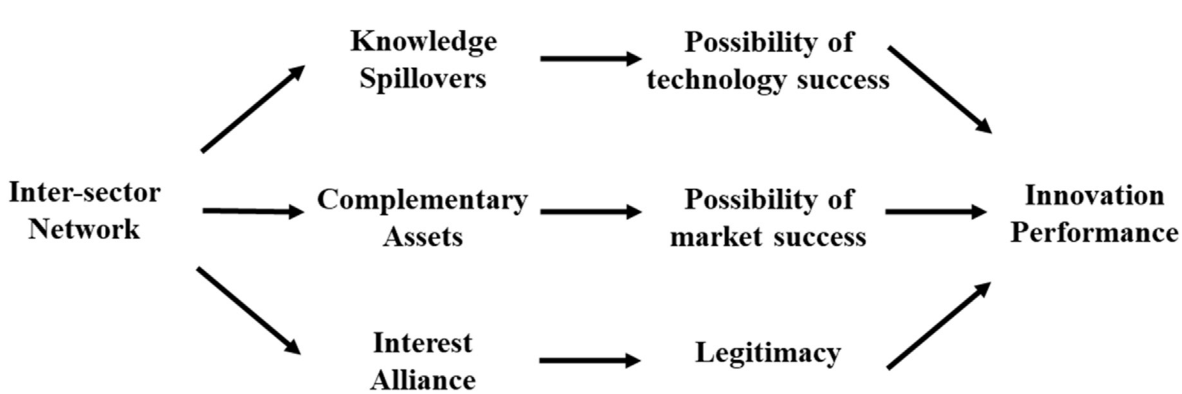

Fig. 1. Mechanisms of the network of related sectors influencing innovation performanceData
source: summarized by authors based on Hippel (2007), Rothaermel (2001), Rothaermel and Hill (2005), Baum et al. (2000) and Jacobsson and Bergek (2004).

Product space theory argues that countries are able to spread to new sectors if they are already able to produce related products around the new sectors (Hidalgo et al., 2007). If a country has more related industries to the new industrial sector, it is more likely to produce related products around the new sector. Hence, the first factor we examine is the size of the inter-sector network, which refers to the number of industrial sectors that are related to the emerging clean energy sector. A larger network of related industries often indicates a larger knowledge base and pool of resources. The extent of an emerging sector's access to information, resources, and linkages usually determine its ease in exploiting current knowledge and learning about upcoming industrial changes (Rodan and Galunic, 2004; Chiu, 2009). In this study, we assume a positive relationship exists between the number of related industrial sectors for wind power and the innovation performance of the wind industry in a country. Thus, we test the following hypothesis:

H1. A country with a larger inter-sector network related to the wind power sector is more likely to have better innovation performance in its wind industry.

Countries follow a diffusion process in which comparative advantages move preferentially toward technological sectors close to existing sectors (Hidalgo et al., 2007; Fraccascia et al., 2018). An emerging sector embedded in a network of efficient and competitive industries has a better industrial foundation to develop its own strength (Porter, 1990; Rigby, 2015). For example, the strength of a country's semiconductor industry is an important determinant of solar PV manufacturing and deployment (Choi and Anadon, 2014). Similarly, if a country's steel and iron industry and generator manufacturing are globally competitive, it provides strong support, in terms of materials, human resources, and manufacturing experience, for the development of the wind industry (Lewis, 2013). In this study, we use the strength of the inter-sector network to describe the global competitiveness of the related industries in a country. We test the relationship between the strength of the inter-sector network for wind power and wind technology innovation:

H2. A country with a stronger inter-sector network related to the wind power sector is more likely to have better innovation performance in its wind industry.

Countries move easily through the product space by developing goods close to those they currently produce (Hidalgo, 2007; Fraccascia et al., 2018). Network proximity refers to the extent to which a sector is closely tied to other industries in the network. Some research argues that strong connection facilitates the exchange of knowledge and complementary assets, which are key ingredients for innovation success (Chiu, 2009). Emerging sectors that are more closely related to existing industrial networks tend to utilize the existing knowledge and resources to ease the development process (Boschma et al., 2013; Colombelli et al., 2014; Heimeriks and Boschma, 2013; Tanner, 2015). Other studies, especially those from social networks and innovation, however, claim that innovators actually receive novel information from weak ties rather than strong ties (Granovetter, 1973). Some distance provides innovators with fewer constraints and better maneuverability, which permits greater leeway to pursue novel and relatively unsanctioned entrepreneurial activities (Rodan and Galunic, 2004; Gilsing et al., 2008). In this paper, we also investigate the relationship between network proximity and innovation in a country's wind industry.

H3. A country with an inter-sector network that is more closely related to the wind power sector is more likely to have better innovation performance in its wind industry.

3. Methods

3.1. Sample

To test the impacts of the inter-sector network on wind technology innovation, we construct a panel of 61 countries from 1997 to 2012. Table 1 lists all the countries in our sample. These countries are selected from the Global Wind Energy Council (GWEC) database if they report any wind power installation by the end of 2014. As shown in Table 1, our sample countries reflect great diversity in terms of region, economic development, industrial structure, and political and cultural environment. Thus, the findings of this study have great generalizability to other countries with similar socio-economic status.

3.2. Basic model

We use the following empirical model as shown in Equation (1), to examine how different inter-sector network features affect innovation in a country's wind power sector:

$$Innovation_{i,t} = \beta_1 Network_{i,t} + \beta_2 X_{i,t} + Year_{dummies} + \mu_{i,t} \tag{1}$$

where $Innovation_{i,t}$ represents the innovative activities in the wind power sector of country i in year t. $Network_{i,t}$ represents the variables that measure key attributes of the inter-sector network for wind power in country i in year t, while $X_{i,t}$ is the vector of other control variables, including policy instruments that support wind innovation, wind resource endowment and economic status of country i in year t. We include year dummies to control time-varying unobservable factors for all countries, such as global technological change and progress on climate change actions, as well as economic shocks.

3.3. Dependent variables

Three types of innovation measurements are commonly used in the clean energy technology innovation literature: 1) input indicators, such as R&D investments and the number of researchers; 2) output indicators, such as patents and publications; and 3) outcome indicators, such as market size and new product values. All of these indicators have their strengths and shortcomings. Given the data availability for cross-country analysis, we use two indicators—patent applications and installed capacity of wind power—to measure the performance of R&D activities and market deployment of wind technologies respectively, which are two major stages in the innovation process as we defined in the introduction.

We use the number of wind power patents applied by inventors from country i in year t ($Npatent_{i,t}$) to measure knowledge generation in a country's wind power sector in a given year (Johnstone et al., 2010). [1] The nationality of each patent application is identified based on the physical location of its inventors. If a patent is shared among inventors from different countries, we add one application to each country. As different countries have different timeframes and criteria for approving a patent application, patent applications can better capture the immediate output of R&D activities and avoid any inconsistency due to the different patent review processes across countries. The wind patent application data is collected from the PATSTAT database by using the International Patent Classification (IPC) F03D.

[1] All patent applications are dated by the priority date, which is the initial date that the application was filed.

Table 1
Sample countries by income category.

Types	Numbers	Countries
High-income countries	32	Austria, Australia, Belgium, Canada, Chile, Croatia, Cyprus, Czech Republic, Denmark, Estonia, France, Finland, Germany, Greece, Hungary, Ireland, Italy, Japan, Lithuania, Luxembourg, Netherlands, New Zealand, Norway, Portugal, Poland, Span, Sweden, Switzerland, South Korea, United Kingdom, United States, Uruguay
Middle-income countries	12	Algeria, Argentina, Brazil, China, Costa Rica, Iran, Mexico, Peru, Romania, South Africa, Thailand, Turkey
Low-income countries	17	Bulgaria, Egypt, Ethiopia, Honduras, India, Kenya, Latvia, Morocco, Mongolia, Nicaragua, Pakistan, Philippines, Tunisia, Tanzania, Ukraine, Uganda, Vietnam,

Note: The classification of income is based on the Atlas method (in 2016 US Dollar) by the World Bank[51].

Table 2
Three approaches to measuring inter-sector relatedness.

Approach	Basis of the relatedness	Measures and data	Literature
I	Underlying technological knowledge	Patent data, such as co-patenting	Kauffman et al. (2000)
II	Inputs for production in different sectors	Input-output data for products, including raw materials, immediate products, and labors, etc.	Feser and Bergman (2000); Feser (2005); Choi and Anadón (2014)
III	Production capacity and management skills of different sectors	Trade data to measure co-location of different sectors in a country	Hidalgo et al., 2007

Data Source: summarized by the authors based on Kauffman et al. (2000), Feser and Bergman (2000), Feser (2005), Choi and Anadón (2014), and Hidalgo et al. (2007).

Our second dependent variable, the newly installed capacity of wind turbines in country i in year t ($Ncapacity_{i,t}$), reflects the market deployment of wind technologies in a country. Market deployment of new technology has been used in many previous innovation studies to measure innovation performance (Lee and Lim, 2001; Mu and Lee, 2005). The ultimate goals of wind technology innovation are to reduce carbon emissions and improve energy sustainability through the large-scale utilization of wind energy in electricity generation. Thus, market deployment of wind technologies is also an important indicator to assess the innovation performance in the wind power sector. Notably, there are several cases that the value of $Ncapacity_{i,t}$ is negative, which refers to the scenario that there are more wind turbines retired than added in that year for a country.

3.4. Inter-sector network variables

There are generally three approaches to measuring inter-sector relatedness as shown in Table 2. We use the co-exportation of products (Hausmann and Klinger, 2006; Hidalgo et al., 2007; Delgado et al., 2015) to calculate the relatedness between industrial sectors. The exportation data is collected from the United Nations Commodity Trade Database (UN Comtrade Database). The calculation of inter-sector relatedness and the selection of wind-related industrial sectors are described in Appendix A. We identify 1991 manufacturing sectors related to the wind power sector. The relatedness between these sectors and the wind power sector ranges from 0.02 to 0.79. Table 3 presents the top 10 most related sectors selected based on our relatedness calculation. Some highly-related sectors provide important inputs for wind equipment manufacturing (Bolinger and Wiser, 2012). For example, glass and woods are the main production materials for turbine blades and electrical boards are key inputs for turbine control systems. Other related sectors, such as cranes and industrial machinery, do not directly provide inputs for the wind industry. However, they have similar production capacity with wind turbines. For example, most of the wind turbine manufacturers in China originated from or are supported by big heavy industry machinery manufacturers (Lewis, 2013).

With the list of sectors related to wind power identified using the above method, we then use the UN Comtrade Database to determine if country i exports products from each of the related sectors on our list in year t. If so, those sectors that country i has exports will be included in the inter-sector network for the wind power sector in country i.

Table 3
The top 10 related sectors and their relatedness to the wind power sector.

Ranks	Sectors	Relatedness
1	Glass; carboys, bottles, flasks etc.	0.79
2	Electrical circuit protectors nes for <1,000 V	0.74
3	Cranes or derricks	0.71
4	Furniture, wooden, nes	0.70
5	Industrial machinery nes	0.70
6	Electrical boards, panels, etc	0.67
7	Parts of refrigerating or freezing equipment	0.67
8	Reservoirs/tanks/vats/etc, iron/steel capacity >300l	0.67
9	Sanitary ware and parts thereof, iron or steel, nes	0.67
10	Silverwares, silverware plated with precious metal	0.65

Data source: Authors calculated the relatedness based on methods and data sources described in Appendix A.

The three structural features of the inter-sector network are measured as follows:

1) The Size of the inter-sector network (*$N\_size_{i,t}$*) is measured as the number of related sectors included in country i's inter-sector network in year t.

2) The strength of the inter-sector network (*$N\_strength_{i,t}$*) is measured as the ratio of the number of related sectors that country i has comparative advantages in year t ($N_{RCA_{i,t}}$) to the size of its inter-sector network ($N\_size_{i,t}$), as shown in equations (2) and (3). [2]

$$N_{strength_{i,t}} = \frac{N_{RCA_{i,t}}}{N_{size_{i,t}}} \tag{2}$$

[2] In equation (2), $RCA_{r,i,t}$ stands for revealed comparative advantage, which measures whether country i exports more products from sector r, as a share of its total exports, than the average share in the world. $RCA_{r,i,t} = 1$ if $\frac{x(i,r,t)}{\sum_r x(i,r,t)} / \frac{\sum_i x(i,r,t)}{\sum_{i,r} x(i,r,t)} > 1$. $RCA_{r,i,t} = 0$ if $\frac{x(i,r,t)}{\sum_r x(i,r,t)} / \frac{\sum_i x(i,r,t)}{\sum_{i,r} x(i,r,t)} \leq 1$, where $x(r.i.t)$ represents the total value that country i exports products from sector r in year t.

Table 4
Summary statistics.

Variables	Units	Number of observations	Mean	SE	Mini.	Maxi.	Definitions
$Ncapacity_{i,t}$	MW	976	284	1296	−5	18928	Newly installed wind capacity
$Npatent_{i,t}$	Count	976	97	313	0	3140	New wind patent applications
$N\_Size_{i,t}$	–	976	1431	434	61	1985	Size of inter-sector network
$N\_strength_{i,t}$	–	976	0.2	0.1	0.04	0.6	Strength of inter-sector network
$N\_Proximity_{i,t}$	–	976	0.3	0.03	0.22	0.39	Proximity of inter-sector network
$Policy\_support_{i,t}$	–	976	1	2	0	7	Policy incentives
$Cpatent_{i,t-1}$	Count	915	564	1724	0	19441	Cumulative patent applications in previous year
$Ccapacity_{i,t-1}$	MW	915	1241	4705	0	62412	Cumulative installed capacity in previous year
$GDP\_per\_capita_{i,t}$	$/capita	976	16563	185053	110	99100	GDP per capita
$Land_i$	100km2	976	12028	23505	26	93882	land area

Data source: 1) capacity data is from World Wind Energy Association (WWEA), 2) patent data is from; 3) policy data is from the International Energy Agency and International Renewable Energy Agency (IEA/IRENA), 4) GDP per capita and land areas are from World Bank, and 5) network indicators are calculated based on data from the United Nations Commodity Trade Database.

$$N_{RCA_{i,t}} = \sum_{1}^{n} RCA_{r,i,t} \quad (3)$$

$$where\ n = N_{size_{i,t}}$$

3) The proximity of the inter-sector network (*$N\_proximity_{i,t}$*) refers to the average relatedness of sectors within the inter-sector network for wind power in country *i* year *t*. We calculate network proximity by using equation (4).

$$N_{proximity_{i,t}} = \frac{\sum_{1}^{n} Relatedness_{r,w,t}}{n} \quad (4)$$

$$where\ n = N_{size_{i,t}}$$

3.5. Control variable: policy instruments

Measuring policy intervention is challenging, especially when conducting a cross-country analysis. We construct policy variables based on the seven policy instruments specifically supporting wind power technology innovation identified by Johnstone et al. (2010). These policy instruments include FITs, RPS, tax incentives, loan incentives, capital investment subsidies, R&D investment, and strategic planning. First, we control the intensity of policy incentives for wind power innovation, which is measured as the number of types of policy tools that a country has adopted out of the above seven policy instruments ($Policy\_support_{i,t}$). The value of $Policy\_support_{i,t}$ ranges from 0 to 7. This is not a perfect indicator because the same policy tool may have different designs and implementation across countries. A country may just adopt one policy, but the stringency and efficiency of this policy tool can be high enough to compete with countries with a variety of policies. However, it is reasonable to believe that a country has a stronger political desire to incentivize clean energy innovation if the government adopts more clean energy policies, which in turn implies a stronger policy intervention. All policy data is collected from the annual reports of the World Wind Energy Association (WWEA) and the International Energy Agency and International Renewable Energy Agency (IEA/IRENA) Joint Policies and Measures Database.

3.6. Other control variables

We also control for available wind resources, knowledge stock, previous market deployment, and the economic status of a country. We use the land area of a country *($land_i$)* to measure available wind resources in a country, as smaller land areas often correspond with fewer wind resources. The level of a country's economic development can shape a country's financial and technological capacity to spur clean energy innovation (Grossman and Krueger, 1991). We measure it by *GDP* per capita. Existing knowledge stock is measured as the cumulative wind patent applications before year t ($Cpatent_{i,t-1}$) (Tang and Popp, 2016), and existing market deployment is measured as the cumulative wind turbine installation ($Ccapacity_{i,t-1}$). Table 4 provides detailed definitions and summary statistics on all the major variables in our paper.

The pairwise correlations among all variables (Table 5) show that there is no strong correlation between the key network variables. Thus, we include all three network variables in our empirical models. Since there is a high correlation between $Cpatent_{i,t-1}$ and $Ccapacity_{i,t-1}$., we only include one of them in the model to avoid multicollinearity.[3]

4. Empirical results

4.1. Results on knowledge generation

We use negative binomial regression to estimate the knowledge generation models because the dependent variable, wind patent applications ($Npatent_{i,t}$), is a nonnegative count variable (Johnstone et al., 2010). The Hausman test (see Appendix B) indicates that the fixed-effects model is better than the random-effects model. Table 6 reports the results of the fixed-effects model. From model 1 to model 3, we gradually introduce the inter-sector network, policy intensity index, and other control variables.

The results show that the size ($N\_size_{i,t}$) and the proximity ($N\_proximity_{i,t}$) of a country's inter-sector network for wind power are positively associated with the knowledge generation in its wind power sector. These results confirm our first and third hypotheses. A country with a larger inter-sector network that is more closely related to wind turbine manufacturing can provide the wind power sector with diverse and stronger complementary assets, human resources, and knowledge spillovers to facilitate R&D activities in the wind industry. However, the strength of the inter-sector network does not significantly influence wind technology innovation measured by patent applications. In addition to the inter-sector network variables, a country's policy support ($Policy\_support_{i,t}$) is also significantly associated with wind technology innovation.

[5] High-income countries refer to those with a GNI per capita above $12, 476. Middle-income countries are those with a GNI per capita between $4,036 and $12, 475. Low-income countries are those with a GNI per capita of $4,036 or less.

[3] In Tables 6 and 7, we present results for models with $Cpatent_{i,t-1}$. We have also estimated models using $Ccapacity_{i,t-1}$ as a control variable. The results are similar to Tables 6 and 7

Table 5
Correlation analysis among all variables.

Variables	$Ncapacity_{i,t}$	$Npatent_{i,t}$	$N\_Size_{i,t}$	$N\_strength_{i,t}$	$N\_proximity_{i,t}$	$Policysupport_{i,t}$	$Cpatent_{i,t-1}$	$Ccapacity_{i,t-1}$	$GDP\_per\_capita_{i,t}$	$Land_i$
$Ncapacity_{i,t}$	1									
$Npatent_{i,t}$	0.43	1								
$N\_Size_{i,t}$	0.25	0.18	1							
$N\_strength_{i,t}$	0.33	0.28	0.24	1						
$N\_proximity_{i,t}$	−0.14	−0.17	−0.15	0.04	1					
$Policy\_support_{i,t}$	0.52	0.33	0.47	0.33	−0.12	1				
$Cpatent_{i,t-1}$	0.92	0.60	0.27	0.39	−0.15	0.50	1			
$Ccapacity_{i,t-1}$	0.64	0.79	0.22	0.34	−0.08	0.39	0.80	1		
$GDP\_per\_capita_{i,t}$	0.32	0.11	0.43	0.25	−0.06	0.57	0.35	0.22	1	
$Land_i$	0.18	0.37	0.19	0.07	−0.41	0.25	0.25	0.28	0.01	1

Table 6
Results on knowledge generation.

	Dependent variable: $Npatent_{i,t}$		
	Model1	Model 2	Model 3
$N\_size_{i,t}$	0.003*** (0.0003)	0.002*** (0.0003)	0.003*** (0.0004)
$N\_strength_{i,t}$	0.36 (0.70)	−1.03 (0.63)	1.24 (0.73)
$N\_proximity_{i,t}$	9.33*** (1.82)	10.61*** (1.85)	5.66*** (2.04)
$Policy\_support_{i,t}$		0.36*** (0.86)	0.15*** (0.03)
$Cpatent_{i,t-1}$			0.00003*** (0.00001)
$GDP\_per\_capita_{i,t}$			6.6e-6** (2.9e-6)
Year fixed effect	NO	NO	YES
Country fixed effect	YES	YES	YES
Constant	−8.03***	−7.00***	−5.50***
Observations	848	848	795
Log likelihood	−2778	−2704	−2488
Wald Chi	104	310	877
Prob>chi	0.000	0.0000	0.000

Notes: ***P < 0.01, **P < 0.05, *P < 0.1.

4.2. Results on market deployment

We use Tobit regression to estimate market development models. Many countries in our sample did not have wind installations for multiple years. Since the dependent variable ($Ncapacity_{i,t}$) in the market deployment model is a typical limited dependent variable, which has a truncated normal distribution rather than a standard normal distribution, we use left-censored Tobit to estimate market deployment models (Wooldridge, 2010;).

Table 7 reports the results of market deployment models. In models 1–3, we gradually introduce the inter-sector network and policy support variables, as well as other control variables.

The consistent results across the three models suggest that the size of the inter-sector network and its strength have positive impacts on wind power market deployment across countries. However, the proximity of the inter-sector network shows significant negative impacts on wind power market deployment across all models. The finding regarding the size of the inter-sector network is consistent with our findings on knowledge generation in the wind power sector, which confirm our first hypothesis that a country will have better innovation performance in its wind industry if the country has a larger inter-sector network. The strength of the inter-sector network, measured as the competitiveness of the industries related to the wind industry, has positive impacts on the market deployment of wind technologies. While a country with an inter-sector network that is more closely related to the wind power

Table 7
Results on market deployment.

	Dependent variable: $Ncapacity_{i,t}$		
	Model1	Model 2	Model 3
$N\_size_{i,t}$	1.80*** (0.54)	1.75*** (0.54)	1.1** (0.50)
$N\_strength_{i,t}$	6631*** (1620)	6537*** (1625)	4489*** (1558)
$N\_proximity_{i,t}$	−23134*** (6024)	−22199*** (6200)	−24588*** (6450)
$Policy\_support_{i,t}$		37.65 (59)	122* (59)
$Cpatent_{i,t-1}$			0.34*** (0.03)
$GDP\_per\_capita_{i,t}$			−0.04*** (0.01)
Year fixed effects	YES	YES	YES
Country fixed effects	YES	YES	YES
Constant	4170*	3869	5669***
Observations	974	974	957
Left_censored observations	416	416	403
Log likelihood	−4880	−4880	−4792
Wald Chi	612	614	820
Prob>chi	0.000	0.000	0.000

Notes: ***P < 0.01, **P < 0.05, *P < 0.1.

sector tends to have more wind patent applications, the proximity of the network has significant negative impacts on market deployment.

Consistent with existing clean energy innovation studies, results from model 3 confirm that strong policy support leads to higher deployment of wind power in a country. Interestingly, we observe a significant and negative impact of a country's GDP per capita on the market deployment of wind power. There are two possible explanations for this negative relationship between GDP per capita and market deployment of wind turbines. One is the technological lock-in assumption that developed countries have been locked in traditional energy technologies and are more difficult to transition to clean energy technologies. In contrast, developing countries with lower incomes have not been locked-in and tend to be easier to leapfrog to new energy technologies. Alternatively, this negative relationship may be distorted by the "emerging economy effect", where emerging economies such as China and India, have lower GDP per capita than the developed countries in our sample (see Table 1). However, they have much higher annual wind installed capacity compared with most of the high-income countries in the sample.[4]

5. Discussion and conclusion

Using panel data from the wind power sector of 61 countries between 1997 and 2012, this paper examines the impacts of the inter-sector network on clean energy innovation. Building on the product space theory from geography economics, this study introduces a novel method to measure a country's inter-sector network related to a specific clean energy sector, such as the wind power sector, based on the similarity of production capacity between different manufacturing sectors. With the novel measurements, we provide the first empirical analysis that comprehensively tests the influences of different inter-sector network features, including the size, strength, and proximity of the inter-sector network, on knowledge generation and market deployment of wind energy technologies. Our comprehensive analysis provides the following insights into the roles of the inter-sector network in clean energy innovation across countries.

5.1. Developing clean energy innovation based on existing inter-sector networks

This paper extends the existing clean energy innovation framework by highlighting the importance of related industrial sectors to the emerging clean energy sector. In addition to energy policy instruments, knowledge base, and political and economic factors that have been identified by previous clean energy innovation research, our empirical findings indicate the critical roles of a country's inter-sector industrial network in its clean energy innovation. The inter-sector network can affect clean energy innovation in both positive and negative ways.

Moreover, our paper sheds light on the network features that are most influential in different stages of wind technology innovation. First, our findings suggest that a country with a larger inter-sector network comprised of globally competitive industries related to wind turbine manufacturing tends to be in a more propitious position for both knowledge generation and market deployment of wind technology. Second, an inter-sector network that is more closely related to the wind power sector can benefit knowledge generation in the wind industry. A potential explanation is that a closer relationship between the wind power sector and its related industrial sectors spurs more knowledge spillovers and therefore facilitates the creation of new knowledge in the wind industry. In contrast, we find that higher relatedness of an inter-sector network is negatively associated with wind installation. It could be that actors from closely related sectors have inertia to transit to the renewable energy sector or they have more direct competition with the wind power sector for resources in the market. Third, an inter-sector network with more sectors having comparative advantages promotes wind power market deployment. However, its impacts on knowledge generation are not clear. A possible explanation is that sectors that are globally competitive often have more financial resources. When firms from these related sectors extend their business to the wind power sector, they have enough financial capacity to develop the capital-intensive wind equipment supply-chain. It is also possible that the involvement of globally competitive firms can increase the social acceptance and legitimacy of wind power technologies, which speed up the market formation. Further qualitative research is needed to explore these alternative explanations.

The impacts of inter-sector networks indicate that a country's selection of clean energy technologies should be aligned with its existing industrial sectors. Specifically, governments should carefully assess the structure and strength of their existing industrial sectors and prioritize the development of clean energy sectors that have strong pre-existing inter-sector networks. The lack of a robust inter-sector network for an emerging clean energy sector may slow the innovation process and result in a waste of public financial resources. Meanwhile, to maximize the potential benefits from existing industrial sectors, governments can facilitate dynamic exchanges between emerging clean energy industries and their inter-sector networks in terms of knowledge, information, and resources. Particularly, governments may need to encourage incumbent actors within the existing inter-sector networks, especially those from sectors with strong competitiveness, to break down their inertia and actively share their knowledge and financial assets with the emerging energy sectors. This interaction will not only promote clean energy innovation but also revive the traditional sectors.

5.2. Implications for clean energy technology leapfrogging in developing countries

An ongoing debate argues that developing countries lag in clean energy transition due to the inability to mitigate their domestic pollution or the transfers of pollution from developed countries (Grossman and Krueger, 1991). Others, however, suggest that developing countries can leapfrog to clean energy systems because they are not locked in polluting technologies with high carbon footprints (Goldemberg, 1998). Leapfrogging may take place in the energy sectors of developing countries under certain conditions, such as adequate access to foreign technologies, absorptive capacity, complementary assets, global learning network, appropriate policy incentives, and organizational and institutional capacities (Murphy, 2001; Lee et al., 2005; Lewis, 2007). In addition to these conditions, our findings suggest that countries may be further bounded by the size, strength, and proximity of their inter-sector networks for clean energy innovation.

On a global scale, developing countries especially tend to have relatively weak industrial networks, which further inhibits their success in the transition to clean energy. For example, as shown in Appendix C, less-developed countries have smaller inter-sector networks that consist of less competitive industries compared with developed countries. Furthermore, inter-sector networks for clean energy sectors cannot be easily constructed and are rarely

[4] We also estimate the model after dropping China, India and Brazil from our sample. The coefficients on GDP per capita becomes statistically insignificant.

influenced by energy policy intervention. Therefore, when designing global climate change initiatives, policymakers may need to take into account the constraints of countries with underdeveloped inter-sector networks and provide them with more policy support.

5.3. Implications for clean energy innovation policy designs

Current clean energy policy studies based on the technology-push and demand-pull policy framework focus on testing what types of demand-side or supply-side energy policy instruments effectively stimulate clean energy technology innovation (Nemet, 2009; Johnstone et al., 2010; Lindman and Söderholm, 2016). The importance of inter-sector networks has not gained enough attention in policymaking. Our paper indicates that in addition to technology-push and demand-pull policies for clean energy technologies, policymakers should think beyond a specific clean energy sector, and strategically develop industrial policies that foster interactions between emerging clean energy sectors and existing related industries. These inter-sector industrial policies can be government R&D programs that support cross-sector R&D, technological training programs that incentivize talent mobility from existing industrial sectors to clean energy sectors, or other industrial policies that could enhance interactions across clean energy sectors. Currently, limited attention has been paid to empirically investigate the designs of these industrial policies and their impacts on clean energy innovation. More research needs to be conducted to explore what types of industrial policies serve to enhance interactions between clean energy sectors and related manufacturing sectors, as well as how these policies can be designed to work effectively.

5.4. Implications for theory, limitations and future research

Our findings contribute to both clean energy innovation research and the product space theory. First, our study extends the existing clean energy innovation system literature by identifying and testing the impacts of different features of a country's existing industry structure on clean energy innovation, which has received little attention in previous studies. Second, our study suggests that high relatedness between a country's existing industries and the new clean energy sector may have a "lock-in" effect, which could hinder the rise of the new energy sector. While this finding seems to contradict the main argument of the product space theory, it suggests a new factor to consider, which is the disruptiveness of the new sector. In the wind power case, the incumbent related industries may have stronger inertia to expand to the wind industry as wind power technologies have some disruptive features, which require radical changes from existing technological competencies. Given the current technological competencies in a country's existing industries, it may be easier for an upgrade to a new industrial sector that requires only incremental change rather than disruptive technological change. Whether the validity of product space theory depends on the radicalness of the new sector can be tested in future research.

This study has several limitations worthy of addressing in future research. The first caveat is that our empirical results demonstrate correlations rather than causal relationships between inter-sector network features and wind power sector innovation. Given the data limitation, there are omitted variables that we cannot control, such as innovative financial tools available in each country and other policies, which can affect both the development of the wind industry and its related sectors. While our methodology provides a comprehensive way to identify the related manufacturing sectors for a specific clean energy sector, the inter-sector relatedness is calculated based on trade data for physical products, which excludes service sectors that may also influence clean energy innovation. Furthermore, this paper only examines the impacts of the inter-sector network on the wind power sector innovation in 61 countries. Future research is necessary to determine whether our key findings are applicable to other clean energy sectors or other countries. Another caveat limiting this study is the static, rather than dynamic, nature of the empirical approach used to measure the inter-sector network. As innovation in the clean energy sector advances, the related inter-sector network may change. Future research should seek measures that can better capture the dynamic interactions between the clean energy sector and its related industries.

Funding

This work is supported by BP, the Hewlett Foundation, and one grant from China's National Science Foundation (No.71520107005).

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

CRediT authorship contribution statement

Fang Zhang: Conceptualization, Methodology, Formal analysis, Validation, Investigation, Writing - original draft, Writing - review & editing. **Tian Tang:** Validation, Writing - review & editing. **Jun Su:** Conceptualization, Methodology. **Keman Huang:** Methodology, Formal analysis, Data curation, Investigation, Writing - review & editing.

Acknowledgments

The authors would like to thank Kelly Sims Gallagher, Lan Xue, and Shulin Gu for their valuable suggestions and support regarding our work. All errors remain the sole responsibility of the authors.

Appendix A. Calculation of relatedness and the selection of related industrial sectors for the Wind Power Sector

A.1Calculation of relatedness

Following the research of Hausmann and Klinger (2006) and Hidalgo et al. (2007), the relatedness between the wind power sector and another sector is measured as the probability that a country can export wind turbines and the major product of another sector at the same time. More specifically, the relatedness between sector r and the wind power sector (w) is calculated as the conditional probability that a country exports products from sector r given that it exports products from the wind power sector w. We use the following equations to construct the relatedness between sector r and the wind power sector (w) in a given year:

$$\mathrm{Relatedness}_{i,w,t} = f_{i,j,t} = \min\{P(X_{i,t}|X_{w,t}), P(X_{w,t}|X_{i,t})\} \tag{A.1}$$

$$X_{r,t} = \frac{\sum_{i=1}^{n} x_{i,r,\ t}}{N} \quad (A.2)$$

$$X_{w,t} = \frac{\sum_{i=1}^{n} x_{i,w,\ t}}{N} \quad (A.3)$$

As shown in equation (A.2), *xi,r,t* represents whether country *i* exports *r* in year *t*. $x_{i,r,t} = 1$ if country *i* exports products from sector *r* in year *t*; otherwise, it equals 0. The numerator captures the number of countries exporting *r* in year *t* globally. *N* represents the total number of countries in the world. Thus, $\mathrm{X_{i,t}}$ *is* the probability that a country would export products from sector *r* in year *t*. Similarly, in equation (A.3), $X_{w,t}$ is the probability that a country would export products from the wind power sector (*w*) in year *t*.

$\mathrm{Relatedness_{i,j,t}}$ is the minimum of the pairwise conditional probability of a country exporting products from sector *r* given that it export products from sector *w*. If $Relatedness_{r,w,t} = 1$, it means that any country that exports products from sector *r* also exports wind turbines, thus suggesting sector *r* and the wind power sector are fully related. If $Relatedness_{r,w,t} = 0.75$, it indicates that there is a 75% chance that a country which exports product r will also export wind turbines. Thus, the two sectors are highly related. When $Relatedness_{r,w,t} = 0$, it suggests that the two sectors are not related to each other.

A.2Data collection and processing

We use trade data from the United Nations Commodity Trade Database (UN Comtrade Database) to calculate the inter-sector relatedness and identify sectors related to the wind power sector. The UN Comtrade Database discloses the trade information among 200 countries/regions. It covers almost 99% of the world trade on more than 6,000 product categories for the past 50 years, which provides very comprehensive international trade data for our analysis .

Figure A.1 demonstrates the process of identifying manufacturing sectors related to the wind power sector and constructing the inter-sector network variables. We use two processes to identify the related sectors to the wind power sector.

The first step is a subjective selection based on expert opinions. We had two researchers separately go through the list of the 1996 Harmonized Commodity Description and Coding Systems (HS 1996). The two researchers read through the description of the sectors at the 6-digit (HS-6) level and then excluded those obviously unrelated sectors, such as agriculture and fishery. Through this process, we first identify 2,023 related manufacturing sectors at the 6-digit (HS-6) level from the 1996 Harmonized Commodity Description and Coding Systems (HS 1996). Products in these related sectors are traded among 174 countries according to the UN Comtrade Database.

The second step is an objective selection based on the relatedness calculation method in Section A.1. We use global trade data from 2008 to 2012 to calculate the inter-sector relatedness between the wind power sector (HS 6-digit code: 850231) and each of the 2,023 related sectors previously identified. Based on the calculated relatedness, we exclude sectors which have minimum relatedness with the wind power sector below 0.02. There are two reasons to use 0.02 as a cutoff point. First, 0.02 is quite low, which suggests minimal relatedness. The other reason is the products with relatedness below 0.02 seems to be less significant for the wind power sectors based on our knowledge of the characteristics of the wind turbine manufacturing. As a result, we further narrow the related sectors to 1,991 manufacturing sectors.

We use global trade data from 2008 to 2012 to calculate inter-sector relatedness for two reasons. Firstly, the trade data has not been sufficiently updated for many of our sample countries after 2012. Thus, the latest comprehensive trade data we can obtain for all the countries in the sample is the 2012 data. Secondly, we exclude data before 2008 in our analysis because the wind power sector, particularly wind turbine manufacturing, was under rapid development before 2008, which may not provide a reliable and comprehensive list of manufacturing sectors related to wind power. We then use the 5-year (i.e. 2008-2012) average inter-sector relatedness to refine the list of wind power related industrial sectors. The reason to calculate the 5-year average inter-sector relatedness is to mitigate the year-to-year variance and the impacts of cyclical changes.

The third step is to choose related sectors for each country to construct the national inter-sector network. We compare the list of the wind related sectors and the list of products that a country can

	Coefficient		(b-B) Differences	Sqrt(diag(V-b-V_B) S.E.
	(b) fixed	(B) random		
$N\_size_{i,t}$	0.002	0.003	−0.0009	0.0002
$N\_strength_{i,t}$	0.061	−0.320	−0.263	0.616
$N\_proximity_{i,t}$	8.245	8.508	−0.263	0.616
$Policy\_regulation_{i,t}$	0.262	0.254	0.009	0.007
$GDP\_per\_capital_{i,t}$	0.0002	0.0002	−2.7e-9	7.9e-7
Chi2(5)	33.30		Prob.>chi2	0.000

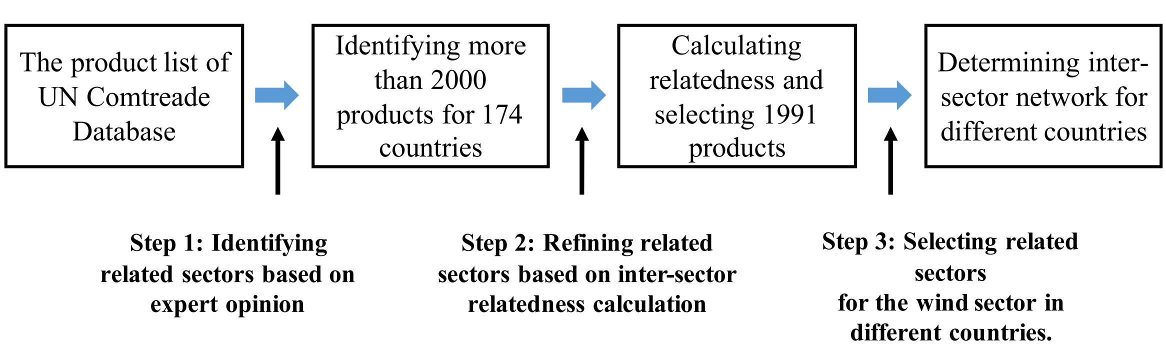

Fig. A.1. Process for building the wind power inter-sector network.

export. The overlaps between the list of export products of a country and the list of the wind related sectors comprise the inter-sector network for the specific country.

Variables		Low-income countries	Middle-income countries	High-income countries
Number of countries		17	12	32
Average value	**$N\_size_{i,t}$**	1239	1495	1640
	$N\_strength_{i,t}$	0.18	0.20	0.25
	$N\_proximity_{i,t}$	0.30	0.30	0.32

Appendix B. Results of the Hausman test

Appendix C. Inter-network characteristics by income level (average value in 2012)

Appendix D. Robustness check by using different estimation methods

To test if our results are robust, we use different methods to estimate our empirical models. Specifically, we use the Poisson regression to run the knowledge generation model, which is another appropriate method for models that use count variables as dependent variables. As shown in Table D-1, the results reconfirm the major conclusions on the positive impacts of size and proximity of the inter-sector network on wind patent applications. The only difference is that the Poisson regression identifies a negative relationship between network strength and patent application once we add year dummies, whereas our original model finds a non-significant relationship between these two variables.

Table D-1
Results on knowledge generation based on Poisson regression

	Dependent variable: *$Npatent_{i,t}$* (fixed effects model)		
	Model1	Model 2	Model 3
$N\_size_{i,t}$	0.01*** (0.0002)	0.005*** (0.0002)	0.002*** (0.0002)
$N\_strength_{i,t}$	0.14 (0.19)	0.20 (0.19)	−0.47** (0.21)
$N\_proximity_{i,t}$	75.93*** (0.60)	78.28*** (0.61)	4.99*** (0.91)
$Policy\_support_{i,t}$		0.44*** (0.004)	0.11*** (0.005)
$Cpatent_{i,t-1}$			0.00003*** (1.8e-6)
$GDP\_per\_capita_{i,t}$			−0.00002** (9.5e-7)
Year fixed effect	NO	NO	YES
Observations	848	848	848
Log likelihood	−25764	−18992	−9263
Wald Chi	21829	32626	42296
Prob>chi	0.000	0.000	0.000

Notes: ***P < 0.01, **P < 0.05, *P < 0.1.

Table D-2
Results on market deployment based on GLS regression

	Dependent variable: *$Ncapacity_{i,t}$*		
	Model 1	Model 2	Model 3
$N\_size_{i,t}$	0.81*** (0.29)	0.68** (0.29)	0.16 (0.26)
$N\_strength_{i,t}$	4926*** (885)	4267*** (905)	2085** (826)
$N\_proximity_{i,t}$	−13218*** (6024)	−10830*** (3632)	−5642* (6450)
$Policy\_support_{i,t}$		142.59*** (45)	98** (41)
$Cpatent_{i,t-1}$			0.40*** (0.03)
$GDP\_per\_capita_{i,t}$			−0.02*** (0.006)
Year fixed effects	YES	YES	YES
Country fixed effects	YES	YES	YES
Constant	3256**	2530*	1383
Observations	976	976	976
R-square	0.38	0.39	0.52
Wald Chi	559	575	986
Prob>chi	0.000	0.000	0.000

Notes: ***P < 0.01, **P < 0.05, *P < 0.1.

We use generalized least squares (GLS) to estimate the market deployment models. The results of GLS regressions (Table D-2) are similar to the results of our market deployment model in Table 7, indicating the robustness of the main results.

References

Adner, R., 2006. Match your innovation strategy to your innovation ecosystem. Harv. Bus. Rev. 84 (4), 98.
Baum, J., Calabrese, T., Silverman, B.S., 2000. Don't go it alone: alliance network composition and startups' performance in Canadian biotechnology. Strat. Manag. J. 21, 267–294.
Binz, C., Anadon, L.D., 2018. Unrelated diversification in latecomer contexts—the emergence of the Chinese solar photovoltaics industry. Environ. Innovat. Soc. Transit. 28, 14–34. https://doi.org/10.1016/j.eist.2018.03.005.
Blanco, M.I., 2009. The economics of wind energy. Renew. Sustain. Energy Rev. 13 (6–7), 1372–1382. https://doi.org/10.1016/j.rser.2008.09.004.
Bolinger, M., Wiser, R., 2012. Understanding wind turbine price trends in the US over the past decade. Energy Pol. 42, 628–641. https://doi.org/10.1016/j.enpol.2011.12.036.
Boschma, R., Minondo, A., Navarro, M., 2013. The emergence of new industries at the regional level in Spain: a proximity approach based on product relatedness. Econ. Geogr. 89 (1), 29–51. https://doi.org/10.1111/j.1944-8287.2012.01170.x.
Campisi, D., Morea, D., Farinelli, E., 2015. Economic sustainability of ground mounted photovoltaic systems: an Italian case study. Int. J. Energy Sect. Manag. 9 (2), 156–175. https://doi.org/10.1108/IJESM-04-2014-0007.
Campisi, D., Gitto, S., Morea, D., 2016. Effectiveness of incentives for wind energy: models and empirical evidence from an Italian case study. J. Sustain. Sci. Manag. 11 (2), 39–48.
Campisi, D., Gitto, S., Morea, D., 2018. Shari'ah-Compliant finance: a possible novel paradigm for green economy investments in Italy. Sustainability 10 (11), 3915. https://doi.org/10.3390/su10113915.
Colombelli, A., Krafft, J., Quatraro, F., 2014. The emergence of new technology-based sectors in European regions: a proximity-based analysis of nanotechnology. Res. Pol. 43 (10), 1681–1696. https://doi.org/10.1016/j.respol.2014.07.008.
Choi, H., Anadón, L.D., 2014. The role of the complementary sector and its relationship with network formation and government policies in emerging sectors: the case of solar photovoltaics between 2001 and 2009. Technol. Forecast. Soc. Change 82, 80–94. https://doi.org/10.1016/j.techfore.2013.06.002.
Chiu, Y.T.H., 2009. How network competence and network location influence innovation performance. J. Bus. Ind. Market. 24 (1), 46–55. https://doi.org/10.1108/08858620910923694.
Delgado, M., Porter, M.E., Stern, S., 2015. Defining clusters of related industries. J. Econ. Geogr. 16 (1), 1–38. https://doi.org/10.1093/jeg/lbv017.
Feser, E.J., Bergman, E.M., 2000. National industry cluster templates: a framework for applied regional cluster analysis. Reg. Stud. 34 (1), 1–19. https://doi.org/10.1080/00343400050005844.
Feser, E., 2005. Industry cluster concepts in innovation policy: a comparison of US and Latin American experience. Spillovers and Innovations 135–155.
Fraccascia, L., Giannoccaro, I., Albino, V., 2018. Green product development: what does the country product space imply? J. Clean. Prod. 170, 1076–1088. https://doi.org/10.1016/j.jclepro.2017.09.190.
Gallagher, K.S., Grübler, A., Kuhl, L., Nemet, G., Wilson, C., 2012. The energy technology innovation system. Annu. Rev. Environ. Resour. 37, 137–162. https://doi.org/10.1146/annurev-environ-060311-133915.
Geels, Frank W., 2004. From sectoral systems of innovation to socio-technical systems: insights about dynamics and change from sociology and institutional theory. Res. Pol. 33 (6), 897–920. https://doi.org/10.1016/j.respol.2004.01.015.
Gilsing, V., Nooteboom, B., Vanhaverbeke, W., Duysters, G., van den Oord, A., 2008. Network embeddedness and the exploration of novel technologies: technological distance, betweenness centrality and density. Res. Pol. 37 (10), 1717–1731. https://doi.org/10.1016/j.respol.2008.08.010.
Goldemberg, J., 1998. Leapfrog energy technologies. Energy Pol. 26 (10), 729–741.
Grafstrom, J., Lindman, A., 2017. Invention, innovation and diffusion in the European

wind power sector. Technol. Forecast. Soc. Change 114, 179–191. https://doi.org/10.1016/j.techfore.2016.08.008.
Granovetter, M., 1973. The strength of weak ties. Am. J. Sociol. 78, 1360–1380. https://doi.org/10.1016/B978-0-12-442450-0.50025-0.
Green, R., Vasilakos, N., 2011. The economics of offshore wind. Energy Pol. 39 (2), 496–502. https://doi.org/10.1016/j.enpol.2010.10.011.
Grossman, G.M., Krueger, A.B., 1991. Environmental Impacts of a North American Free Trade Agreement. National Bureau of Economic Research. No. w3914.
Hamwey, R., Pacini, H., Assunção, L., 2013. Mapping green product spaces of nations. J. Environ. Dev. 22 (2), 155–168. https://doi.org/10.1177/1070496513482837.
Hausmann, Ricardo, Klinger, Bailey, 2006. Structural Transformation and Patterns of Comparative Advantage in the Product Space. KSG Working Paper. No. RWP06-041. https://papers.ssrn.com/sol3/papers.cfm?abstract_id=939646.
Heimeriks, G., Boschma, R., 2013. The path-and place-dependent nature of scientific knowledge production in biotech 1986–2008. J. Econ. Geogr. 14 (2), 339–364. https://doi.org/10.1093/jeg/lbs052.
Hidalgo, C.A., Klinger, B., Barabási, A.-L., Hausmann, R., 2007. The product space conditions the development of nations. Science 317 (5837), 482–487. https://doi.org/10.1126/science.1144581.
Hippel, E., 2007. The sources of innovation. Das Summa Summarum des Management, pp. 111–120.
Hiroux, C., Saguan, M., 2010. Large-scale wind power in European electricity markets: time for revisiting support schemes and market designs? Energy Pol. 38 (7), 3135–3145. https://doi.org/10.1016/j.enpol.2009.07.030.
Huenteler, Joern, Tang, Tian, Chan, Gabriel, Anadon Diaz, Laura, 2018. Why is China's wind power generation not living up to its potential? Environ. Res. Lett. 13 https://doi.org/10.1088/1748-9326/aaadeb.
Jacobsson, S., Bergek, A., 2004. Transforming the energy sector: the evolution of technological systems in renewable energy technology. Ind. Corp. Change 13 (5), 815–849. https://doi.org/10.1093/icc/dth032.
Jaffe B., Adam, Newell G., Richard, Starvins N., Robert, 2005. A tale of two market failures: Technology and environmental policy. Ecol. Econ. 54 (2–3), 164–174. https://doi.org/10.1016/j.ecolecon.2004.12.027.
Jennie, C.S., Wilson, E.J., 2016. Climate change, technological innovation. Bull. At. Sci. 72 (1), 4–6.
Johnstone, N., Hascic, I., Popp, D., 2010. Renewable energy policies and technological innovation: evidence based on patent counts. Environ. Resour. Econ. 45 (1), 133–155.
Junginger, M., Faaij, A., Turkenburg, W.C., 2005. Global experience curves for wind farms. Energy Pol. 33 (2), 133–150. https://doi.org/10.1016/S0301-4215(03)00205-2.
Kauffman, Stuart, Lobo, Jose, Macready G., William, 2000. Optimal search on a technology landscape. J. Econ. Behav. Organ. 43 (2), 141–166. https://doi.org/10.1016/S0167-2681(00)00114-1.
Kim, J.E., Tang, T., 2020. Preventing early lock-in with technology-specific policy designs: the Renewable Portfolio Standards and diversity in renewable energy technologies. Renew. Sustain. Energy Rev. 123 (5) https://doi.org/10.1016/j.rser.2020.109738.
Lacasa, I.D., Shubbak, M.H., 2018. Drifting towards innovation: the co-evolution of patent networks, policy, and institutions in China's solar photovoltaics industry. Energy Res. Soc. Sci. 38, 87–101. https://doi.org/10.1016/j.erss.2018.01.012.
Lee, K., Lim, C., 2001. Technological regimes, catching-up and leapfrogging: findings from the Korean industries. Res. Pol. 30 (3), 459–483. https://doi.org/10.1016/S0048-7333(00)00088-3.
Lee, K., Lim, C., Song, W., 2005. Emerging digital technology as a window of opportunity and technological leapfrogging: catch-up in digital TV by the Korean firms. Int. J. Technol. Manag. 29, 40–63. https://doi.org/10.1504/IJTM.2005.006004.
Lewis, J.I., 2007. Technology acquisition and innovation in the developing world: wind turbine development in China and India. Stud. Comp. Int. Dev. 42 (3–4), 208–232. https://doi.org/10.1007/s12116-007-9012-6.
Lewis, J., 2013. Green Innovation in China: China's Wind Power Industry and the Global Transition to a Low-Carbon Economy. Columbia University Press, New York, NY.
Lindman, A., Söderholm, P., 2016. Wind energy and green economy in Europe: measuring policy-induced innovation using patent data. Appl. Energy 179, 1351–1359. https://doi.org/10.1016/j.apenergy.2015.10.128.
Mendonça, S., 2009. Brave old world: accounting for 'high-tech'knowledge in 'low-tech'industries. Res. Pol. 38 (3), 470–482.
Morea, D., Poggi, L.A., 2017. An innovative model for the sustainability of investments in the wind energy sector: the use of green sukuk in an Italian case study. Int. J. Energy Econ. Pol. 7 (2), 53–60.
Mu, Q., Lee, K., 2005. Knowledge diffusion, market segmentation and technological catch-up: the case of the telecommunication industry in China. Res. Pol. 34 (6), 759–783. https://doi.org/10.1016/j.respol.2005.02.007.
Murphy, J.T., 2001. Making the energy transition in rural East Africa: is leapfrogging an alternative? Technol. Forecast. Soc. Change 68 (2), 173–193. https://doi.org/10.1016/S0040-1625(99)00091-8.
Nemet, G.F., 2009. Demand-pull, technology-push, and government-led incentives for non-incremental technical change. Res. Pol. 38 (5), 700–709. https://doi.org/10.1016/j.respol.2009.01.004.
Nemet, G.F., 2012. Subsidies for new technologies and knowledge spillovers from learning by doing. J. Pol. Anal. Manag. 14 (4), 469–494. https://doi.org/10.1002/pam.21643.
Popp, David, 2002. Induced innovation and energy prices. Am. Econ. Rev. 91 (1), 160–180. https://doi.org/10.1257/000282802760015658.
Porter, M.E., 1990. The competitive advantage of nations. Compet. Intell. Rev. 1 (1), 14-14.
Qiu, Y., Diaz Anadon, L., 2012. The price of wind power in China during its expansion: technology adoption, learning-by-doing, economies of scale, and manufacturing localization. Energy Econ. 34, 825–835. https://doi.org/10.1016/j.eneco.2011.06.008.
Quitzow, R., Huenteler, J., Asmussen, H., 2017. Development trajectories in China's wind and solar energy industries: how technology-related differences shape the dynamics of industry localization and catching up. J. Clean. Prod. 158, 122–133. https://doi.org/10.1016/j.jclepro.2017.04.130.
REN21. Renewables, 2015. Global Status Report. 2016. Available through: http://www.ren21.net/wp-content/uploads/2015/07/REN12-GSR2015_Onlinebook_low1.pdf.
Rigby, D.L., 2015. Technological relatedness and knowledge space: entry and exit of US cities from patent classes. Reg. Stud. 49 (11), 1922–1937. https://doi.org/10.1080/00343404.2013.854878.
Rodan, S., Galunic, C., 2004. More than network structure: how knowledge heterogeneity influences managerial performance and innovativeness. Strat. Manag. J. 25 (6), 541–562. https://doi.org/10.1002/smj.398.
Rothaermel, F.T., 2001. Complementary assets, strategic alliances, and the incumbent's advantage: an empirical study of industry and firm effects in the biopharmaceutical industry. Res. Pol. 30 (8), 1235–1251. https://doi.org/10.1016/S0048-7333(00)00142-6.
Rothaermel, F.T., Hill, C.W.L., 2005. Technological discontinuities and complementary assets: a longitudinal study of industry and firm performance. Organ. Sci. 16 (1), 52–70. https://doi.org/10.1287/orsc.1040.0100.
Sarasa-Maestro, C.J., Dufo-López, R., Bernal-Agustín, J., 2013. Photovoltaic remuneration policies in the European Union. Energy Pol. 55, 317–328. https://doi.org/10.1016/j.enpol.2012.12.011.
Tang, T., Popp, D., 2016. The learning process and technological change in wind power: evidence from China's CDM wind projects. J. Pol. Anal. Manag. 35 (1), 195–222. https://doi.org/10.1002/pam.21879.
Tang, T., 2018. Explaining technological change in the US wind industry: energy policies, technological learning, and collaboration. Energy Pol. 120, 197–212.
Tanner, A.N., 2015. The emergence of new technology-based industries: the case of fuel cells and its technological relatedness to regional knowledge bases. J. Econ. Geogr. 16 (3), 611–635. https://doi.org/10.1093/jeg/lbv011.
Wooldridge M., Jeffrey, 2010. Econometric Analysis of Cross Section and Panel Data. the MIT Press.
Zhang, F., Gallagher, K.S., 2016. Innovation and technology transfer through global value chains: evidence from China's PV industry. Energy Pol. 94, 191–203. https://doi.org/10.1016/j.enpol.2016.04.014.