Research Policy 51 (2022) 104558

Contents lists available at ScienceDirect

Research Policy

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

How do global manufacturing shifts affect long-term clean energy innovation? A study of wind energy suppliers

Claudia Doblinger [a,#], Kavita Surana [b,c,#,*], Deyu Li [d,e], Nathan Hultman [b], Laura Díaz Anadón [d,f]

[a] Technical University of Munich, Campus Straubing for Biotechnology and Sustainability and School of Management, Straubing, Germany
[b] Center for Global Sustainability, School of Public Policy, University of Maryland, College Park, MD, United States of America
[c] Complexity Science Hub, Vienna, Austria
[d] Centre for Environment, Energy and Natural Resource Governance, Department of Land Economy, University of Cambridge, Cambridge, United Kingdom
[e] Department of Human Geography and Spatial Planning, Utrecht University, Utrecht, the Netherlands
[f] Belfer Center for Science and International Affairs, Harvard Kennedy School, Harvard University, United States

ARTICLE INFO

JEL codes:
Q4
Q55
O3
L6
L2
L5

Keywords:
Temporal dimension of innovation
Wind energy
Clean energy
Global value chains
Suppliers

ABSTRACT

Clean energy technologies are important for meeting long-term climate and competitiveness goals. But clean energy industries are part of global value chains (GVCs), where past manufacturing shifts from developed to emerging economies have raised questions on a decline in long-term innovation. Our research centers on how geographic shifts in the GVC shape long-term innovation, i.e., innovation in a time frame within which "mission-oriented", societal, or firm strategic objectives need to be met rather than tactical, near-term market competitiveness alone. Focusing on wind energy, we introduce a temporal measure to distinguish between long-term and short-term innovation, applying natural language processing methods on patent text data. We consider supply-side value chain factors (i.e., manufacturing supplier relationships with original equipment manufacturers (OEMs)) and demand-side factors (i.e., policy-induced clean energy market growth), shaping the patenting activities of 358 global specialized wind suppliers (2006–2016). Our findings suggest that the wind industry did not suppress long-term innovation during manufacturing shifts, in this case to China. After 2012 when China developed a large wind market, long-term innovation increased by 80.7% in European suppliers working with non-European OEMs (including Chinese) and by 67.2% in Chinese suppliers working with non-Chinese OEMs. Our results highlight the importance of coupling international manufacturing relationships with sizeable local demand for inducing long-term innovation. Our results advance research in innovation, GVCs, and green industrial policy with implications for several industries that can contribute to climate mitigation.

1. Introduction

Accelerating innovation in clean energy technologies is urgently needed for addressing climate change mitigation goals (i.e., long-term net-zero targets and emission reduction) and economic and development goals (i.e., competitiveness and employment in rapidly expanding green industries). Estimates suggest that currently mature technologies are sufficient to meet only a quarter of the long-term emission reduction targets through 2070 (IEA, 2020). This means that the direction of innovation must focus not only on generating breakthroughs or radical changes (Breakthrough Energy, 2021), but also on ensuring that different technologies can deliver on long-term societal goals (e.g., at least 10–20 years in the future) to avoid locking in technologies that are already mature.

Delivering the innovation needed to meet climate-related societal goals requires introducing a *temporal dimension* to the analysis of innovation and its relationship with changing markets and industries—i.e., with the provision of *short-term* innovation related to current needs and the provision of *long-term* innovation linked to anticipated future needs. The temporal dimension complements extant approaches on measuring innovation through novelty (e.g., breakthroughs, radicalness, exploration) (e.g., Arts et al., 2021; Funk and Owen-Smith, 2017; Kelly et al., 2018; Verhoeven et al., 2016). Existing approaches do not explicitly consider innovation relative to societal challenges, industry needs, or

Abbreviations: GVC, Global value chain; OEM, Original equipment manufacturer.

* Corresponding author.
E-mail address: ksurana@umd.edu (K. Surana).
# equal contributions.

https://doi.org/10.1016/j.respol.2022.104558
Received 15 September 2021; Received in revised form 13 May 2022; Accepted 13 May 2022
Available online 23 May 2022

longer-term strategic competitiveness goals for innovating firms. The novel temporal dimension can be crucial for scholars and policymakers grappling with the challenge of enabling long-term innovation for climate change, economic, and development goals, as exemplified by efforts of the European Commission to translate the concept of 'mission-oriented innovation' in various areas into their institutions or in technology-specific plans (e.g., for lithium-ion batteries) in the United States (U.S.) (Anadón, 2012; European Commission, 2021; Foray et al., 2012; Mazzucato, 2018; U.S. Department of Energy, 2021).

While enabling long-term clean energy innovation outcomes is important for meeting climate-related societal goals, firms must also quickly react to growing global demand and expanding international competition and networks, especially with many new entrants from China and other emerging economies. Such globalization of supply (changes in location of manufacturing) and demand (changes in location of deployment) can shape innovation outcomes in different directions (Binz and Truffer, 2017; Meckling and Hughes, 2018; Nemet, 2009)—and in some cases, significantly limit some types of innovation efforts. The global value chains (GVCs) for manufacturing clean energy technologies have shifted from Europe, the U.S., and Japan to emerging economies since 2010, most notably to China (Sandor et al., 2020; Surana et al., 2020; Zhang and Gallagher, 2016). Experience from other modern industries such as optoelectronics, automobiles, and rare-earth element technology suggests that shifts in manufacturing from developed to emerging economies could suppress long-term innovation by moving innovation away from technologies that are further from commercialization (Fifarek et al., 2008; Fuchs, 2014; Fuchs et al., 2011; Fuchs and Kirchain, 2010). However, the location of demand is also important, as the proximity between manufacturing and deployment could create learning effects that spur innovation (Fuchs, 2014; Nemet, 2009; Von Hippel, 1994). For clean energy, manufacturing activities in China have been associated with innovation that has short-term benefits for scale-up and cost reductions, often linked to the increase in domestic demand (Helveston and Nahm, 2019; Lam et al., 2017). However, these manufacturing shifts to China may have suppressed advanced or next generation alternative designs with long-term benefits (Sivaram et al., 2018), as has been suggested for other areas like optoelectronics (Fuchs and Kirchain, 2010). This raises the question whether shifts in manufacturing from developed countries to emerging economies such as China combined with strong local demands in emerging economies promote or suppress long-term clean energy innovation necessary for meeting societal goals.

The relationship between the location of supply, demand, and the temporal dimension of innovation is not only important when it comes to the end products (e.g., wind turbines or solar panels) and lead firms (i.e., Original Equipment Manufacturers, or OEMs), but also for the components and suppliers in the GVC of these final products (Gao and Rai, 2019; Meckling and Hughes, 2017; Sandor et al., 2020; Surana et al., 2020; van der Loos et al., 2022; Zhang and Gallagher, 2016). Suppliers' and OEMs' locations depend on local public policies, skills of the suppliers, the complexity of the components they manufacture, or market size, while firm strategy (e.g., the strategic priorities of suppliers or OEMs and their relationships in the value chain) and the location of firms can shape innovation (Nemet, 2009; Surana et al., 2020; Von Hippel, 1994). OEMs and their end products have been extensively studied in extant literature on energy innovation (Awate et al., 2015; Garud and Karnoe, 2003), but research trying to understand the activities of hundreds of specialized suppliers remains limited to a few studies (e.g., Zhang and Gallagher, 2016; Haakonsson and Slepniov, 2018; Hipp and Binz, 2020; Surana et al., 2020). Understanding the activities of suppliers is particularly important in general (see Ambos et al., 2021 for a review) and specifically in clean energy technologies such as wind turbines that are complex products and systems where innovation takes place at the component-level, involving hundreds of suppliers (Huenteler et al., 2016a; IEA Wind 2013; IEA Wind 2001).

This paper analyzes if supplier-OEM relationships in the GVC of clean energy manufacturing (supply) and the proximity to deployment (demand) over time promote or suppress long-term innovation activities of suppliers. In particular, we introduce the temporal dimension of innovation, where we define short-term innovation as likely to be in the market within 0–10 years, and long-term innovation as technologies that have a possible impact in the market at least 10–20 years into the future. Specifically, we focus on wind energy suppliers and study how different types of domestic or international manufacturing relationships (i.e., between suppliers and OEMs) in the GVC and demand-pull in major wind energy markets (shifting over time from Europe to China) shape long-term innovation. To do so, we first map the GVC of wind energy, examining the supplier-OEM manufacturing relationships between 2006 and 2016. For each supplier and OEM, we analyze the filed patents with a novel measure for the temporal dimension of innovation, where we map the innovation needs and timelines identified by global research-industry consortia (IEA Wind 2013; IEA Wind 2001) to the content of patent descriptions identified through natural language processing methods (i.e., term frequency analysis and topic modeling). Finally, we quantify the link between supplier-OEM manufacturing relationships, their proximity to deployment of wind energy, and their impact on long-term innovation efforts. We focus on the home-country of the supplier and OEM to assess whether the relationship is local (e.g., Chinese supplier with Chinese OEM) or international (e.g., Chinese supplier with OEM from Europe). To relate this to deployment, we distinguish two time windows in our statistical analysis: (a) 2006 to 2012, when the European wind energy market showed high increases in new installed wind energy capacity; and (b) 2012 to 2016, when the Chinese wind energy market clearly dominated annual installations (IRENA, 2021).

Our analysis suggests that European wind energy suppliers did not reduce their long-term innovation activities because of manufacturing shifts to China, in part because of the importance of the large local market. From 2006–2012, when the European wind energy market dominated global installations, long-term innovation activities increased for European suppliers (by 87.4% for relationships with European OEMs). From 2012–2016, when China had developed a policy-driven, large, and attractive wind market, long-term innovation increased for international relationships for both European suppliers (by 80.7% with non-European OEMs, including Chinese) and for Chinese suppliers (by 67.2%, with non-Chinese OEMs). Overall, our findings suggest that international relationships combined with local demand matter more for long-term innovation than the country of origin of the supplier, i.e., whether their home country is an emerging or a developed economy.

These findings have several implications for research and public policy. *First*, we introduce a novel, temporal dimension to the direction of innovation that complements established perspectives on measuring novelty or radicalness (e.g., Arts et al., 2021; Kelly et al., 2018; Verhoeven et al., 2016). The temporal dimension can be particularly important for assessing and advancing clean energy innovation in the context of mission-oriented policies. *Second,* our analysis is one of the few that centers on suppliers rather than OEMs (Gao and Rai, 2019; Haakonsson and Slepniov, 2018; Hipp and Binz, 2020; Surana et al., 2020; Zhang and Gallagher, 2016). Assessing the drivers of innovation in the full GVC is essential for understanding the contribution of all types of firms to long-term innovation. *Third*, our assessment of the drivers of long-term innovation in relation to the location of suppliers in the GVC, their relationships (i.e., their local or international relationships with OEMs), and the location of demand expands prior notions on the direction of innovation in developed vs. emerging economies (especially China) (Fuchs et al., 2011; Fuchs and Kirchain, 2010; Helveston and Nahm, 2019; Lam et al., 2017; Sivaram et al., 2018). Instead of reductions in longer-term innovation activities due to manufacturing shifts in technology-intensive industries, our findings provide novel evidence for previous claims on how increases in the globalization of value chains in emerging economies may be able to drive long-term innovation when combined with strong local markets (Fuchs, 2014). *Finally*, to meet climate, economic, and development goals for green growth while ensuring long-term innovation, we suggest that policymakers continue to strengthen collaborations between research and the large number of industry stakeholders that must cut emissions, enable large markets through stable policy-induced incentives, and foster international supplier-OEM collaborations with China and other emerging economies with large or growing markets.

The rest of the paper is structured as follows. Section 2 provides an overview of the literature on the direction of innovation and its drivers in the global value chain. Section 3 provides the case context. Section 4 presents our data and methodological approach. Section 5 presents results. Section 6 discusses our findings and the contributions to research. Section 7 concludes with implications for public policy.

2. Theoretical background

We first review the research on measuring energy innovation and the need for including a temporal dimension to the direction of innovation (2.1) and follow with the (largely qualitative) literature on how suppliers in the GVC of clean energy technologies can shape the direction of innovation (2.2).

2.1. The temporal dimension of innovation

The direction of innovation in clean energy technologies can refer to various types of innovation: e.g., carbon-intensive vs. low-carbon technologies (Anadón, 2012; Mazzucato and Semieniuk, 2018; Schmidt et al., 2012) or incremental vs. radical innovation (also related to breakthrough or exploratory innovation) (Hoppmann et al., 2013; Li et al., 2021; Nemet, 2009). With consensus on the need for low-carbon innovation, energy innovation scholars have often pointed to the need for novelty: i.e., promoting radical innovations for meeting net-zero climate goals, rather than only focusing on incremental innovation that delivers small improvements in the performance of existing clean energy technologies (Nemet, 2009; Sivaram et al., 2018; Wilson, 2018). However, these novelty-oriented aspects have overlooked the importance of the temporal perspective—i.e., whether the focus of technological developments over time is aligned with what is needed for simultaneously meeting different societal and competitiveness goals for net-zero emissions and green growth.

Research to date from the general innovation literature, applied to energy innovation, offers valuable insights for measuring and analyzing novelty and radical innovation.[1] For example, scholars have proxied non-incremental innovations in wind technology by using highly cited patents (Nemet, 2009), developed novelty measures for solar technologies based on the similarities of patent codes (Li et al., 2021 as proposed by Verhoeven et al., 2016), and studied breakthrough solar innovations considering novelty and relevance based on topics generated from natural language processing (Sun et al., 2021 based on Dahlin and Behrens, 2005). However, these novelty-oriented measures of innovation have two limitations in their ability to provide insights regarding the expected time-horizon for specific technologies to reach commercialization. *First*, important characteristics may get obscured in large patent datasets. For example, analyzing the average characteristics of a full set of patents (i.e., all patents from universities, research institutes, industry, or individuals) overlooks features from the subset of patents of industry stakeholders well-positioned to quickly commercialize technology improvements. Similarly, the novelty indicators that are sector-agnostic in identifying general radical innovations (e.g., Verhoeven et al., 2016) may not be targeted enough for developing meaningful policy implications for specific industries, green growth, and competitiveness considering the heterogeneity in energy technologies[2] (Huenteler et al., 2016b; IEA, 2020; Malhotra and Schmidt, 2020; Meng et al., 2021; Wilson et al., 2020). *Second*, patent citations as indicators of novelty, as often used in the innovation literature, have several drawbacks. Patent citations may vary based on different citation practices in different patent offices or the individual patent examiner, they could depend on the strategic decisions of firms in what they cite as prior art, and most important, they can only be analyzed several years ex-post (Jaffe and Rassenfosse, 2017).

The temporal approach we develop to understand the direction of innovation builds on—and expands—methods in innovation studies and other novelty literature. It analyzes the content of patents and links them closely to both societal needs (e.g., climate change goals) and industry motivations (e.g., specific technology targets). It is distinct from existing novelty measures in two ways. *First*, technology development for long-term climate goals may not always link to radical innovation. Radical innovation, or the new combination of existing scientific principles, is often measured as the first combination of patent codes (Verhoeven et al., 2016). But these approaches would not classify technologies such as offshore wind as a radical innovation in the early 2000s. Even though onshore wind was still not cost-competitive at that time, offshore wind was hardly in the horizon and thus, developing capabilities in offshore wind technologies was important for meeting longer-term climate and competitiveness goals.[3] *Second*, for suppliers and OEMs, research efforts would be designed to yield profits or competitive advantage based on temporal needs and requirements, and not on the potentially transformational impact on markets. For long-term innovation, the difference to novelty relates to how much suppliers 'think ahead' in terms of meeting societal goals through their innovative activities, and the need to balance considering how long-term innovation aligns (or not) with the anticipated future needs of their OEM partners. Short-term innovation is connected to the OEM's current market needs. In relation to novelty, it may be linked to both incremental innovation with regard to improvements in existing products, or to radical innovation when working on a component for a specific OEM that can potentially have a transformational impact on markets (Hoppmann et al., 2013; Nemet, 2009; Tushman and Anderson, 1986).

Evaluating the direction of clean energy innovation centering on a temporal dimension is therefore crucial for developing policy and management approaches to deliver the time-dependent, technology-specific innovation needs to meet climate, economic, and development goals and to avoid lock-ins and limiting future technology options (e.g., IEA, 2020; IEA Wind, 2013).

[1] In the broader innovation literature, the novelty dimension of innovation has been assessed based on patent data using different indicators. Prominent measurements for radicalness or novelty are based on (1) the number of forward citations (Ahuja and Lampert, 2001; Phene et al., 2006; Singh and Fleming, 2010); (2) the centrality of patents in the citation network (Corredoira and Banerjee, 2015; Verspagen, 2007); (3) the introduction of new combination of patent codes (Verhoeven et al., 2016); (4) new combination of keywords (Arts et al., 2021) or topics (Kaplan and Vakili, 2015) based on natural language processing; and (5), more advanced measurements combine novelty and impact, investigating how similar patents are compared to previous and future patents based on co-citation or text based similarity measures (Dahlin and Behrens, 2005; Kelly et al., 2018).

[2] For example, innovation in some technologies may be in processes (e.g. in solar photovoltaics) while others may be in components or products (e.g. in wind) (Huenteler et al., 2016b). And even within a specific low carbon technology (e.g. solar) the focus of innovation may be in incumbent technologies (e.g. silicon solar cells) or in new technologies (e.g. perovskite solar cells).

[3] For example, the codes indicating offshore wind, i.e., F03D (wind motors) and B63B (ships or other waterborne vessels; related equipment), appear together in a patent with priority year as early as 1973 (JPS51135399U), and in our filtered database, already before 2006 (see, for example, DE10055973A1, EP1101935A2, JP2004019470A). Relying on the first combination of patent codes for novelty would not classify all of these as novel, even though they would be a long-term innovation as offshore wind was not commercially viable in the early 2000s.

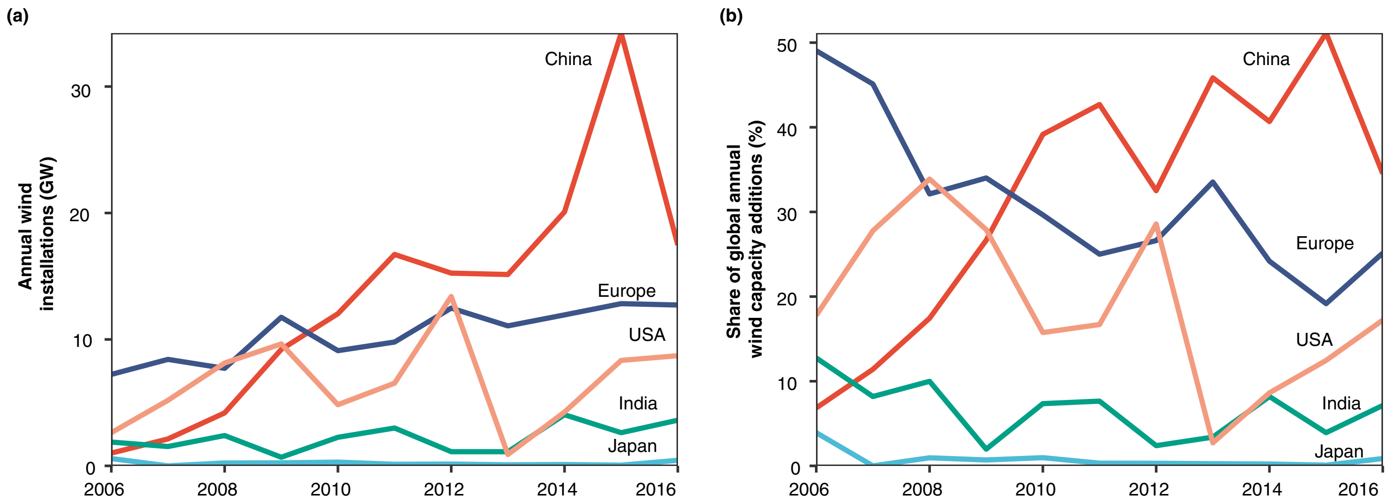

Fig. 1. Evolution of key wind energy markets (2006–2016) based on (a) annual installed wind energy capacity (in Gigawatts, GW) and (b) share of global installed wind energy capacity (%).

2.2. Suppliers and innovation in global value chains

In addition to measuring the temporal dimension of innovation, it is important to understand what drives long-term innovation, especially in the context of GVCs (Ambos et al., 2021; Pietrobelli and Rabellotti, 2011; Van Assche, 2017). GVCs represent the multifaceted patterns of internationalization and fragmented innovation and manufacturing in modern technologies (Gereffi et al., 2005; Pietrobelli and Rabellotti, 2011; Taglioni and Winkler, 2016; The World Bank, 2017; Zhang and Gallagher, 2016). These GVCs comprise a few leading firms, or OEMs, that integrate and deliver end products and the hundreds of suppliers that deliver components to the OEMs. While either OEMs or only their suppliers have been extensively studied in the broader GVC literature, a recent review by Ambos et al. (2021) emphasizes the need to center on the suppliers and their interactions with OEMs (rather than the OEMs only) in shaping the direction of innovation in the GVCs.

We expand this broader OEM-centric perspective by evaluating the drivers of long-term innovation at the level of suppliers based on three related dimensions discussed in the GVC and manufacturing literature. *First*, the relationship between the OEMs and their suppliers, known as the GVC governance, can drive innovation (e.g., Gereffi et al., 2005; Pietrobelli and Rabellotti, 2011; Buciuni and Pisano, 2021). Suppliers respond to the different strategies or needs of the OEMs they work with—for example, whether the OEMs 'make' (in-house) or 'buy' (arm's length), the complexity of components involved, the extent of competition with other suppliers, the size of markets, proximity to consumers that provide co-location cost benefits, and other cost drivers (Baldwin and Venables, 2013; Cattaneoet al., 2013; Novak and Eppinger, 2001; Surana et al., 2020; Taglioni and Winkler, 2016).

Second, suppliers' innovation activities can depend on how they source knowledge, for example by connecting to a global network of OEMs or of other suppliers (Ambos et al., 2021). Suppliers working with multiple OEMs from different countries may have more capacity to absorb external knowledge through knowledge transfer and learning that spur long-term innovation —and have pressures to meet international standards—when compared with suppliers only supplying to one OEM or only domestic OEMs (Pietrobelli and Rabellotti, 2011). Suppliers with stronger technological capabilities, especially those from industrialized countries such as the U.S. or Europe, are perhaps more likely to engage in long-term innovation (Haakonsson and Slepniov, 2018; Surana et al., 2020). Suppliers might also benefit differently in terms of gaining knowledge from working with different OEMs. OEMs from industrialized countries tend to have stronger technology capabilities and locate in more central positions in the global knowledge network of a technology than their peers from emerging countries (Awate et al., 2012; Zhou et al., 2016). In addition, their OEM interaction may otherwise shape their Research and development (R&D) priorities towards long-term or short-term innovation. Suppliers from emerging economies like China may therefore be influenced by their interactions in the course of supplying components to OEMs from industrialized countries. The learning process to meet technology standards or policy goals may increase their long-term innovation as they are exposed to new technological developments (Ambos and Ambos, 2011; Pietrobelli and Rabellotti, 2011; Zhang and Gallagher, 2016).

Third, the proximity of manufacturing (supply) and deployment (demand) can facilitate long-term innovations given the geographical dispersion of GVCs (Fuchs and Kirchain, 2010; Pisano and Shih, 2012, 2009; Yang et al., 2016). For example, prior research on the optoelectronics industry has suggested that manufacturing shifts from the U.S. to the 'East' had unfavorable consequences on more 'advanced' technological innovation that could have reduced costs in the longer-term—both in the home country (i.e., the U.S.) and for the technology in general (Fuchs and Kirchain, 2010). This lowering of a firm's capability to innovate could be explained by reduced communications between development and production when production activities are moved to a different country and reduced (Tyre and von Hippel, 1997; Von Hippel, 1994), constrained and small global markets, as well as the low strength or enforcement of intellectual property rights (Fuchs, 2014). As previously mentioned, differences across industrial and cost structures, shippability, as well as policy and manufacturing contexts may affect how manufacturing shifts influence the focus of research.

While the supplier-centric GVC lens we take in this paper offers a comprehensive approach to analyze the drivers of innovation in clean energy technologies, it would be insufficient without also accounting for the impact of public policies as well-established drivers of energy innovation indicators, especially market-pull deployment policies (see systematic reviews in Grubb et al., 2021; Peñasco et al., 2021; Popp, 2019). Research has highlighted the importance of demand-pull through a stable domestic market, enabled by public policies, for advancing innovation and technological improvements in clean energy industries through economies of scale and learning by doing (Dechezleprêtre and Glachant, 2014; Lewis, 2011; Lewis and Wiser, 2007; Quitzow et al., 2014; Sagar and van der Zwaan, 2006). Although demand-pull alone may not lead to non-incremental innovations in clean energy (Nemet 2009), it could make a difference and accelerate rather than reduce innovation in the case of manufacturing shifts to emerging economies. This is because the proximity between firms and growing (instead of small, constrained) markets might facilitate the communications and interactions needed to help advance technical problem-solving (Fuchs, 2014; Von Hippel, 1994). This could be particularly relevant in the context of clean energy technologies, especially complex products and systems such as wind energy, where technologies are not as easily shippable and need to be adapted to local physical conditions or regulations (Schmidt and Huenteler, 2016). Thus, the proximity to lead markets might also facilitate the long-term innovations of suppliers in the clean energy industry.

In sum, we expect that the origin and technological capabilities of suppliers, relations with international OEMs, and the proximity to lead markets will shape the direction of innovation of suppliers, especially the temporal dimension, in the GVC of the clean energy industry.

3. Research setting: the global wind energy industry

The wind energy industry is an important, relevant, and suitable empirical setting for analyzing the temporal dimension of innovation in the context of supply-side developments along the GVC—including both suppliers and OEMs—and its proximity to demand, for the following three reasons.

First, wind energy represents one of the key renewable technologies for meeting climate goals and is one of the most mature clean energy technologies today. Despite its maturity, the temporal dimension of innovation matters for wind energy. R&D activities have led to larger turbines that have enabled cost-effective deployment of onshore wind energy (e.g., Enevoldsen and Xydis, 2019). However, innovation is still needed to ensure continually larger turbines, low materials use, efficient manufacturing, grid stability, or operation in new settings (e.g., buildings, low wind speeds) (IEA, 2020). In addition, offshore wind energy is still not deployed at scale outside early markets, such as the UK, and innovation is needed to enhance installation processes, foundation designs, operation under different conditions (e.g., hurricanes), and transmission connections with demand regions (IEA, 2020).

Second, the wind energy industry has experienced shifts in location in terms of demand and supply in the last decades, shaped by public policy, with an increasingly prominent role of China. Deployment (demand) in the rapidly expanding wind energy industry shifted from Europe and the U.S. to China between 2006 and 2016 (our study period, see Fig. 1).[4] This shift started in 2010 but clearly stabilized and dominated after 2012, where the Chinese wind energy market became the fastest growing globally (see Fig. 1a and 1b),[5] enabled by systemic policy incentives for deployment as well as manufacturing and innovation (Surana and Anadón, 2015; Zhu et al., 2022). Trends in the supply of wind energy technologies paralleled trends in demand. OEMs from countries such as Denmark, Germany, Netherlands, and the U.S.—with extensive R&D activities—initially dominated with around 97% of the global market share in 2000 (BTM Consult, 2001). The growing demand in new markets (such as China and India) led to the rise of new OEMs in these emerging economies. By 2012, domestic OEMs (and a few joint ventures) served 80% of the Chinese market and over 50% of the Indian market, while the rest was served by foreign subsidiaries (Surana and Anadón, 2015). The rise of domestic OEMs in large emerging markets meant that the share of European and U.S. OEMs in total global turbine sales declined over time; by 2016 four of the largest Chinese OEMs held 25% of the global market share (Ren21, 2017). And with the OEM shifts to China, suppliers also followed as they emerged or evolved in working with different international OEMs (Surana et al., 2020). Thus, wind is an interesting case from the perspective of understanding the relationships between changes in manufacturing location and the temporal dimension of innovation.

Third, suppliers are central to innovation in wind energy. Wind turbines are complex products with high-level system integration and structural interactions between different components, and innovation takes place at the component rather than the process-level (Huenteler et al., 2016a; Malhotra and Schmidt, 2020; Schmidt and Huenteler, 2016). Prior research on wind energy innovation has highlighted the importance of public policies, locational factors and collaboration, focusing on countries or OEMs (Awate et al., 2015; Garud and Karnoe, 2003; Gosens and Lu, 2014; Haakonsson and Kirkegaard, 2016; Lema and Lema, 2012; Lewis, 2011; Nemet, 2009; Qiu and Anadón, 2012; Surana and Anadón, 2015). But despite the crucial roles of suppliers in developing these components, the extent to which their research focuses on different types of innovation remains a major gap.

4. Methodology

Our approach for understanding the drivers of long-term innovation in the global wind industry comprises three steps: setting up a database on wind GVCs (4.1), developing a novel measure for the temporal dimension of innovation (long-term and short-term) by analyzing the content of patents (4.2), and generating measures and variables to analyze where innovation occurs, how it changes over time, and how the location of suppliers in the GVC is associated with long-term innovation (4.3).

4.1. Data generation on industry-specific GVCs

We use a global database of component suppliers to major OEM for wind turbines, building on Surana et al. (2020). The database is based on industry reports from Navigant Consulting (2006, 2008, 2010, 2012, and 2014) (Navigant Research, 2014), complemented with additional data and verification from Orbis, Amadeus, or Bloomberg or the suppliers' webpages. The database includes information on 358 major component suppliers such as firm size, founding year, or geographical location. The database also includes similar information on the OEMs that suppliers deliver nine components to, and the relationships of the supplier firms with OEMs (either as in-house development of components for the OEMs or as external or outsourced from OEM to the supplier). The database assumes that each supplier-OEM relationship is reported for a 3-year horizon, therefore covering a study period from 2006 to 2016. The dataset also includes a metric of technology complexity applied at the component level representing the differences across wind energy components (Surana et al., 2020).

The location of suppliers and OEMs is based on the headquarter addresses in the case of larger companies with multiple facilities (mostly in the case of OEMs). Additionally, wind companies experienced multiple mergers and acquisitions in the timeframe of our study (e.g., Suzlon, REPower, and Senvion). The dataset considers them as individually operating companies if they are not integrated and continued to operate under a different brand (Awate et al., 2015).

The OEMs were firms with the greatest global market shares between 2006 and 2016 and were based in Germany (Siemens, Nordex, Enercon, REPower/Senvion), Denmark (Vestas), Spain (Gamesa), the U.S. (General Electric), Japan (Mitsubishi), China (Goldwind, Mingyang, Dongfang, United Power), and India (Suzlon). The majority of suppliers (38.5% of 358 suppliers) are from Europe (i.e., Austria, Belgium, Czech Republic, Denmark, Finland, France, Germany, Ireland, Italy, Netherlands, Norway, Poland, Portugal, Slovakia, Spain, Sweden, Switzerland, UK), which we treated as one 'region' due to physical proximity between the countries and the EU trading zone. The aggregate of European suppliers consists primarily of German, Spanish, and Danish

[4] The annual new installed global wind capacity grew from around 15 GW in 2006 to 51 GW in 2016 (IRENA, 2021). In 2006, over 80% of the cumulative global wind capacity was in Europe (65%) and the US (15%) with only a small amount in China (3%). However, by 2016, the Chinese wind market had grown so rapidly that it accounted for 32% of global wind capacity (IRENA, 2021).

[5] Most of the installations were in the technologically mature onshore wind technologies. In terms of emerging large-scale offshore wind, Europe (and specifically the UK) showed highest installations.

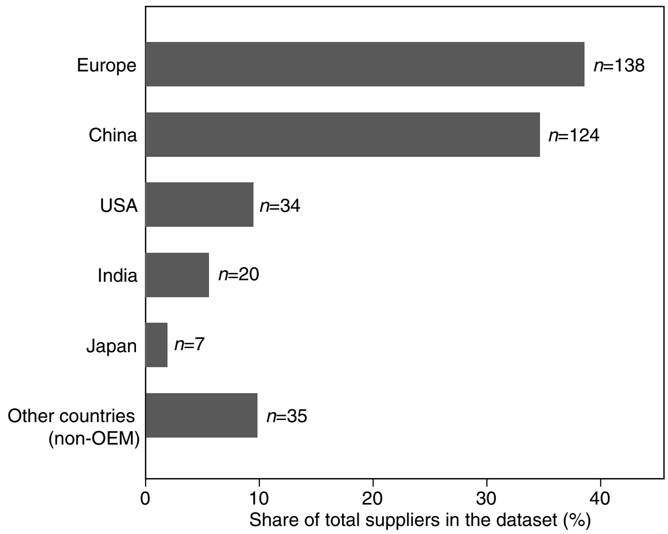

Fig. 2. Home country of suppliers in our dataset. *n* represents the number of firms.

suppliers, where we found no major differences to the European average. Chinese suppliers also dominate our sample, accounting for 34.6% of all suppliers. A smaller share of suppliers originated from the U.S. (9.5%), India (5.6%), Japan (2.0%), and other countries (9.8%, e.g., in Turkey, Brazil, Egypt, South Korea, Australia, Indonesia) (see Fig. 2).

Given the centrality of the European and Chinese markets in the global wind energy sector and the fact that approximately two-thirds of the suppliers included in our sample originate from Europe and China, we present detailed findings for these two markets in Section 5.

4.2. The temporal dimension of innovation

We identified the anticipated long-term and short-term research priorities using expert reports published by the International Energy Agency's Implementing Agreement for Co-operation in the Research, Development, and Deployment of Wind Energy Systems (or IEA-Wind), in 2001 and 2013 (IEA Wind 2013; IEA Wind 2001). IEA-Wind comprises key stakeholders involved in wind energy planning–including national government agencies (such as the U.S. Department of Energy) and industry associations (such as the Chinese Wind Energy Association). IEA-Wind conducts periodic assessments of experts to determine research, development, and demonstration needs for wind energy, which are published in reports. From these reports, we identified innovations expected to lead to commercialization in the short-to-mid-term (0–10 years) and long-term (10–20 years) (see Table A1).

After identifying the research and innovation needs, we analyzed the content of patents to identify what firms and inventors aim to achieve from innovation in terms of the focus of technology. To do so, we first obtained global patent data from all reported patent offices from the Derwent Innovations Index, accessed through Web of Science, using a rigorous keyword search covering all global wind energy patents between 1998 and 2018 (i.e., two years after the last supplier-OEM relationship in our dataset). The keyword search was based on prior work published by Huenteler et al., (2016a,b). Our initial dataset (of all wind patents) comprised over 70,000 patents of which 12,975 patents corresponded to a supplier or an OEM in our GVC dataset. The remaining patents involved individuals, universities or research institutes, and other firms that are not directly or actively involved in the wind GVC (e.g., Airbus, OEMs with small global market shares (e.g., World Wind India), start-ups, spin-offs, entrepreneurial firms, or those that design or maintain wind turbines (e.g., Aerodyn or Availon)). These were not included in our primary analysis (Section 5.2) but were instead compared with our sample in the sensitivity analyses (Section 5.3). We extracted patent information (e.g., title, abstract including translated abstracts, description, technology classification, priority country where the patent was first filed, and date of application) on each of the firms. Our search methodology limited patent results to wind energy technologies and components even for suppliers and OEMs that engage in multiple industries (e.g., large conglomerates like Siemens and GE). Our approach does (purposefully) not include all patenting activity that contributes to wind energy innovation but is not specific to wind energy (e.g., in jet engines, unless the patent is tagged with a wind-relevant classification code or keyword). However, we expect our approach to be thorough in capturing the innovation across the wind industry as our analysis emphasizes on the content of the patent in its specified linkages to wind-related R&D. Then, we used the text from the title and description (until the independent claim) of each patent to create a text corpus for natural language processing (NLP) using R (version 3.6.2). We assigned a greater weight to the title (through repetition) with the assumption that the keywords presented in the title are most representative of the focus of innovative activity. The patent information was prepared for text-based analysis using the text mining package *tm* (Feinerer et al., 2008) for pre-processing of the text corpus in the title and description text; (e.g., by removing redundant words in patent language such as 'section' or 'description', which are likely to be present in most patents, but do not add any significant meaning to the technical content of the invention). We also applied standard data cleaning approaches such as stemming words, removing punctuation and numbers, and removing stop words (commonly occurring words such as 'a', 'the', 'if' etc.).

We used multiple natural language processing methods on the text corpus developed above to identify the focus of innovation and manually matched it to the temporal dimension of innovation (based on the IEA-Wind outlook, Table A1). We linked patents to long-term innovation if *any* of the rigorous approaches mentioned below distinctly pointed towards long-term innovation. *First*, we used probabilistic topic modeling with Latent Dirichlet Allocation (LDA) to identify clusters of similar topics, using the *topicmodels* package for NLP (Grün and Hornik, 2011). LDA discovers similar topics in multiple documents (in this case patents) and automatically classifies documents under these topics by assigning a probability for each document to be associated with each topic. The *topicmodels* package allowed us to differentiate the technological focus of innovation in patents by clubbing together topics with similar word occurrences (Chan, 2015; Kim et al., 2014). We used 45 topics after assessing for the optimal number of topics (based on Deveaud et al., 2014), given the size of the corpus and the level of detail in the long-term innovation directions. Using the IEA-wind reports (see Table A1), we identified topics clearly associated with long-term research areas with at least 30% probability of being associated with long-term research needs. *Second*, we used the international patent classification (IPC) system to identify long-term innovation. We identified the various IPC codes appearing in our dataset and manually mapped the IPC class with general topic areas, where we classified some as long-term research (see Table A1 and Table A2). *Third,* we used another NLP technique, i.e., term frequency analysis, of the content of patents, where we counted keywords likely to be associated with long-term innovation needs (based on Table A1 and with more contextual details available in the IEA reports). For example, we specifically searched for keywords associated with offshore wind to classify those as long-term innovation during the time period considered, based on information in the IEA reports (Table A3). In addition, we conducted a sensitivity check by comparing our approach with existing measures of novelty (e.g., Verhoeven et al., 2016, see also Sections 2.1 and 5.3).

4.3. Measures and variables

4.3.1. Dependent variables

Our main dependent variable is *long-term patenting activity*, which we

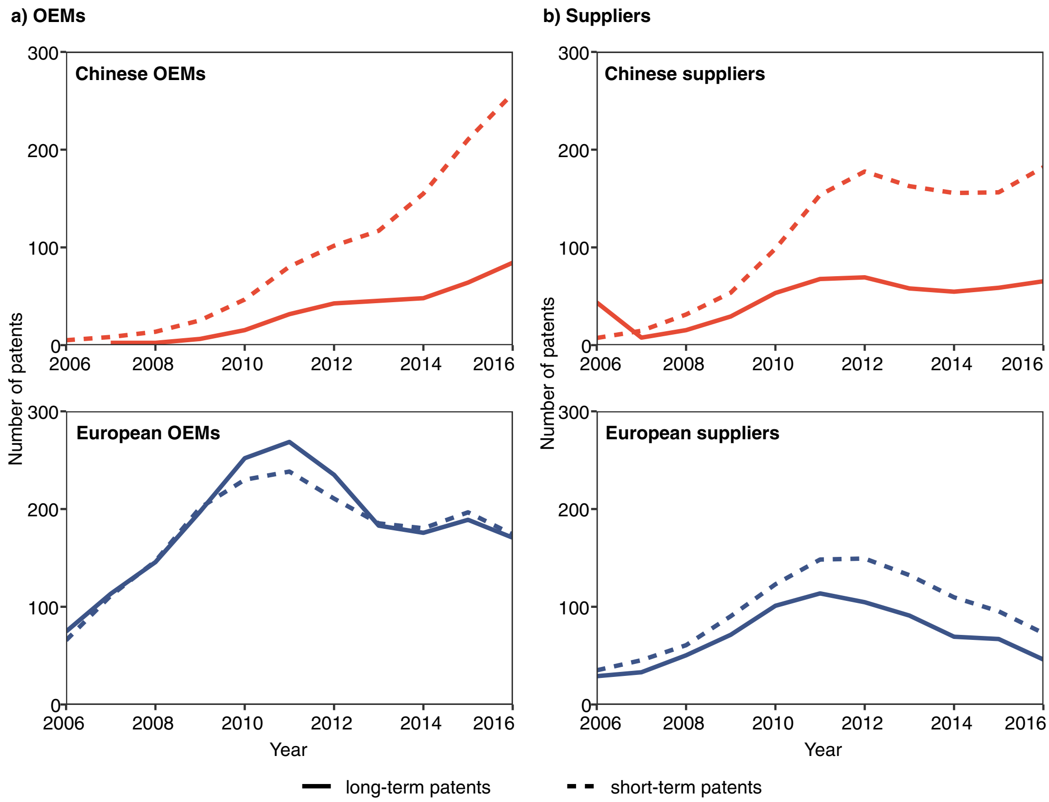

Fig. 3. The number of long-term and short-term wind patents filed in China and Europe by (a) OEMs and (b) suppliers. Figures show three-year rolling averages.

estimate as the annual number of long-term patents per supplier and per year. We also report the findings for short-term patenting activity using the same approach to identify changes in trajectories. To generate the variables, we matched and analyzed the patents to individual suppliers (i.e., where the supplier was an assignee on the patent) per year (see Section 3.2). While patents are by no means a complete reflection of the extent of R&D or innovation activities in a company, they are a well-established measure for indicating the focus of innovation within a company that is validated in an external examination process (Griliches, 1990; Hall et al., 2005; Howell, 2017). Moreover, they are especially relevant in industries with longer product life cycles (e.g., energy), which explains the high reliance on patents as measures of innovation in the wind energy context (Huenteler et al., 2016a, 2016b; Nemet, 2009). To account for the time-span between starting an innovation project and filing for a patent, we used time-lags based on the number of patents in the two years that followed the observation of the independent variables ($t + 1$ and $t + 2$). Both long-term and short-term patenting activity are count variables.

4.3.2. Independent variables

Our main independent variables are the *international* and *local relationships* of the suppliers with the OEMs, based on the home country of both. To quantify the relationships between supplier firms and OEMs over different reported time periods (i.e., 2006 and 2014), we used network analysis techniques (Taglioni and Winkler, 2016), specifically degree centrality. The degree centrality for each supplier captures the number of relationships of the supplier ('node') and is the simplest network measure that allows more intuitive interpretation of results (Doblinger et al., 2019). A relationship describes inter-firm linkages between a supplier and an OEM based on market transactions of supplying products or goods (e.g., Titan Wind (supplier) supplied to Vestas (OEM) in 2014–2016). A local relationship refers to suppliers supplying to OEMs that are headquartered in the same country as the supplier, whereas an OEM headquartered in a different country is treated as an international relationship. As we are interested in understanding if and how access to international knowledge shapes innovation outcomes in terms of long-term patenting, we used the headquarter of the OEMs and suppliers as explained above. As OEMs also have manufacturing and R&D locations in other countries than their headquarter or home-country, we control for this potential impact in our statistical models (see Section 4.3.3 and 4.4).

4.3.3. Control variables

We included several control variables in our statistical models at the level of the supplier-year. *Pre-sample patents* account for the diminishing importance of earlier knowledge. We included prior patents of the suppliers in terms of the pre-sample patent stock as a control variable, annually depreciated at a rate of 15 percent (e.g., Popp, 2004; Qiu and Anadón, 2012). Following Schilling and Phelps (2007), we included the annually depreciated value of pre-sample patents (before 2006 or before entering the sample) to control for unobserved heterogeneity in firm patenting activity. We split the variable in three groups (no prior patents, one or two patents, and three or more prior patents). *Specialization* accounts for potential effects from whether the supplier specialized in wind energy (=1) or was active in other sectors outside of the wind industry (=0). *Size* estimates the number of employees, based on last available data of full-time employees (or equivalents) as time varying data is not available for many private firms. We split the variable in two groups of less and more than 250 employees, following the common definition of Small and Medium Enterprises (SMEs) (European Commision, 2021). *Age* represents the time interval since the founding year of the supplier. We split the variable in three groups (<10 employees, 10–50 employees, >50 employees). *Technology complexity* represents the complexity of the component(s) in which the supplier is active accounting for potential differences that result from distinct internationalization and patenting behaviors prevalent in different components (e.g., towers vs. gearboxes). *Outsourcing* or insourcing strategies applied by the OEMs indicate how dependent each supplier is on the OEM,

Table 1
Descriptive statistics.

Variable	Obs	Mean	Std. Dev.	Min	Max
Long-term patents	1867	1.284	6.385	0	107
Short-term patents	1867	2.126	8.626	0	165
International relationship	1867	1.245	1.483	0	8
Local relationship	1867	1.329	1.372	0	11
Specialized	1867	0.242	0.428	0	1
Pre-sample patents (range)	1867	0.572	0.802	0	2
Component complexity	1867	0.398	0.488	−0.42	1.73
Size (range)	1867	0.606	0.489	0	1
Age (range)	1867	1.193	0.498	0	2
OEM outsource	1867	0.917	0.262	0	1
Cumulative installed capacity (MW)	1867	242,287	103,096	14,753	408,721

reflecting the governance approaches for procuring components from suppliers (Nieto and Rodríguez, 2011; Surana et al., 2020). This is a continuous variable ranging from 0 (only in-house relationships) to 1 (only outsourced relationships). *R&D/Manufacturing locations* of large OEMs are often in countries different from the one they are headquartered in. This is a factor variable that distinguishes the following five cases: (i) European OEM with R&D/manufacturing location(s) in a developing country; (ii) European OEM with R&D/manufacturing location(s) in an industrialized country only; (iii) Chinese OEM with R&D/manufacturing locations(s) in industrialized country; (iv) Chinese OEM with R&D/manufacturing in developing country only; (v) Mixed. *Cumulative installed capacity* captures the cumulative learning effects and the knowledge stock that develops over time within the global wind industry due to increases in global deployment (Qiu and Anadón, 2012). The variable consists of the annual cumulative installed capacity (Megawatts, MW) of wind energy as reported by IRENA (2006–2016).

4.4. Statistical models

To estimate the impact of international and local relationships on long-term (and short-term) patenting activity, we conducted a set of Negative Binomial Regression analyses from 2006 to 2016 using statistical modeling in Stata (version 16). We use negative binomial regressions because our dependent variables are based on the count of patenting activity and because of overdispersion when estimating Poisson regressions. In the regression results, the long-term and short-term patenting activity ($Y_{i(t+1,\,t+2)}$) for supplier i is estimated using the following Negative Binomial Regression model:

$$\log\left(Y_{i(t+1,\,t+2)}\right) = \beta_0 + \beta_1 \text{local relationships}_{it} + \beta_2 \text{international relationships}_{it} + \beta_3 \text{specialized}_{it} + \beta_4 \text{ component complexity}_{it} + \beta_5 \text{presample patents}_i + \beta_6 \text{size}_i + \beta_7 \text{age}_i + \beta_8 \text{OEM outsource}_{it} + \beta_9 \text{OEM strategy}_{it} + \beta_{10} \text{cumulative installed capacity}_{it} + \varepsilon_i \quad (1)$$

where β_{1-2} are the coefficients of interest, β_{3-10} the coefficients of the control variables including the continuous linear time trend (cumulative installed capacity per year). We clustered the standard errors by supplier in all models. While we present the direct coefficients in the models, they can be converted to incidence rate ratios between suppliers by calculating exp(β). Given the importance of the large and stable Chinese wind energy market after 2012 (see Section 3), we distinguish between pre- and post-2012 developments in our statistical models by presenting findings separately for these two time periods using sample splits. Moreover, in the negative binomial regression models, we focus on comparing the findings for European and Chinese suppliers during these two time periods and refer to the findings for all global suppliers in the Appendix (see Table A4).

Table 2
Correlations.

	Long-term patents	Short-term patents	International relationship	Local relationship	Specialized	Pre-sample patents (range)	Component complexity	Size (range)	Age (range)	OEM outsource	Cumulative installed capacity
Long-term patents	1										
Short-term patents	0.713***	1									
International relationship	0.0373	0.0306	1								
Local relationship	0.161***	0.167***	0.0552**	1							
Specialized	0.0376	0.0871***	0.0965***	0.0855***	1						
Pre-sample patents (range)	0.289***	0.289***	0.0807***	0.209***	0.0425	1					
Component complexity	0.177***	0.174***	−0.0422	0.0878***	0.0365	0.329***	1				
Size (range)	0.124***	0.146***	0.198***	0.114***	−0.131***	0.217***	0.144***	1			
Age (range)	0.0359	0.0766***	−0.0655***	0.0193	−0.201***	0.116***	0.183***	0.220***	1		
OEM outsource	−0.0351	−0.0998***	0.160***	0.0259	−0.206***	−0.0013	−0.0836***	0.0107	0.0226	1	
Cumulative installed capacity	−0.0662***	−0.0166	0.0932***	0.00572	0.00232	0.124***	−0.0692***	−0.03	−0.0561**	−0.0497**	1
Observations	1867										

*** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table 3
Results from negative binomial regressions.

	Long-term patenting activity				Short-term patenting activity			
	(1) European suppliers before 2012	(2) European suppliers after 2012	(3) Chinese suppliers before 2012	(4) Chinese suppliers after 2012	(1) European suppliers before 2012	(2) European suppliers after 2012	(3) Chinese suppliers before 2012	(4) Chinese suppliers after 2012
Main effects								
International relationship	−0.807	0.592***	0.125	0.514***	−0.499	0.369	−0.117	0.518**
	(0.245)	(0.006)	(0.570)	(0.002)	(0.363)	(0.108)	(0.570)	(0.027)
	[0.694]	[0.214]	[0.220]	[0.163]	[0.549]	[0.230]	[0.206]	[0.235]
Local relationship	0.628***	0.151	−0.503	0.320	0.497**	0.401**	0.235	0.197
	0.000	(0.263)	(0.330)	(0.277)	(0.020)	(0.028)	(0.545)	(0.500)
	[0.125]	[0.135]	[0.516]	[0.295]	[0.214]	[0.182]	[0.388]	[0.292]
Controls								
Specialized	1.602*	2.128***	0.616	−0.595	1.425*	1.851**	1.243	−0.259
	(0.085)	0.000	(0.663)	(0.206)	(0.090)	(0.012)	(0.110)	(0.489)
	[0.931]	[0.488]	[1.414]	[0.470]	[0.842]	[0.735]	[0.777]	[0.374]
Component complexity	1.274***	0.750	−0.119	−0.293	0.266	1.522***	−1.002	0.159
	(0.006)	(0.124)	(0.921)	(0.650)	(0.600)	(0.002)	(0.164)	(0.755)
	[0.462]	[0.487]	[1.192]	[0.646]	[0.507]	[0.483]	[0.720]	[0.508]
Pre-sample patents (range)	1.983***	0.861**	2.777***	1.128***	2.073***	1.118***	1.232***	1.043***
	0.000	(0.019)	(0.005)	0.000	0.000	0.000	(0.005)	0.000
	[0.345]	[0.368]	[0.985]	[0.298]	[0.357]	[0.277]	[0.438]	[0.232]
Size (range)	1.209*	1.665***	16.163***	0.107	−1.248	−0.013	1.371	0.525
	(0.098)	(0.005)	0.000	(0.825)	(0.103)	(0.981)	(0.123)	(0.268)
	[0.730]	[0.594]	[0.707]	[0.485]	[0.765]	[0.530]	[0.889]	[0.473]
Age (range)	−1.729**	0.270	0.886	−0.114	0.149	0.781*	1.257	0.593
	(0.026)	(0.516)	(0.716)	(0.866)	(0.841)	(0.051)	(0.174)	(0.310)
	[0.775]	[0.416]	[2.433]	[0.674]	[0.739]	[0.400]	[0.925]	[0.584]
OEM outsource	0.519	2.191	−5.169***	−1.032	3.407***	1.865**	−3.654***	−1.289
	(0.686)	(0.103)	(0.001)	(0.302)	(0.009)	(0.044)	0.000	(0.371)
	[1.283]	[1.344]	[1.605]	[1.000]	[1.305]	[0.924]	[0.722]	[1.441]
Cumulative installed capacity	0.000***	−0.000***	0.000	0.000	0.000*	−0.000***	0.000	0.000
	(0.009)	0.000	(0.881)	(0.301)	(0.062)	0.000	(0.539)	(0.671)
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
lnalpha	0.688**	0.984***	0.077	1.183***	1.151***	1.165***	1.272***	1.361***
	(0.029)	(0.003)	(0.937)	(0.002)	(0.001)	0.000	0.000	0.000
	[0.315]	[0.331]	[0.964]	[0.379]	[0.353]	[0.330]	[0.309]	[0.200]
Constant	−4.622***	−5.987***	−15.842***	−3.655**	−6.419***	−6.225***	0.511	−2.151
	(0.002)	0.000	0.000	(0.022)	0.000	0.000	(0.722)	(0.276)
	[1.515]	[1.127]	[2.765]	[1.591]	[1.396]	[1.449]	[1.439]	[1.975]
Observations	237	534	150	457	237	534	150	457
OEM Strategy FE	YES	YES	YES	YES	YES	YES	YES	YES
Pseudo R^2	0.241	0.24	0.382	0.147	0.16	0.197	0.122	0.0724

p-value in parentheses *** p<0.01, ** p<0.05, * p<0.1; firm-clustered standard error in brackets.

5. Results

5.1. Descriptive results

In total, we have an unbalanced panel of 1867 observations of 358 suppliers from 2006 to 2016. Our descriptive analysis shows the following key features, which we present for Chinese and European suppliers. The total number of patents was lower in China compared to Europe. Fig. 3 shows the annual long-term and short-term wind patents filed by suppliers in China and Europe. These graphs suggest that while the overall patenting activity, especially for long-term innovation, was higher in Europe, there was an upward trend in China during the last three years of our observation period (2014–2016). We also observe an overall decline in patenting activity in Europe after 2011–2012 coinciding with a period of industry consolidation (e.g., through mergers and acquisitions), relatively low gas prices, as well as with the general reduction of renewable energy patents after 2012 (Probst et al., 2021). Although the total number of suppliers active in the market decreased in the study period, the remaining suppliers intensified their patenting activities.

We summarize the descriptive statistics and correlations in Table 1. A supplier had on average 1.25 international and 1.33 home-country relationships. Moreover, the 358 suppliers were 41.3 years old on average (ranging from 4 to 311 years). Overall, a supplier filed for 1.29 long-term patents per year (ranging from 0 to 107), and 2.12 short-term patents (ranging from 0 to 165). Table 2 shows the correlations between our variables, which are not highly correlated.

5.2. Results from negative binomial regression analyses

We present our regression results in Table 3 and plot the coefficients in Figs. 4a (long-term innovation) and 4b (short-term innovation). In Table 3, we use sample splits in Models 1–2 for European suppliers, and Models 3–4 for Chinese suppliers. The same set of explanatory and control variables presented in Eq. (1) in Section 4.4 are used in all cases.

Figs. 4a and 4b as well as Model 1 in Table 3 imply that for European suppliers, local relationships (i.e., European supplier-European OEM) are significantly positively associated with long-term and short-term patenting activity before 2012. As negative binomial regressions model the log of incident counts, long-term patenting increased by 87.4% for every additional local relationship (β = 0.628, p-value = 0.000, Model 1), yet this long-term patenting advantage became

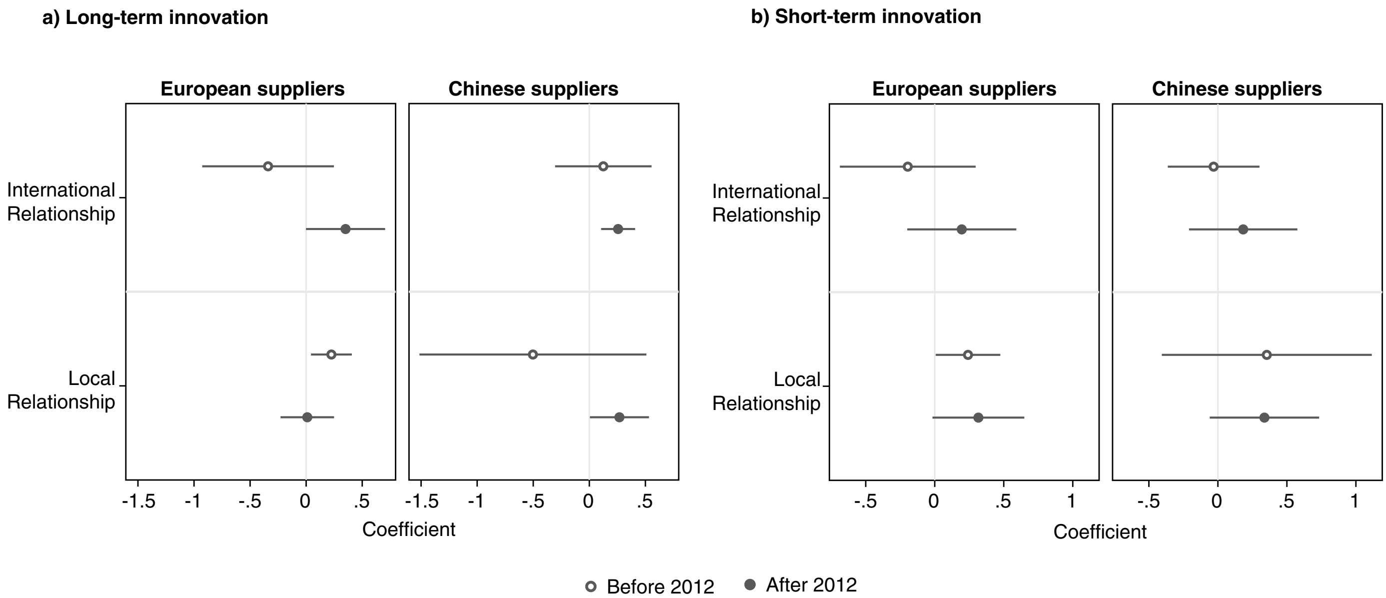

Fig. 4. Comparison of coefficients for European and Chinese suppliers, before and after 2012, for (a) long-term innovation and (b) short-term innovation. A significant negative association is depicted at the left side of the gray line, positive at the right. Significance of the relationships is indicated if estimation and confidence interval are on one side of the gray line. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.).

insignificant when market growth shifted to China after 2012. Interestingly, the opposite holds for international relationships. Long-term patenting is negative but insignificantly associated with every additional international relationship (i.e., European supplier-non European OEM) before 2012. Yet after 2012, long-term patenting activity increased by 80.7% with every additional international relationship ($\beta = 0.592$, p-value $= 0.006$, Model 2). Short-term patenting significantly increased with every additional local relationship irrespective of where market growth was stronger ($\beta = 0.497$, p-value $= 0.020$, Model 1 (before 2012); $\beta = 0.401$, p-value $= 0.0028$, Model 2 (after 2012)), whereas international relationships are not significantly associated with short-term patenting before and after 2012 (Models 1 and 2). This implies that European suppliers benefit from collaborating with European OEMs for generating more long-term and short-term innovation. However, when considering that global market demands shifted 2012 onwards, primarily to China, we note that internationalization was a key driver for long-term patenting within European suppliers.

For Chinese suppliers, a comparison of Models 3 and 4 (Figs. 4a and 4b) implies that despite the growing local market in China after 2012, local relationships (i.e., Chinese suppliers – Chinese OEMs) were not associated with higher long-term or short-term patents. However, after 2012, we observe that long-term patenting increased by 67.2% with every additional international relationship ($\beta = 0.514$, p-value $= 0.002$, Model 4), whereas short-term patenting increased at a similar level (67.8%) for every additional international relationship ($\beta = 0.518$, p-value $= 0.027$, Model 4). This implies that Chinese suppliers increased their long-term and short-term innovation activities based on international relationships, but only after the Chinese market was more attractive for international OEMs after 2012. There are, however, no patenting advantages when collaborating with Chinese OEMs.

5.3. *Sensitivity analyses*

We conducted several additional analyses to evaluate the robustness of our findings, including comparing our temporal dimension to a measure for the novelty of innovation, alternative model specifications, an additional control variable on the country of priority of the patent, an instrumental variable analysis, and a comparison of our sample to the one of other actors active in wind innovation.

We compared the findings with our metric on long-term and short-term patenting activities to a measure of novelty,[6] based on the concept that radical innovations result from the new combination of existing scientific principles (Arthur, 2007; Fleming, 2001; Hargadon, 2002). However, we use this only as a sensitivity test because all long-term innovations may not be radical (see Section 2.1).[7] When comparing the findings from negative binomial regressions using the same models (see Eq. (1)) for the alternative measure based on IPC group codes, we get comparable, but not the same findings (see Table A5 in the Appendix). One of the main differences is that the novelty measure reveals a positive, yet insignificant association between international relationships and long-term patenting for Chinese suppliers after 2012 ($\beta = 0.307$, p-value $= 0.138$, Model 4), which was significantly positive using our temporal-dimension. Moreover, for both Chinese and European suppliers, the novelty approach reveals a negative and significant association between international relationships and long-term innovation before 2012, which was insignificant in the models based on our temporal dimension approach. Although both metrics are correlated and offer an ex-ante assessment of the focus of innovation, the

[6] We use the approach proposed by Verhoeven, Bakker and Veugelers (2016) that uses patent classification group codes (8-digit level in the IPC system) to proxy the scientific principles that patents focus on. When a pair of such codes combines for the first time compared to previous patents, it is classified as a highly novel or radical innovation.

[7] Taking the example of offshore wind within our dataset, only 23.76% of the patents classified as long-term with our approach were classified as radical with this approach. A comparison of the correlations between the two measures (long-term patenting vs. radicalness) still showed high and significant values (long-term patents: r = 0.833, p-value = 0.000; short-term-patents: r = 0.962, p-value = 0.000).

small but clear differences suggest that our industry-specific assessment of the temporal dimension of innovation offers more nuanced insights.

We also estimated alternative model specifications. We started by estimating logit regressions to understand the differences between applying for the first long-term or short-term patent when compared to the drivers affecting the annual total number of patents, which revealed comparable estimates (see Table A6). We next estimated the percentage of international relationships by dividing international relationships by all relationships (sum of local and international). These findings, again, show similar trends (see Table A7), but it is hard to disentangle the likely effects of international vs. local relationships. Here, we observe that there is an insignificant, but negative association between the percentage of international relationships and long-term patenting ($\beta = -0.994$, p-value = 0.192, Model 2). Hence, it is the absolute increase in international relationships that seems to drive long-term patenting activities (see Table 3), and not the shift of suppliers' strategies towards more international activities at the cost of local relationships.

Moreover, we investigate if the country of priority of the patent affects our findings to understand if patents filed in China are different from the ones in other countries (Lam et al., 2017). We estimated our main models including an additional control variable for the percentage share of Chinese long-term and short-term patents (i.e., with priority in China) in the total patents per supplier (see Table A8). The key findings are the same, showing how both European and Chinese suppliers significantly increased their long-term patenting activity in response to relationships with international OEMs. We only observe differences to Table 3 regarding the role of relationships with Chinese OEMs for Chinese suppliers, which were positive yet insignificant in the main model, and turn out to be relevant for long-term patenting after 2012 when including the fraction of Chinese patents (Table A8, Model 4). Hence, accounting for the potential differences between Chinese and other patents does not affect our main findings on the drivers of long-term innovation before and after market shifts to China but displays more nuances regarding the role of local relationships.

We addressed potential endogeneity concerns that more patenting activities lead to more relationships through various approaches. We include time-lags between the relationship and the outcome in terms of patents ($t + 1$ and $t + 2$, see Section 4.3.1). We also include the pre-sample patents, i.e., the number of patents that each supplier acquired before 2006, in all our models that allows us to account for the possibility that patents lead to more supplier-OEM relationships in the first place. We also conducted an instrumental variable regression (IV) analysis (2SLS) by using trade agreements between countries as an instrument. We collected the trade agreements on goods and services in our time period from the World Trade Organization webpage (WTO, 2021). The relevance criterion holds because trade agreements are likely to have a positive impact on the ease of engaging in internationalization endeavors. The exogeneity assumption is also likely to be met because a trade agreement between two countries is unlikely to affect or lead to adaptations of type and amount of patents (typically affected by factors such as prior patents, financing, age, size, etc.). While trade agreements are a weak instrument when focusing on the time-period between 2006 and 2012 ($F = 2.20$) for European suppliers, this instrument is strong in the second observation window between 2012 and 2016 ($F = 25.21$ for both long-term and short-term patenting activity) (Stock and Watson, 2007). The results from the 2SLS analysis suggested similar findings of a significant positive association of international relationships for long-term innovation ($\beta = 3.44$, p-value = 0.000) (see Table A9).[8]

Finally, we examined whether our focus on long-term innovation in suppliers and OEMs in the GVC reflected broader wind technology innovation trends, including the activities from other actors. We collected additional information on other actors innovating across wind components, especially universities and research institutes, and applied our methodology (see Section 4.2) to assess if those actors have distinct developments over time when compared with our sample. However, we observe a comparable share of long-term vs. short-term patents of suppliers and OEMs (see Fig. A1) with the one of research institutes and universities (see Fig. A2).[9] Given that we observe similar trends in patenting activity for both suppliers and OEMs and that these stakeholders are known to collaborate with universities and knowledge intensive firms (Haakonsson and Kirkegaard, 2016; Haakonsson and Slepniov, 2018), we expect that their ability to innovate in the long-term can also be a good proxy for how they integrate and improve any long-term innovations developed by other actors.

6. Discussion

Our study highlights how a combination of location of manufacturing, GVC governance, the proximity of suppliers and OEMs for learning effects, and policy-induced demand-pull supported innovation in clean energy technology suppliers for meeting long-term climate goals. Our analysis suggests that, in this policy-induced industry, internationalization has a positive association with long-term innovation, as value chains become increasingly globalized and manufacturing shifts to emerging economies such as China. For European suppliers, local relationships with European OEMs were associated with an 87.4% increase in long-term innovation activities, but only before 2012, when the European wind energy market dominated global new wind energy installations. As the Chinese market became more attractive after 2012, European suppliers with international OEM relationships were associated with an 80.7% increase in their long-term innovation activities. International relationships and markets were thus a key driver for long-term patenting within European suppliers. For Chinese suppliers, relationships with international OEMs increased their long-term innovation activities by 67.2%, but only after 2012 when the Chinese market became attractive for international OEMs. Meanwhile, also after 2012, there were no long-term patenting advantages of local relationships, i.e., with Chinese OEMs. Overall, our findings suggest that manufacturing shifts to China did not suppress long-term innovation in the wind energy industry. These findings allow us to contribute in the following three ways to research on clean energy innovation and GVCs.

6.1. The temporal dimensions of innovation

Our study introduces a temporal dimension to the direction of innovation that can more effectively assess innovation in the context of long-term societal goals, including net-zero emissions, economic competitiveness, and development. The temporal perspective complements existing discussions on accelerating innovation that have so far focused on low-carbon vs. high-carbon or radical vs. incremental innovation (e.g., Anadón, 2012; Schmidt et al., 2012; Mazzucato and

[8] Please note that we are only able to use this instrumental variable approach for our findings for the sub-sample of European firms, as there is hardly any variance in the sub-sample of Chinese suppliers (there are no relevant trade agreements applying to Chinese suppliers within our observation time window).

[9] We also calculated the shares of more and less novel patents using the novelty measure described in the first robustness check for all European and Chinese wind energy patents of all actors, including individuals and other firms that are not directly or actively involved in the wind GVC. We did this additional step using the novelty metric rather than the temporal dimension approach because the methodological and computational approach required to develop and run the topic models classifying more than 77,000 patents into long-term and short-term and organizing them around various types of innovators (e.g., OEMs, suppliers, universities, individuals) requires a dedicated research approach and methodological contribution that was beyond the scope of this work. Figure A3 displays the shares for all Chinese and European patents, which again did not show major changes between the shares of low and high novelty over time.

Semieniuk, 2018; Li et al., 2021; Nemet, 2009). By introducing a different level of analysis (i.e., the long-term and short-term impact of clean energy innovation) at a granular technology and component level (e.g., not just the wind turbine but all the parts and processes that comprise the turbine and its operation), our approach can concretely assess progress and trends in individual technologies relative to long-term societal goals. In that, we contribute to research on quantifying energy innovation focused on monitoring and evaluating existing efforts (e.g., Bettencourt et al., 2013; Choi and Anadón, 2014; Huenteler et al., 2016b; Johnstone et al., 2010; Popp et al., 2011). Our approach can potentially also support efforts to improve representations of technological innovation in integrated assessment and other models, given our focus on the temporal dimensions and volumes of innovation (e.g., Anadón et al., 2017; Meng et al., 2021). Our novel approach opens new pathways to developing new and automatized datasets to understand the direction of innovation through advanced machine learning tools. The metric for the temporal dimension of innovation can also be applied to other technologies or sectors beyond clean energy as we build on, and complement, existing approaches in the broader novelty literature (e.g., Arts et al., 2021; Kelly et al., 2018; Verhoeven et al., 2016) (see also Section 6.3).

6.2. The role of suppliers in shaping innovation in GVCs

Our research on innovation in GVCs centers on suppliers rather than the OEMs, which offers compelling new evidence of their important role in shaping the direction of innovation. In that, we address three major gaps by: (i) focusing on suppliers (and components) that have been generally overlooked in the broader GVC innovation literature (see e.g., Ambos et al., 2021), (ii) mapping and empirically assessing the GVC of a rapidly expanding modern industry, where despite growing questions around globalization of supply and demand GVCs remain 'heavily debated but hardly measured' (OECD, 2018), and (iii) showing how international relationships do not only help emerging economy firms to implement cost reductions, but also promote long-term innovation.

Our empirical evidence of the importance of suppliers in shaping the direction of innovation in GVCs advances emerging theories on innovation in global value chains (Cattaneo et al., 2013; Haakonsson and Kirkegaard, 2016; Haakonsson and Slepniov, 2018; Jurowetzki et al., 2018; Pietrobelli and Rabellotti, 2011; Surana et al., 2020; Zhang and Gallagher, 2016), especially for technologies associated with complex products and systems (see also Section 6.3). While these theories link innovation to the governance of the GVC, firm strategies or competences, mostly from the OEM perspective, our paper is one of the few quantitative assessments of suppliers that also differentiates by location (see also Surana et al., 2020). In that, our work specifically adds to discussions that clean energy innovation in China is primarily linked to cost reductions or to reducing dependence on foreign knowledge and investment (e.g., Gosens and Lu, 2014; Lam et al., 2017; Sivaram et al., 2018). Our findings indicate that international relationships may not only shape cost reductions (Tang and Popp, 2016), but also support long-term innovation for Chinese suppliers. However, when comparing the shares of long-term vs. short-term patents (see Fig. A1), our results suggest that there might still be a stronger short-term orientation among Chinese suppliers when compared with European suppliers, especially after 2010.

6.3. The direction of innovation and manufacturing shifts

Our comprehensive evaluation of the location of GVC (i.e., both suppliers and OEMs in Europe and China) and their local or international relationships adds to previous research that emphasizes the importance of proximity between manufacturing location and demand for innovation (Fuchs and Kirchain, 2010; Von Hippel, 1994). However, we also offer new insights that differ from prior findings on the direction or emphasis of innovation in developed vs. emerging economies. We show how proximity between demand and supply can drive long-term innovation in a policy-induced, internationally dispersed value chain—and not suppress more advanced innovation as suggested in the optoelectronics industry (e.g., Fuchs and Kirchain, 2010; Yang et al., 2016). In the study period, wind energy technologies were often not cost competitive with conventional energy supply and needed government interventions to scale up. European wind energy suppliers were operating in a context of growing market sizes abroad, even stronger than in their home markets. On the contrary, the studied firms in optoelectronics faced a trade-off after offshoring their manufacturing activities between meeting the needs of the current market more competitively and investing in future market needs due to constrained market sizes (Fuchs, 2014). In optoelectronics and other industries such as automotive, manufacturing and R&D initially occurred in the country with the highest market value and later moved to emerging economies for low-cost production to supply new, global markets (Vernon, 1966; Fuchs and Kirchain, 2010). In the case of clean energy, supply shifts to China occurred also because of Chinese policy-induced incentives for clean energy, which enabled large and stable demand, supported domestic R&D, and helped develop domestic manufacturing to meet local and global demands (Surana and Anadón, 2015; Zhang and Gallagher, 2016). With the large Chinese market demands, international relationships in the GVC ensured learning effects resulting from the proximity of manufacturing to the users of turbines (Nemet, 2009; Sagar and van der Zwaan, 2006; Tang and Popp, 2016; Von Hippel, 1994), yet without the tradeoffs resulting from constrained market sizes. Thus, for scholars working on manufacturing and GVCs, our approach illustrates the need to account for local market sizes and growing demand in emerging economies and supplier relationships, which might spur rather than suppress long-term innovation.

However, this interpretation of continued long-term innovation despite market shifts to China also needs to be considered in the light of the technology. Wind energy technologies are complex components and systems that require local adaptations and are characterized by high shipment costs and lumpiness (Huenteler et al., 2016a; Malhotra and Schmidt, 2020; Wilson et al., 2020), which might spur local R&D. Other technologies with similar characteristics in terms of design intensity or customization could include concentrating solar power, green hydrogen technologies, long-duration energy storage, decarbonized industrial process technologies, carbon capture and storage, carbon dioxide removal, and modular nuclear reactors (Malhotra and Schmidt, 2020). Many of these have similar industry structures (with multiple suppliers, and few OEMs), are harder to scale up, and urgently need long-term innovation. For other clean energy technologies with different characteristics, primarily solar energy where deployment policies are of similar importance, our findings on the drivers of long-term innovation might not be fully applicable given lower shipment costs and process-driven engineering challenges (independent of the location) instead of local adaptations (Huenteler et al., 2016b; Malhotra and Schmidt, 2020). As solar energy technologies are similar to optoelectronics (in that innovation challenges are process-driven yet not characterized by small, constrained markets given the strong presence of deployment policies), we encourage future research to take a time perspective on solar energy innovation and explore if and how long-term innovation is affected by manufacturing shifts to emerging or developing economies.

7. Policy implications and conclusions

This paper emphasizes the need for understanding the temporal dimension of clean energy innovation given the need for meeting long-term societal goals and to avoid locking in technologies that may be inferior. For policymakers, this calls for the design of green industrial or mission-oriented policy considering the full GVC, targeting diverse timelines rather than focusing on scaling up R&D or deployment activities in isolation. Such approaches are indeed gaining traction, for example in the U.S. battery supply chain policy (U.S. Department of

Energy, 2021). In this context, our research offers three major policy implications.

First, our research emphasizes previous insights that public research funding needs to incentivize innovation in line with long-term societal goals. This means in one sense, not simply focusing on breakthroughs, but also supporting long-term evolutionary changes in existing technologies. It also adds the explicit aspect that firms could view long-term outcomes as not only separate from short-term market competitiveness, but something that firms themselves also see strategic value in. International forums (e.g., IEA's Technology Collaboration Programs, Mission Innovation) provide important platforms for governments, research organizations, and industry to discuss innovation needs for clean energy and climate technologies where long-term innovation is needed (e.g., hydrogen, negative emissions, and carbon removal technologies), and to ensure that R&D spending is allocated with a long-term outlook (UNFCCC, 2021) and enabling future options.

Second, policymakers need to ensure that their decarbonization ambitions increase and enable large demand across the many sectors that need to cut emissions, but that these also come with policy stability. Consistent signaling and transparency from governments about long-term or short-term targets and national climate strategies is a critical part of ensuring that the future competitive landscape is communicated clearly to innovating firms. This helps link their internal prioritization and resource allocation with the solidifying vision of, for example, 2050 net zero goals and associated policy pathways. In contrast, repeated policy reversals and a lack of long-term goals can be detrimental to creating this type of strategic clarity. For example, large number of suppliers in China compared to the relatively few number of suppliers in other countries with large wind markets (such as the U.S. or India) suggest that demand alone is not enough and that policy flipflops can restrict local industry development (e.g., Barradale, 2010; Surana and Anadón, 2015). Increasing the ambition for clean energy deployment and communicating policy pathways transparently and clearly can increase confidence, even in a not-perfectly-certain policy future. This can help develop a local industry as suppliers emerge, innovate because of the learning effects from proximity to users, and in turn become more competitive.

Third, in the specific case of China, creating collaborations on clean energy may provide a more effective strategy to deliver on long-term clean energy goals than competing (see also Helveston and Nahm, 2019). China has been central to manufacturing in general in the last decades, and to clean energy in particular. While tensions exist between China and many other countries in manufacturing and exports of various technologies, China continues to be one of the largest markets for clean energy. Restricting international supply networks (e.g., through tariffs) has limited demonstrated benefits (Sharma et al., 2022). Instead, they can hurt firms' long-term innovation in clean energy technologies, which then limits their competitiveness to compete in global markets.

Our work has two main limitations. One, we use the headquarter location of component supplier (or OEM) rather than the location of manufacturing (e.g., supplier subsidiaries in other countries) because of incomplete publicly available data on manufacturing especially for smaller firms (Surana et al., 2020). The internationalization of R&D and the co-location of international R&D with manufacturing activities might affect the direction of innovation (Ambos et al., 2021). Two, our measure for long-term and short-term innovation is sensitive to industry context or technology characteristics and requires additional verification. Ideally, an evaluation after 10 or 20 years would help in determining the actual contributions to research areas currently identified as being 'long-term innovation,' something which can only be fully determined in retrospective. We see exciting opportunities for future research to further develop our approach on quantifying the temporal dimension of innovation and applying it to study the relationships between the location of manufacturing, demand, and long-term and short-term innovation in other clean energy technologies.

Data statement

The dataset on the wind energy global manufacturing value chain builds on Surana et al. (2020), where related supplier data (without the supplier company name) are available at https://github.com/kavsurana/tech-complexity-project. The dataset uses information from third-party reports (Navigant Consulting) and datasets (Orbis, Amadeus, Bloomberg and DerwentWorld Patents Index) that are not publicly available. Data are however available upon reasonable request from the corresponding author.

CRediT authorship contribution statement

Claudia Doblinger: Conceptualization, Software, Methodology, Formal analysis, Investigation, Validation, Data curation, Visualization, Writing – original draft, Writing – review & editing, Project administration. **Kavita Surana:** Conceptualization, Software, Methodology, Formal analysis, Investigation, Validation, Data curation, Visualization, Writing – original draft, Writing – review & editing, Project administration, Funding acquisition. **Deyu Li:** Software, Formal analysis, Validation, Visualization, Writing – review & editing. **Nathan Hultman:** Conceptualization, Writing – review & editing, Funding acquisition. **Laura Díaz Anadón:** Conceptualization, Methodology, Writing – review & editing, Project administration, Funding acquisition.

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.

Acknowledgments

This work was supported by the U.S. National Science Foundation (NSF) [grant number 1829252]; UK Research and Innovation (UKRI) [grant number ES/S010688/1]. The authors thank Mel George and Anna Hammerstingl for their valuable research assistance. Early versions of this work were presented at the U.S. National Academies of Science, Engineering, and Medicine (NASEM) workshop on Innovation, Global Value Chains, and Globalization Measurement in 2021 and at the Association for Public Policy Analysis & Management (APPAM) Fall Research Conference in 2020. The authors thank two anonymous reviewers for their constructive feedback which greatly improved this manuscript.

APPENDIX

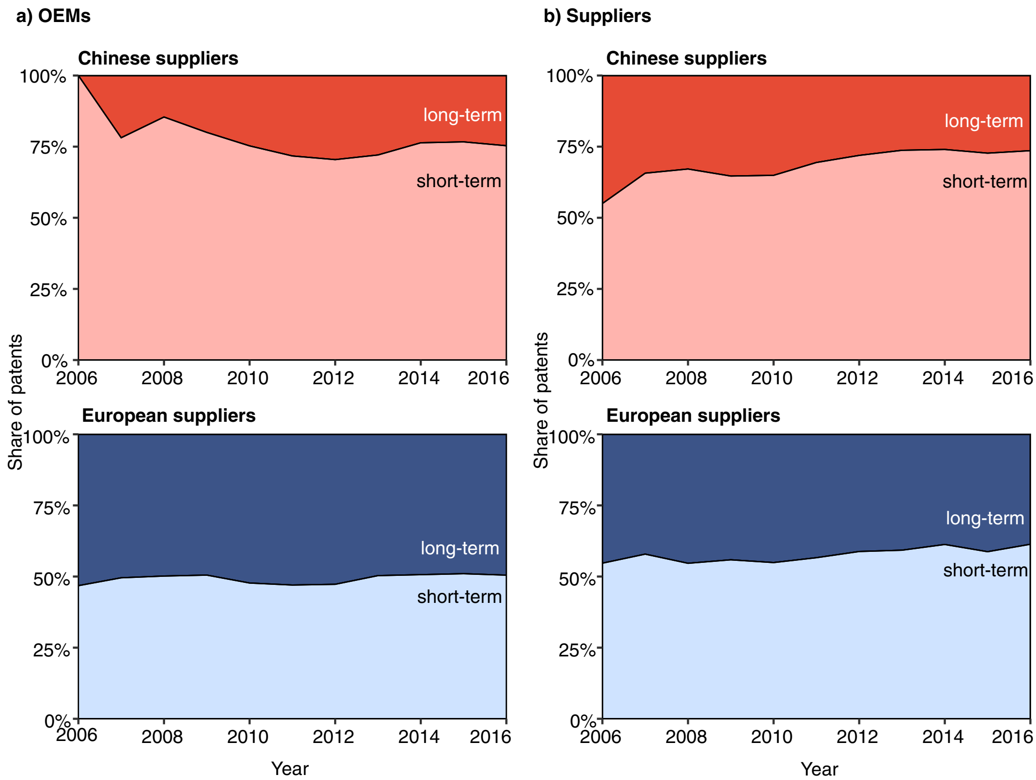

Fig. A1. The share of long-term and short-term wind patents filed in China and Europe by (a) OEMs and (b) suppliers. Figures show three-year rolling averages.

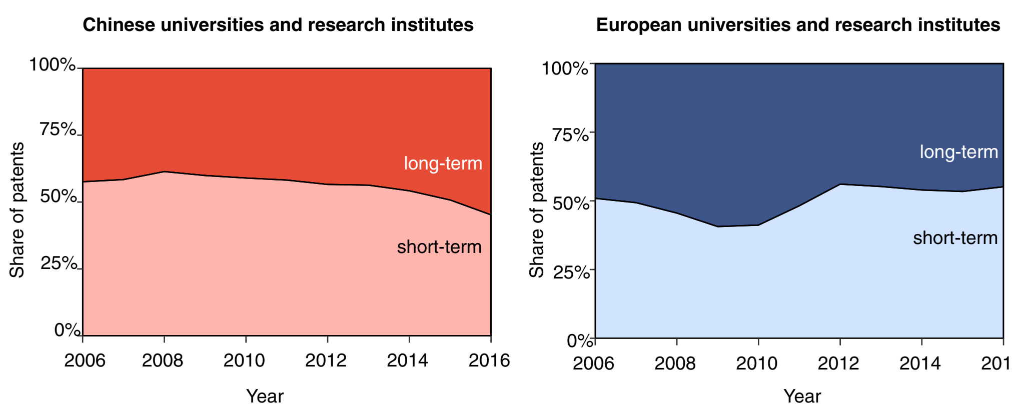

Fig. A2. The share of long-term and short-term wind patents filed in China and Europe by universities and research institutions. Figure shows three year rolling averages.

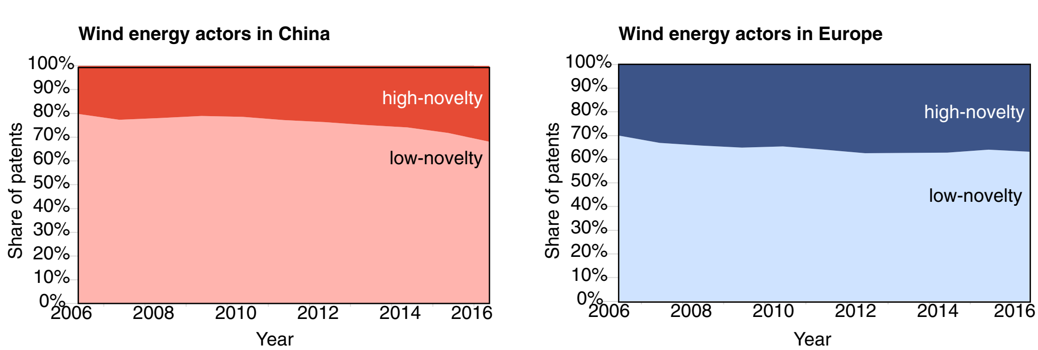

Fig. A3. The share of high and low novelty wind patents from all wind energy actors in China and Europe. Figure shows three year rolling averages.

Table A1
Long-term and short-term wind energy research needs (in the period of analysis). Source: IEA reports and authors' assessment (IEA Wind 2013; IEA Wind 2001)

Description	IEA report assessment	Authors' assessment
Atmospheric flow modeling	Long-term	Long-term
Marine environment	Long-term	Long-term
Floating offshore wind plants	Long-term	Long-term
Blade control system	Long-term	Long-term
Blade materials	Long-term	Long-term
Advanced generator, superconductor, medium speed	Long-term	Long-term
Offshore support, floating foundation	Long-term	Long-term
Power plant control, optimization, reliability, lifetime	Long-term	Long-term
Advanced manufacturing, carbon fiber, segmented blades, automation, anti-fatigue, recyclable	Long-term	Long-term
Improved reliability, more lifetime for components, less temperature cycling	Long-term	Long-term
Smart grid	Long-term	Long-term
Turbine design tools for onshore and offshore	Medium-term	Long-term
Blade sensor and control devices	Medium-term	Long-term
Offshore installation and logistics, vessel	Medium-term	Long-term
Transmission infrastructure, HVDC	Medium-term	Long-term
Offshore transmission	Medium-term	Long-term
Studies for flexible reserve, demand side response, storage integration	Medium-term	Long-term
Power plant design and optimization	Medium-term	Long-term
Noise reduction or increased tip speed	Medium-term	Long-term
Direct drive, drivetrain design	Medium-term	Long-term
System design and scaling	Medium-term	Long-term
Scaling, large turbines	Medium-term	Long-term
Flexible rotor, large rotor	Medium-term	Long-term
Siting	Medium-term	Short-term
Power plant flow modeling	Medium-term	Short-term
Wind forecast	Medium-term	Short-term
Power production forecast	Medium-term	Short-term
Different operating conditions, cold weather, tropical weather etc.	Medium-term	Short-term
Power electronics, high efficiency	Medium-term	Short-term
Light material and steel replacement for towers	Medium-term	Short-term
Operational data, failure rate, repair time	Medium-term	Short-term
O&M diagnostic, failure more, modeling damage on cracks, repairing techniques	Medium-term	Short-term
Component and system testing facility	Medium-term	Short-term
Building-integrated small wind	Medium-term	Short-term
Distributed wind	Medium-term	Short-term
Manufacturing of small wind turbines	Medium-term	Short-term
Distributed wind, SCADA for small wind and smart grid integration	Medium-term	Short-term
Resource assessment, wind atlas	Short-term	Short-term
Characterizing icing and ice	Short-term	Short-term
Remote sensing, lidar, sodar, radar	Short-term	Short-term
Electricity market	Short-term	Short-term
Grid code, compliance testing, voltage source convertor	Short-term	Short-term
Voltage and frequency control systems to monitor and predict voltage dips	Short-term	Short-term
Small turbine testing	Short-term	Short-term

Table A2
Topics identified in the IPC description and corresponding mapping to the temporal dimension of innovation. Note: patent sub-group codes are listed inside the parentheses next to the main-group codes

Topics identified in the IPC description	IPC codes	Temporal dimension of innovation
Offshore wind	B63B-021 (50); B63B-035 (44); E02B-017 (00); E02D-027 (52); F03B-013 (10, 12, 14, 26); F03D-013 (25); F16D-001 (06); H02G-001 (10)	Long-term
Blade and control system	F01D-007 (00, 02); F01D-017 (00, 02, 06); F03B-015 (00, 06)	Long-term
Wind and energy storage	F03D-009 (11, 12, 17, 18, 19)	Long-term
Testing components	G01M-013 (02, 021, 028)	Long-term
Meteorology	G01S-017 (95); G01W-001 (00, 02, 06, 10, 16)	Long-term
Wind and other technologies (hybrid)	H02S-010 (12); H02S-040 (32)	Long-term
Forgings	B21C-037 (29); B21D-001 (08); B21D-003 (16); B21D-039 (03); B21D-047 (00); B21K-023 (04); B21K-025 (00); B22C-009 (00); B22D-007 (00); B22D-019 (00, 04); B22D-025 (02); B22F-003 (00); B24B-000 (00); B24B-009 (20); B24B-019 (14, 26); B24B-027 (00); B24B-029 (00); B24B-041 (06); B24B-049 (00); B24B-051 (00); B24B-055 (02); B24C-001 (10); B24D-005 (02); C21C-001 (10); C21D-001 (06, 09, 10, 18, 20, 26, 28, 42); C21D-006 (00); C21D-007 (06); C21D-009 (32, 40); C22C-037 (04); C22C-038 (00, 02, 04, 06, 18, 22, 24, 26, 28, 40, 42, 44, 46, 48, 50, 60); C23C-008 (26, 32, 80); C23C-014 (00, 06, 08); C23F-013 (00, 02); C23F-015 (00)	Short-term
Bearings	B21D-053 (10); F03B-011 (06); F03D-001 (00, 02, 06); F03D-003 (00, 02, 04); F04D-029 (04, 056); F16C-000 (00); F16C-003 (02, 08); F16C-011 (04); F16C-013 (02, 04); F16C-017 (00, 02, 03, 04, 06, 08, 10, 12, 20, 24, 26); F16C-019 (00, 02, 04, 06, 08, 10, 14, 16, 18, 20, 22, 24, 26, 28, 30, 34, 36, 38, 40, 49, 50, 52, 54, 55, 56); F16C-021 (00); F16C-023 (00, 02, 04, 06, 08); F16C-025 (02, 04, 06, 08); F16C-027 (00, 04, 06); F16C-032 (00, 04, 06); F16C-033 (00, 02, 04, 06, 08, 10, 12, 14, 20, 30, 32, 34, 36, 37, 372, 38, 40, 41, 42, 44, 46, 48, 49, 50, 51, 52, 54, 56, 58, 60, 62, 64, 66, 72, 74, 76, 78, 80); F16C-035 (00, 02, 04, 06, 063, 067, 07, 073, 077, 08); F16C-037 (00); F16C-039 (02, 04, 06); F16C-041 (00, 02, 04); F16C-043 (00, 02, 04, 06)	Short-term
Installation, maintenance, or construction	B25B-005 (14); B25B-011 (00, 02); B25B-021 (00); B25B-023 (14); B25B-027 (00, 02, 06, 14); B25B-029 (02); B25J-005 (00); B25J-009 (16); B25J-011 (00); B25J-019 (02); B26D-001 (00, 06, 08); B26D-003 (00, 02, 10); B26D-007 (06, 08); B27B-025 (00); B66B-000 (00); B66B-005 (00); B66B-007 (02); B66B-009 (00, 02, 16, 187); B66B-011 (00, 02, 04, 06); B66C-000 (00); B66C-001 (00, 08, 10, 12, 16, 18, 22, 24, 42, 44, 54, 62, 66); B66C-005 (02); B66C-013 (00, 04, 06, 08, 16, 18, 46); B66C-017 (00, 04, 06); B66C-019 (00); B66C-023 (00, 02, 16, 18, 20, 26, 28, 30, 32, 34, 36, 62, 72, 52); B66D-001 (00, 26, 36, 60); B66D-003 (00); B66F-003 (24, 35, 46); B66F-011 (00, 04); B66F-019 (00); E02B-017 (02); E02D-000 (00); E02D-005 (22, 34, 54, 72, 74, 80); E02D-007 (00, 26); E02D-011 (00); E02D-013 (00, 04); E02D-023 (00); E02D-027 (00, 10, 12, 16, 32, 42, 44, 50); E02D-035 (00); E02D-037 (00); E02F-009 (12); E04B-001 (00, 04, 16, 18, 19, 21, 24, 342, 343, 35, 38, 41, 58, 61, 62, 66, 92, 98); E04C-002 (04, 20); E04C-003 (00, 08, 30); E04C-005 (06, 08, 12, 16); E04F-011 (022); E04F-021 (00); E04G-000 (00); E04G-001 (00, 20, 36); E04G-003 (00, 24, 28, 30, 32); E04G-005 (00); E04G-011 (20); E04G-013 (02); E04G-021 (00, 02, 04, 12, 14, 16, 18, 24, 32); E04G-023 (00); E04H-000 (00); E04H-001 (00, 12); E04H-003 (00); E04H-005 (02, 04); E04H-009 (04, 14); E04H-014 (00); E05B-065 (00); E05D-005 (02); E06B-001 (00, 52, 60); E06B-003 (70); E06B-005 (00); E06C-007 (18); E06C-009 (00, 02); E21B-033 (00, 13, 134); E21B-041 (00); F03D-009 (02, 10, 30); F03D-013 (00, 10, 35, 30, 20, 40); F03D-080 (50, 55); F16B-000 (00); F16B-001 (00, 02); F16B-002 (00); F16B-004 (00); F16B-005 (00, 02); F16B-007 (00, 18, 20); F16B-011 (00); F16B-019 (02); F16B-031 (02, 06); F16B-033 (00); F16B-035 (00, 04, 06); F16B-037 (00, 14); F16B-039 (10); F16B-041 (00); F16B-043 (00); H02G-000 (00); H02G-001 (08); H02G-003 (00, 02, 04, 22, 30, 32, 38); H02G-005 (00, 02, 06); H02G-007 (12); H02G-009 (00, 02, 06); H02G-011 (00, 02); H02G-013 (00); H02G-015 (007, 02); H02K-015 (00, 02, 03, 04, 06, 085, 10, 12, 14, 16)	Short-term
Transport (except for offshore wind)	B60P-003 (00, 022, 40, 41); B60P-007 (00, 06, 08, 12, 13, 135); B60T-008 (50); B60T-013 (10, 22, 66, 68); B60W-010 (04, 10); B61B-007 (00); B61B-012 (02); B61B-013 (00); B61D-000 (00); B61D-003 (14, 16); B62B-003 (04, 10); B62D-021 (14); B62D-053 (00, 04); B63B-001 (04, 10, 12); B63B-003 (48, 56); B63B-009 (00, 06); B63B-011 (00); B63B-015 (00); B63B-019 (08, 12, 16, 197); B63B-021 (00, 56); B63B-022 (00, 02, 04, 18, 20); B63B-025 (00, 18, 28); B63B-027 (00, 10, 12, 14, 16); B63B-029 (02); B63B-035 (00, 34); B63B-039 (00, 03, 06, 08); B63B-043 (06); B63B-059 (04); B63C-011 (04); B63H-000 (00); B63H-001 (00, 06, 14, 20, 26, 28); B63H-003 (00, 06, 08, 10); B63H-005 (00, 125); B63H-007 (00, 02); B63H-009 (02); B63H-011 (00); B63H-021 (17, 20); B63H-023 (12, 24); B63H-025 (00, 06, 38, 40, 42); B63J-003 (02, 04); B63J-099 (00)	Short-term
Tower	E04H-012 (00, 02, 04, 06, 08, 10, 12, 14, 16, 18, 20, 22, 24, 28, 34)	Short-term
Sealing	F01D-011 (00, 02, 04); F04D-029 (08); F16J-015 (00, 02, 06, 10, 16, 18, 32, 3204, 3232, 3288, 34, 44, 447, 54)	Short-term
Safety	F01D-019 (00); F01D-021 (00, 04, 12, 14, 20); H02H-001 (00, 04, 06); H02H-003 (00, 02, 08, 087, 10, 16, 20, 22); H02H-005 (04); H02H-007 (00, 04, 06, 08, 085, 09, 093, 10, 12, 122, 125, 18, 22, 24, 26, 30); H02H-009 (00, 02, 04, 06); H02H-011 (00)	Short-term
Nacelle	F01D-025 (00, 02, 04, 06, 12, 14, 16, 24, 26, 28, 34, 36); F03B-011 (02); F03D-011 (04); F03D-080 (30, 40); F04D-029 (40, 54, 56, 58, 60, 66, 68); F16M-001 (00); F16M-005 (00); F16M-007 (00)	Short-term
Lubricant	F01M-001 (02, 16); F01M-005 (00); F01M-011 (00, 04, 10); F16N-000 (00); F16N-001 (00); F16N-007 (00, 14, 20, 28, 32, 36, 38, 40); F16N-009 (02); F16N-011 (00); F16N-013 (00, 02); F16N-017 (04); F16N-019 (00); F16N-021 (00); F16N-025 (00); F16N-029 (00, 02, 04); F16N-031 (00, 02); F16N-039 (00, 02, 04, 06)	Short-term
Power converter and control system	F03B-017 (00); F03D-007 (00, 02, 04, 06); F03D-080 (10, 20); F16P-003 (08); H02J-000 (00); H02J-001 (00, 08, 10, 12, 14); H02J-003 (00, 01, 02, 04, 06, 12, 14, 16, 18, 24, 26, 28, 30, 32, 34, 36, 38, 40, 42, 44, 46, 48, 50); H02J-004 (00); H02J-005 (00); H02J-007 (00, 02, 04, 10, 14, 32, 34, 35); H02J-009 (00, 02, 04, 06, 08); H02J-011 (00); H02J-013 (00); H02J-015 (00); H02J-017 (00); H02M-007 (483, 487, 49, 493, 537, 5387, 757, 797)	Short-term
Wind energy (general)	F03D-000 (00); F03D-001 (04); F03D-011 (00); F03D-080 (00)	Short-term
Adapt to new conditions	F03D-009 (00, 22)	Short-term
Measuring and testing	F03D-017 (00); G01B-000 (00); G01B-003 (44); G01B-005 (00, 30); G01B-007 (00, 02, 14, 16, 30); G01B-009 (02); G01B-011 (00, 02, 06, 14, 16, 24, 25, 26); G01B-015 (00, 02, 06); G01B-017 (02); G01B-021 (02, 08, 16, 22, 32); G01C-001 (00); G01C-003 (00, 08); G01C-009 (00); G01C-019 (02); G01D-001 (14); G01D-003 (02, 08); G01D-005 (00, 12, 244, 26, 353); G01D-009 (00); G01D-018 (00); G01D-021 (00, 02); G01F-001 (00); G01F-017 (00); G01F-023 (00, 26); G01F-025 (00); G01G-019 (14); G01H-001 (00, 06, 08, 12, 16); G01H-003 (00); G01H-009 (00); G01H-013 (00); G01H-017 (00); G01J-001 (04, 42); G01J-005 (00); G01K-001 (14); G01K-011 (32); G01K-013 (00, 08); G01L-001 (00, 04, 12, 16, 18, 20, 22, 24, 25, 26); G01L-003 (00, 02, 10, 14, 24); G01L-005 (00, 12, 16, 24); G01L-007 (00); G01L-009 (00); G01L-011 (02); G01L-025 (00); G01M-000 (00); G01M-001 (00, 12, 16, 22, 28); G01M-003 (00, 26, 40); G01M-005 (00); G01M-007 (00, 02, 04, 06, 08); G01M-009 (00, 02, 06); G01M-011 (00, 08); G01M-013 (00, 04, 045); G01M-015 (00, 02, 12, 14); G01M-017 (007); G01M-019 (00); G01M-099 (00); G01N-000 (00); G01N-001 (28); G01N-003 (00, 02, 08, 12, 32, 34, 36); G01N-015 (06); G01N-017 (00, 02, 04); G01N-019 (02); G01N-021 (00, 27, 35, 3581, 47, 53, 55, 59, 64, 84, 88, 94, 95, 954); G01N-023 (00, 04, 083, 201); G01N-025 (72); G01N-027 (00, 02, 22, 26, 60, 90); G01N-029 (00, 04, 07, 11, 14, 22, 24, 26, 265, 44); G01N-033 (00, 20, 26, 28, 30, 32); G01P-003 (00, 36, 44, 481, 487); G01P-005 (00, 02,	Short-term

(*continued on next page*)

Table A2 (*continued*)

Topics identified in the IPC description	IPC codes	Temporal dimension of innovation
	06, 14, 165, 20, 24, 26); G01P-013 (00, 02, 04); G01P-015 (00, 18); G01P-021 (00, 02); G01R-000 (00); G01R-011 (32, 56); G01R-013 (02); G01R-015 (18, 20); G01R-019 (00, 06, 10, 165, 25); G01R-021 (00, 06, 127, 133, 14); G01R-023 (00, 02, 16, 167, 20); G01R-025 (00); G01R-027 (00, 02, 08, 16); G01R-029 (00, 08); G01R-031 (00, 02, 08, 26, 28, 327, 34, 36, 40, 42); G01R-033 (00, 02, 07, 12); G01S-001 (68); G01S-011 (02); G01S-013 (00, 08, 87, 88, 93, 95); G01S-017 (58, 88, 89)	
Cooling or heating	F25D-021 (14)	Short-term
Program control and computing tools	G06F-000 (00); G06F-001 (12, 26, 28, 30, 32); G06F-003 (00, 01); G06F-007 (00); G06F-009 (00, 44, 445); G06F-011 (00, 20, 30); G06F-015 (00, 16, 173, 177, 18); G06F-017 (00, 10, 18, 30, 40, 50, 60); G06F-019 (00); G06F-021 (44); G06G-007 (48, 54); G06K-009 (00); G06N-003 (08); G06N-020 (00); G06N-099 (00); G06Q-010 (00, 04, 06); G06Q-030 (00); G06Q-050 (00, 04, 06, 10); G06T-001 (00); G06T-007 (00, 70); G06T-011 (20)	Short-term
Cables	H01B-005 (02); H01B-007 (00, 02, 04); H01B-009 (00); H01B-011 (00)	Short-term
Power electronics	H01F-000 (00); H01F-003 (04); H01F-005 (04); H01F-006 (06); H01F-007 (02, 06); H01F-013 (00); H01F-027 (00, 02, 06, 08, 10, 12, 16, 24, 25, 26, 28, 30, 32, 38, 40); H01F-029 (04); H01F-030 (00, 12); H01F-037 (00); H01F-038 (00, 14, 18); H01F-041 (00, 02, 08, 12); H01G-004 (38); H01H-001 (00); H01H-009 (54); H01H-019 (18); H01H-033 (59); H01H-047 (00); H01H-071 (10); H01H-083 (00); H01L-021 (00, 48, 67); H01L-023 (34, 367, 427, 473, 62); H01L-025 (07, 11, 18); H01L-031 (042); H01L-041 (09, 113); H01M-002 (10); H01M-004 (58); H01M-008 (00, 06, 18); H01M-010 (42, 44, 46, 48, 50); H01Q-001 (22, 28, 40, 42, 50); H01Q-003 (02); H01Q-015 (00, 14); H01Q-017 (00); H01R-000 (00); H01R-011 (00, 01); H01R-013 (24, 533); H01R-039 (00, 08, 18, 24, 38, 46, 58, 64); H01R-043 (00, 10, 14); H01T-001 (22); H01T-004 (00, 02, 08); H01T-019 (00, 04); H02B-001 (00, 04, 20, 24, 28, 30, 32, 56); H02B-005 (00); H02B-007 (00); H02B-013 (00, 02, 025); H02M-000 (00); H02M-001 (00, 08, 084, 088, 10, 12, 14, 15, 32, 34, 36, 42, 44); H02M-003 (00, 02, 04, 135, 155, 157, 158, 24, 28, 335, 337); H02M-005 (00, 04, 10, 22, 257, 293, 297, 40, 42, 44, 45, 451, 458); H02M-007 (00, 02, 04, 06, 10, 12, 162, 19, 21, 217, 219, 42, 44, 48, 497, 501, 53, 538, 539, 5395, 66, 68, 72, 81); H02M-054 (58); H03D-009 (00); H03K-000 (00); H03K-007 (08); H03K-017 (04, 12, 16, 56)	Short-term
Gearbox	B21D-053 (28); F01D-015 (12); F03D-015 (00, 10, 20); F03D-080 (70); F16D-001 (00, 02, 033, 04, 05, 076, 08, 09, 091, 095, 10, 108); F16D-003 (00, 02, 18, 20, 58); F16D-007 (00, 02); F16D-009 (06); F16D-011 (00, 10); F16D-031 (02); F16D-041 (06, 064, 067, 07); F16D-048 (06); F16D-055 (00, 02, 22, 224, 226); F16D-063 (00); F16D-065 (00, 02, 12, 14, 16, 18, 20, 38); F16D-066 (00, 02); F16D-069 (00, 02); F16D-121 (00, 02, 04, 24); F16D-125 (02); F16H-000 (00); F16H-001 (00, 02, 04, 06, 08, 10, 12, 16, 20, 22, 24, 26, 28, 32, 36, 46, 48); F16H-003 (08, 44, 54, 62, 64, 70, 72); F16H-007 (00, 02); F16H-009 (00); F16H-013 (08); F16H-019 (04); F16H-025 (02); F16H-035 (00, 02, 06, 08, 10, 18); F16H-037 (02, 04, 06, 08); F16H-039 (02, 20); F16H-047 (02, 04, 06, 08); F16H-048 (06, 11); F16H-053 (02); F16H-055 (06, 08, 12, 17, 18); F16H-057 (00, 01, 02, 021, 022, 023, 025, 027, 028, 029, 031, 033, 038, 08, 10, 12, 04); F16H-059 (00); F16H-061 (00, 4017, 4026, 4035, 4043, 4148, 4165, 4183, 42, 421, 423, 431, 433, 46, 468, 475)	Not identified
Blade	B21D-053 (78); B21K-003 (04); B29L-031 (08); B64C-011 (04, 06, 16, 24, 26, 28); B64C-027 (00, 46); F01D-000 (00); F01D-001 (06, 18); F01D-005 (00, 02, 08, 10, 12, 14, 16, 18, 22, 26, 28, 30, 32); F03B-003 (12, 14); F03D-003 (06); F03D-011 (02); F04D-029 (18, 26, 38, 34, 36)	Not identified
Material	B29C-000 (00); B29C-031 (00, 04, 08); B29C-033 (00, 02, 04, 10, 12, 14, 16, 20, 22, 26, 28, 30, 34, 38, 40, 42, 44, 50, 56, 68, 76); B29C-035 (00, 02, 04, 08, 16); B29C-037 (00); B29C-039 (00, 02, 10, 12, 18, 24, 26, 42, 44); B29C-041 (00, 04, 20, 38, 42); B29C-043 (00, 10, 12, 18, 20, 22, 32, 34, 36, 52, 56, 58); B29C-044 (00, 04, 12, 18, 34, 44, 50, 56); B29C-045 (00, 02, 14, 26, 42); B29C-047 (00, 02, 76); B29C-051 (00, 10, 14, 16); B29C-053 (56, 58, 60, 62, 68, 80, 82); B29C-059 (02); B29C-063 (00, 04, 22); B29C-064 (106); B29C-065 (00, 02, 08, 10, 14, 16, 34, 36, 48, 50, 52, 54, 56, 62, 70, 72, 78, 80); B29C-067 (00, 20, 24); B29C-069 (00); B29C-070 (00, 02, 04, 06, 08, 10, 12, 14, 16, 18, 20, 22, 24, 28, 30, 32, 34, 36, 38, 40, 42, 44, 46, 48, 50, 52, 54, 56, 68, 70, 72, 74, 76, 78, 84, 86, 88); B29C-071 (00); B29C-073 (00, 02, 04, 10, 12, 26, 30, 32, 34); B29D-000 (00); B29D-022 (00); B29D-023 (00); B29D-024 (00); B29D-031 (00); B29D-099 (00); B29K-023 (00); B29K-025 (00); B29K-027 (18); B29K-031 (00); B29K-063 (00); B29K-067 (00); B29K-075 (00); B29K-101 (10, 12); B29K-105 (06, 00, 04, 06, 08, 10, 12, 20, 24); B29K-307 (00, 04); B29K-309 (08); B29K-311 (14); B29K-705 (00); B29K-707 (04); B29K-709 (08); B29L-000 (00); B29L-009 (00); B29L-022 (00); B29L-031 (00, 30); B29L-31 (08, 30); B32B-000 (00); B32B-001 (00, 04, 08); B32B-003 (00, 02, 06, 08, 10, 14, 16, 20, 26, 28, 30); B32B-005 (00, 02, 04, 06, 08, 10, 12, 14, 16, 18, 20, 22, 24, 26, 28, 32); B32B-007 (00, 02, 04, 08, 12); B32B-009 (00, 04); B32B-015 (01, 04, 08, 14); B32B-017 (00, 02, 04, 06, 10); B32B-021 (04, 14); B32B-025 (08, 10, 14); B32B-027 (00, 02, 04, 06, 08, 12, 20, 28, 30, 32, 36, 38, 40); B32B-033 (00); B32B-037 (00, 02, 06, 10, 12, 14, 15, 18, 24, 26); B32B-038 (00, 04, 08, 10, 18); B32B-041 (00); B32B-043 (00); B33Y-010 (00); B33Y-080 (00); C02F-001 (44); C08F-002 (34); C08F-010 (00); C08F-210 (16); C08G-018 (32, 42, 48, 66); C08G-059 (40, 50, 56); C08J-003 (24); C08J-005 (00, 04, 06, 10, 12, 18, 24); C08J-007 (04, 12); C08J-009 (00, 12, 14, 36); C08K-003 (04, 08, 22); C08K-007 (02, 06, 14, 22, 28); C08L-027 (18); C08L-033 (06); C08L-063 (00); C08L-067 (00); C08L-075 (04); C08L-101 (00); C09D-007 (12); C09D-163 (00); C09D-175 (04); C09J-005 (00); C09J-011 (04); C09J-175 (04); C09J-201 (00); C10M-101 (02); C10M-105 (04, 18, 32); C10M-107 (02); C10M-115 (08); C10M-117 (00); C10M-125 (22, 24); C10M-129 (68); C10M-137 (04, 10); C10M-169 (00, 02, 04); C10N-010 (02, 04); C10N-020 (00, 02); C10N-030 (00, 08); C10N-040 (02, 04); C10N-050 (10)	Not identified
Generator and control system	F01D-009 (02); H02N-006 (00); H02P-000 (00); H02P-001 (54); H02P-003 (00, 08, 12, 14, 18, 22, 24); H02P-004 (00); H02P-005 (00, 46); H02P-006 (00, 10, 18); H02P-007 (00, 06, 28, 298, 36, 635); H02P-009 (00, 02, 04, 06, 08, 10, 12, 14, 26, 30, 36, 38, 40, 42, 44, 46, 48); H02P-011 (00, 06); H02P-013 (00, 06); H02P-021 (00, 05, 06, 12, 13, 14, 22, 24); H02P-023 (00, 04, 14, 26); H02P-025 (02, 022, 20, 22); H02P-027 (00, 04, 05, 06, 08, 14, 16); H02P-029 (00, 02, 024, 032, 50); H02P-101 (15); H02P-103 (20)	Not identified
Generator	F01D-009 (04); F01D-015 (10); F01P-001 (00, 06); F01P-003 (00, 18); F01P-007 (06); F02B-063 (04); F03D-009 (25, 28); F03D-080 (60); H02K-000 (00); H02K-001 (00, 02, 04, 06, 08, 12, 14, 16, 17, 18, 20, 22, 24, 26, 27, 28, 30, 32); H02K-003 (00, 02, 04, 12, 14, 16, 18, 20, 24, 28, 30, 32, 34, 38, 40, 46, 48, 487, 50, 51, 52); H02K-005 (00, 04, 08, 10, 15, 16, 167, 173, 18, 20, 22, 24); H02K-007 (00, 02, 06, 08, 09, 10, 102, 104, 106, 108, 116, 12, 14, 18, 20); H02K-009 (00, 02, 04, 06, 08, 10, 12, 14, 16, 18, 19, 197, 20, 22, 26, 28); H02K-011 (00, 01, 02, 04, 042, 049, 20, 25, 30, 33, 40); H02K-013 (00, 02); H02K-015 (08, 09); H02K-016 (00, 02, 04); H02K-017 (00, 16, 30, 42, 44); H02K-019 (00, 02, 10, 12, 16, 22, 24, 26, 28, 34, 36, 38); H02K-021 (00, 02, 04, 12, 14, 16, 22, 24, 40, 48); H02K-023 (02, 60); H02K-029 (00, 03); H02K-037 (20); H02K-041 (02, 03); H02K-049 (10); H02K-051 (00); H02K-055 (00, 02, 04); H02N-001 (12)	Not identified
Control system	F02C-009 (00, 28); F02D-001 (06); F02D-009 (00); F02D-028 (00); F02D-029 (06); F02D-041 (00); G05B-000 (00); G05B-009 (02, 03); G05B-011 (01, 36); G05B-013 (00, 02, 04); G05B-015 (00, 02); G05B-017 (02); G05B-019 (04, 042, 048, 05, 18, 402, 406, 414, 418); G05B-021 (02); G05B-023 (00, 02); G05D-001 (00); G05D-003 (00, 12); G05D-005 (00); G05D-007 (00, 06); G05D-009 (00); G05D-011 (00); G05D-017 (00, 02); G05D-019 (00, 02); G05D-022 (00, 02); G05D-023 (00, 19); G05F-001 (10, 12, 455, 618, 66, 67, 70); G05F-003 (04); G05F-005 (00, 04); G08B-001 (08); G08B-005 (00, 22, 38); G08B-021 (00, 18); G08B-023 (00); G08C-015 (00); G08C-017 (00, 02); G08C-019 (00); G08G-005 (00, 04)	Not identified

Table A3
Keyword search related to short-term and long-term innovation. Note that word stems have been trimmed as part of the data cleaning process.

Keywords	Temporal dimension of innovation
ice, freez, frost, froz, ic, deic, lidar, sodar, sonar, radar, remot sens, remote sens, resolut, resource assess, atlas, wind tunnel, windtunnel, model, protocol, cost, econom, lcoe, cheap, inexpens, price, discount, budget, affordabl, instal, crane, truck, road, vehic, lorr, ladd, pulley, transport, logist, construct, assembl, lift, mount, arrang, gondola, repair, maint, mttr, mttf, dirt, debri, hardwareinloop, hardware in loop, cabl, wire, cord, enclosure, nacell, hous, casing, cabin, main fram, hub, brack, shell, plate, cast, molt metal, brack, flange, bolt, screw, lock, weather, cyclon, typhoon, storm, seism, rain, hail, snow, earthquake, earth quake, lightn, thunder, cold climat, warm climat, tropic, gust, low wind, data manag, data collect, manag* data, collect data, database, data base, data, processor, digit, analysis, analyze, condition, predict, monitor, diagno, failuremod, fialure mode, failure mode, statis, crack, defect, wrinkl, crack, dry glass, dri glass, fractur, flaw, deform, lubric, oil, grease, emulsif, foam, viscosity, surfac ten, surface ten, seal, cool, outlet, inlet, hole, switch, power conver, filter, inductor capacit, circuit, break, rectifi, inverter, thyrist, transist, transform, converter, fabricat, cost, bear, safety, fire, biodegradabl, bio degradabl, eco friendly, ecofriend, recycl, flax, bamboo, coir, timber, reus	Short-term
meteorolog, climatol, complex terrain, complex flow model, offshor, off shor, sea, marin, harbour, deepwater, float, water depth, coastal, buoy, shore, hybrid tower, tall tower, light material, lt blade, large blade, larg blade, light weigh, stiff, smart blade, load shed, load control, thick airfoil, thick air foil, activ flow, control surf, vortex, flexibl blade, flexibl rotor, adapt rotor, adapt blade, rotor control, advanc blade, advanc rotor, activ blade, rotor blade, turbine blade, turbin blade, gearbox, blade control, blade compress, mult blade, multi blade, multi rotor, mult rotor, bladeless, blade less, blade free, curv tip, glass fi, fiber glass, fibre glass, glassfib, fiberglass, fibreglass, pmc, thermoplast, thermo plast, aramid, aromatic polyamide, carbon fib, fiber woven, woven fiber, crystallin, nano, fiber carbon, fibre carbon, polyacrylonitril, acrylonitril, carbon nano, cnt, squirr, scig, dfig, doubli fed induct, doubl fed induct, direct current generator, dcgenerat, dc generat, super conduc, superconduc, synchron, temperaturcycl, temperatur cycl, temperature cycl, lifetime, life time, prepreg, pre preg, pre impreg, preimpreg, resin infus, epoxy infus, vaccuum infus, vacuum infus, mold, mould, addit manufact, additiv manufact, virtual grid, virtu* grid, smart, intellig, hvdc, high voltag direct current, high voltage direct current, high voltag dc, high voltage dc, energ* storag, batteri, fly wheel, flywheel, supercap, fuel cell, fuelcell, lithi, ultracap, grid storag, power storag, monopil, mono pil, direct driv, directdriv, neodym, boron, ferr, rare earth, rareearth, lanthanid, grid stab, power qual, voltage stab, voltag stab, frequency stab, freq stab, frequen stab, harmonic dist, harmon dist, brownout, brown out, power qual, low harmon, power rat, frequency control, freq control, frequen control, grid control, phase transfor, network voltag, voltage network, voltag network, control sys, system control, optim, reliab, drivetrain, drive train, direct drive, network, windfarm, powerpl, hydrogen, landscap, ornament, aesth, beaut, flor, faun, bird, specie, anima, bat, ecolog, fatal, scare, grass, wild, fish, organism, fright, foliage, nois, tip speed, loud, torque control, control torque, pitch control, control pitch, yaw control, control yaw, small turbin, rooftop, roof top, residen, grid, urban, integrat op, distribut gen, scada	Long-term

Table A4
Results from negative binomial regressions for all suppliers.

	Long-term patenting activity (1) All suppliers before 2012	(2) All suppliers after 2012	Short-term patenting activity (1) All suppliers before 2012	(2) All suppliers after 2012
Main effects				
International relationship	−0.239	0.115	−0.103	0.152*
	(0.552)	(0.226)	(0.573)	(0.093)
	[0.402]	[0.095]	[0.183]	[0.091]
Local relationship	0.422***	0.291***	0.266*	0.347***
	(0.005)	(0.001)	(0.094)	0.000
	[0.150]	[0.090]	[0.159]	[0.090]
Controls				
Specialized	1.152*	1.302***	1.330**	1.372**
	(0.080)	(0.002)	(0.017)	(0.018)
	[0.657]	[0.429]	[0.559]	[0.581]
Component complexity	1.174***	0.321	0.212	0.801***
	(0.005)	(0.377)	(0.628)	(0.005)
	[0.414]	[0.364]	[0.437]	[0.285]
Pre-sample patents (range)	1.946***	1.161***	1.559***	1.138***
	0.000	0.000	0.000	0.000
	[0.290]	[0.208]	[0.299]	[0.168]
Size (range)	1.845***	0.810**	0.680	0.484
	(0.001)	(0.034)	(0.193)	(0.160)
	[0.581]	[0.382]	[0.522]	[0.344]
Age (range)	−1.490**	0.029	0.314	0.895***
	(0.031)	(0.925)	(0.573)	(0.003)
	[0.693]	[0.304]	[0.558]	[0.298]
OEM outsource	−0.156	0.848	0.284	0.930
	(0.844)	(0.155)	(0.741)	(0.222)
	[0.791]	[0.597]	[0.861]	[0.761]
Cumulative installed capacity	0.000***	−0.000***	0.000***	−0.000***
	(0.007)	(0.003)	0.000	(0.001)
	[0.000]	[0.000]	[0.000]	[0.000]
lnalpha	0.675**	1.456***	1.374***	1.410***
	(0.027)	0.000	0.000	0.000
	[0.306]	[0.211]	[0.221]	[0.180]
Constant	−5.499***	−3.730***	−3.614***	−3.295***
	0.000	0.000	(0.003)	0.000
	[1.237]	[0.740]	[1.198]	[0.926]
Observations	509	1358	509	1358
OEM Strategy FE	YES	YES	YES	YES
Country FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Pseudo R^2	0.27	0.168	0.147	0.147

Table A5
Sensitivity analysis using innovation radicalness.

	Long-term patenting activity				Short-term patenting activity			
	(1) European suppliers before 2012	(2) European suppliers after 2012	(3) Chinese suppliers before 2012	(4) Chinese suppliers after 2012	(1) European suppliers before 2012	(2) European suppliers after 2012	(3) Chinese suppliers before 2012	(4) Chinese suppliers after 2012
Main effects								
International relationship	−1.097**	0.450**	−0.934***	0.307	−0.499	0.397*	−0.076	0.552**
	(0.024)	(0.011)	(0.005)	(0.138)	(0.424)	(0.057)	(0.723)	(0.013)
	[0.487]	[0.176]	[0.333]	[0.207]	[0.625]	[0.208]	[0.215]	[0.223]
Local relationship	0.723***	0.149	−0.292	−0.145	0.570***	0.327**	0.168	0.321
	(0.001)	(0.226)	(0.482)	(0.658)	(0.001)	(0.030)	(0.656)	(0.210)
	[0.220]	[0.123]	[0.416]	[0.327]	[0.175]	[0.150]	[0.377]	[0.256]
Controls								
Specialized	2.512***	1.480**	1.163	−0.944	0.922	1.933***	1.183	−0.302
	(0.007)	(0.040)	(0.182)	(0.112)	(0.260)	(0.003)	(0.140)	(0.429)
	[0.929]	[0.720]	[0.870]	[0.593]	[0.819]	[0.662]	[0.802]	[0.381]
Component complexity	0.991*	0.998**	−0.947	0.207	0.612	1.288***	−0.826	0.136
	(0.050)	(0.040)	(0.250)	(0.686)	(0.194)	(0.005)	(0.291)	(0.792)
	[0.506]	[0.485]	[0.823]	[0.511]	[0.472]	[0.454]	[0.782]	[0.515]
Pre-sample patents (range)	2.604***	1.010***	1.511***	0.690***	1.598***	1.061***	1.535***	1.030***
	0.000	(0.001)	(0.003)	(0.001)	0.000	0.000	(0.003)	0.000
	[0.452]	[0.301]	[0.504]	[0.214]	[0.346]	[0.261]	[0.516]	[0.241]
Size (range)	−0.287	1.096**	16.155***	0.603	−0.131	0.425	1.329	0.395
	(0.725)	(0.016)	0.000	(0.304)	(0.867)	(0.396)	(0.152)	(0.411)
	[0.815]	[0.453]	[0.673]	[0.587]	[0.778]	[0.501]	[0.927]	[0.480]
Age (range)	−1.001	0.410	0.081	0.294	−0.327	0.628*	1.445	0.555
	(0.162)	(0.278)	(0.948)	(0.571)	(0.704)	(0.079)	(0.132)	(0.346)
	[0.717]	[0.378]	[1.243]	[0.518]	[0.860]	[0.357]	[0.958]	[0.589]
OEM outsource	2.033*	1.668		−2.671**	1.140	1.939**	−3.738***	−0.695
	(0.072)	(0.206)		(0.043)	(0.375)	(0.041)	0.000	(0.581)
	[1.129]	[1.320]		[1.320]	[1.285]	[0.950]	[0.782]	[1.261]
Cumulative installed capacity	0.000	−0.000***	0.000	0.000	0.000***	−0.000***	0.000	0.000
	(0.201)	0.000	(0.775)	(0.160)	(0.004)	0.000	(0.446)	(0.395)
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
lnalpha	0.892**	0.792	0.824	1.692***	0.964***	1.013***	1.279***	1.345***
	(0.012)	(0.101)	(0.184)	0.000	(0.008)	(0.002)	0.000	0.000
	[0.354]	[0.483]	[0.620]	[0.410]	[0.364]	[0.335]	[0.297]	[0.198]
Constant	−6.779***	−4.886***	−16.621***	−1.540	−3.907***	−5.868***	0.335	−3.045*
	0.000	0.000	0.000	(0.302)	(0.006)	0.000	(0.818)	(0.088)
	[1.724]	[1.353]	[1.603]	[1.492]	[1.423]	[1.315]	[1.456]	[1.785]
Observations	237	534	150	457	237	534	150	457
OEM Strategy FE	YES	YES	YES	YES	YES	YES	YES	YES
Pseudo R^2	0.222	0.26	0.233	0.0776	0.162	0.199	0.131	0.0804

p-value in parentheses *** $p<0.01$, ** $p<0.05$, * $p<0.1$; firm-clustered standard error in brackets.

Table A6
Sensitivity analysis using logit regressions.

	Long-term patenting activity				Short-term patenting activity			
	(1) European suppliers before 2012	(2) European suppliers after 2012	(3) Chinese suppliers before 2012	(4) Chinese suppliers after 2012	(1) European suppliers before 2012	(2) European suppliers after 2012	(3) Chinese suppliers before 2012	(4) Chinese suppliers after 2012
Main effects								
International relationship	0.025	0.625***	0.349	0.569**	1.565*	0.640***	−0.258	0.370**
	(0.987)	(0.005)	(0.527)	(0.015)	(0.087)	(0.006)	(0.302)	(0.048)
	[1.552]	[0.221]	[0.551]	[0.235]	[0.915]	[0.231]	[0.250]	[0.188]
Local relationship	0.548***	0.267**	−0.645	0.334	0.450**	0.666***	0.076	0.333
	(0.009)	(0.039)	(0.225)	(0.146)	(0.023)	(0.001)	(0.851)	(0.117)
	[0.210]	[0.129]	[0.532]	[0.230]	[0.198]	[0.199]	[0.405]	[0.213]
Controls								
Specialized	2.111**	2.097***	−0.122	0.215	0.763	1.447**	1.332*	0.685
	(0.011)	(0.002)	(0.920)	(0.696)	(0.361)	(0.040)	(0.069)	(0.168)
	[0.830]	[0.683]	[1.223]	[0.550]	[0.835]	[0.704]	[0.733]	[0.496]
Component complexity	1.194**	0.285	−0.518	−0.553	−0.234	1.157**	−0.198	−0.390
	(0.043)	(0.627)	(0.689)	(0.330)	(0.630)	(0.033)	(0.798)	(0.476)
	[0.590]	[0.586]	[1.294]	[0.568]	[0.487]	[0.543]	[0.775]	[0.548]
Pre-sample patents (range)	1.931***	0.934**	3.182***	1.448***	1.977***	1.401***	1.568***	1.317***
	0.000	(0.024)	(0.008)	0.000	0.000	(0.001)	(0.003)	0.000
	[0.553]	[0.415]	[1.209]	[0.286]	[0.530]	[0.411]	[0.524]	[0.258]
Size (range)	2.151**	1.897**		0.899	0.220	0.531	1.143	0.884*
	(0.012)	(0.025)		(0.132)	(0.735)	(0.365)	(0.167)	(0.075)
	[0.860]	[0.848]		[0.596]	[0.651]	[0.586]	[0.827]	[0.496]
Age (range)	−1.502*	−0.058	0.948	0.078	−0.916	0.176	0.141	−0.142
	(0.096)	(0.908)	(0.739)	(0.894)	(0.385)	(0.732)	(0.905)	(0.780)
	[0.903]	[0.503]	[2.841]	[0.587]	[1.055]	[0.515]	[1.177]	[0.508]
OEM outsource	1.136	2.078		0.605	1.906	0.414		1.220*
	(0.406)	(0.288)		(0.418)	(0.241)	(0.718)		(0.096)
	[1.367]	[1.957]		[0.747]	[1.624]	[1.144]		[0.733]
Cumulative installed capacity	0.000	−0.000**	0.000	0.000	0.000	−0.000*	0.000	0.000
	(0.244)	(0.013)	(0.993)	(0.310)	(0.385)	(0.066)	(0.137)	(0.986)
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Constant	−7.898***	−6.969***	−5.089	−7.407***	−6.667***	−6.123***	−1.589	−5.005***
	(0.002)	0.000	(0.123)	0.000	(0.004)	0.000	(0.287)	0.000
	[2.513]	[1.822]	[3.296]	[1.818]	[2.313]	[1.398]	[1.493]	[1.309]
Observations	237	534	118	424	237	534	148	457
OEM Strategy FE	YES	YES	YES	YES	YES	YES	YES	YES
Pseudo R^2	0.555	0.41	0.436	0.3	0.446	0.476	0.196	0.234

p-value in parentheses *** $p<0.01$, ** $p<0.05$, * $p<0.1$; firm-clustered standard error in brackets.

Table A7
Sensitivity analysis using the percentage of international relationships (i.e., share of international relationships in the total relationships).

	Long-term patenting activity				Short-term patenting activity			
	(1) European suppliers before 2012	(2) European suppliers after 2012	(3) Chinese suppliers before 2012	(4) Chinese suppliers after 2012	(1) European suppliers before 2012	(2) European suppliers after 2012	(3) Chinese suppliers before 2012	(4) Chinese suppliers after 2012
Main effects								
International percentage	−5.469***	−0.994	−1.198	1.454	−6.511***	−3.983***	−0.705	1.497
	(0.007)	(0.192)	(0.546)	(0.408)	(0.006)	(0.001)	(0.313)	(0.275)
	[2.029]	[0.761]	[1.985]	[1.757]	[2.350]	[1.246]	[0.700]	[1.371]
Controls								
Specialized	1.494*	2.120***	0.338	0.094	1.433**	1.760**	1.321*	0.185
	(0.092)	0.000	(0.867)	(0.859)	(0.041)	(0.011)	(0.075)	(0.608)
	[0.888]	[0.541]	[2.022]	[0.528]	[0.701]	[0.691]	[0.742]	[0.362]
Component complexity	0.967**	0.633	0.101	0.305	0.003	1.209***	−1.093	−0.149
	(0.021)	(0.268)	(0.950)	(0.597)	(0.995)	(0.007)	(0.102)	(0.727)
	[0.420]	[0.572]	[1.610]	[0.576]	[0.500]	[0.449]	[0.669]	[0.427]
Pre-sample patents (range)	2.111***	1.419***	2.733***	1.287***	2.238***	1.625***	1.193***	1.103***
	0.000	0.000	(0.001)	0.000	0.000	0.000	(0.003)	0.000
	[0.369]	[0.369]	[0.818]	[0.310]	[0.343]	[0.258]	[0.395]	[0.231]
Size (range)	1.104	1.882***	17.554***	0.447	−1.401*	0.196	1.407**	0.725
	(0.131)	(0.004)	0.000	(0.347)	(0.065)	(0.729)	(0.049)	(0.147)
	[0.731]	[0.651]	[1.134]	[0.475]	[0.761]	[0.566]	[0.716]	[0.500]
Age (range)	−2.004***	−0.370	0.581	0.100	0.216	0.400	1.105	0.546
	(0.005)	(0.423)	(0.859)	(0.893)	(0.754)	(0.328)	(0.210)	(0.336)
	[0.711]	[0.462]	[3.261]	[0.743]	[0.690]	[0.409]	[0.880]	[0.568]
OEM outsource	−0.822	2.721*	−4.769***	−0.951	1.439	2.102**	−3.746***	−1.560
	(0.459)	(0.067)	0.000	(0.292)	(0.291)	(0.019)	0.000	(0.137)
	[1.110]	[1.485]	[0.931]	[0.903]	[1.361]	[0.896]	[0.579]	[1.049]
Cumulative installed capacity	−5.469***	−0.994	0.000	0.000	0.000	−0.000***	0.000	0.000
	(0.007)	(0.192)	(0.830)	(0.288)	(0.106)	0.000	(0.413)	(0.451)
	[2.029]	[0.761]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
	0.815***	1.253***	−0.063	1.465***	1.130***	1.258***	1.261***	1.421***
lnalpha	(0.004)	(0.001)	(0.971)	0.000	(0.001)	0.000	0.000	0.000
	[0.284]	[0.385]	[1.706]	[0.283]	[0.340]	[0.343]	[0.317]	[0.199]
	0.219	−3.737***	−16.862***	−3.342	−1.359	−2.358**	1.085	−1.306
Constant	(0.887)	(0.002)	(0.001)	(0.105)	(0.546)	(0.020)	(0.408)	(0.448)
	[1.534]	[1.193]	[5.284]	[2.059]	[2.252]	[1.010]	[1.310]	[1.720]
Observations	237	534	150	457	237	534	150	457
OEM Strategy FE	YES	YES	YES	YES	YES	YES	YES	YES
Pseudo R^2	0.225	0.205	0.377	0.124	0.165	0.184	0.123	0.0629

p-value in parentheses *** $p<0.01$, ** $p<0.05$, * $p<0.1$; firm-clustered standard error in brackets.

Table A8
Sensitivity analysis including the percentage of Chinese patents as control.

	Long-term patenting activity				Short-term patenting activity			
	(1) European suppliers before 2012	(2) European suppliers after 2012	(3) Chinese suppliers before 2012	(4) Chinese suppliers after 2012	(1) European suppliers before 2012	(2) European suppliers after 2012	(3) Chinese suppliers before 2012	(4) Chinese suppliers after 2012
Main effects								
International relationship	−0.676	0.451**	0.125	0.256***	−0.612	0.167	−0.117	0.066
	(0.176)	(0.015)	(0.570)	(0.001)	(0.110)	(0.279)	(0.570)	(0.529)
	[0.500]	[0.185]	[0.220]	[0.076]	[0.383]	[0.155]	[0.206]	[0.105]
Local relationship	0.509***	0.138	−0.503	0.272**	0.456**	0.311**	0.235	0.135
	0.000	(0.271)	(0.330)	(0.040)	(0.032)	(0.025)	(0.545)	(0.433)
	[0.117]	[0.126]	[0.516]	[0.133]	[0.212]	[0.139]	[0.388]	[0.173]
Controls								
Specialized	0.958	1.777***	0.616	−0.540**	0.913	0.775*	1.243	−0.137
	(0.188)	0.000	(0.663)	(0.038)	(0.203)	(0.068)	(0.110)	(0.573)
	[0.728]	[0.462]	[1.414]	[0.260]	[0.718]	[0.425]	[0.777]	[0.244]
Component complexity	1.066**	0.803*	−0.119	−0.400	0.271	1.051***	−1.002	−0.074
	(0.014)	(0.054)	(0.921)	(0.240)	(0.584)	(0.006)	(0.164)	(0.757)
	[0.432]	[0.418]	[1.192]	[0.340]	[0.494]	[0.379]	[0.720]	[0.240]
Pre-sample patents (range)	1.959***	0.930***	2.777***	0.245	1.924***	1.444***	1.232***	0.097
	0.000	(0.009)	(0.005)	(0.150)	0.000	0.000	(0.005)	(0.627)
	[0.329]	[0.358]	[0.985]	[0.170]	[0.330]	[0.296]	[0.438]	[0.201]
Size (range)	2.072***	2.117***	16.163***	−0.521	−0.831	0.433	1.371	0.262
	(0.010)	0.000	0.000	(0.122)	(0.219)	(0.381)	(0.123)	(0.305)
	[0.800]	[0.540]	[0.689]	[0.337]	[0.676]	[0.494]	[0.889]	[0.255]
Age (range)	−1.384*	0.415	0.886	−0.608***	0.638	0.848**	1.257	−0.048
	(0.052)	(0.366)	(0.716)	(0.004)	(0.341)	(0.039)	(0.174)	(0.900)
	[0.711]	[0.459]	[2.433]	[0.212]	[0.670]	[0.411]	[0.925]	[0.378]
OEM outsource	−0.080	1.881	−5.169***	−1.161***	2.736**	2.350	−3.654***	−1.180
	(0.941)	(0.363)	(0.001)	(0.010)	(0.029)	(0.348)	0.000	(0.163)
	[1.086]	[2.068]	[1.605]	[0.450]	[1.250]	[2.506]	[0.722]	[0.846]
Cumulative installed capacity	0.000***	−0.000***	0.000	0.000	0.000*	−0.000***	0.000	0.000
	(0.008)	(0.001)	(0.881)	(0.286)	(0.059)	0.000	(0.539)	(0.185)
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
% long-term Chinese patents	4.956***	5.240***		6.245***				
	(0.007)	0.000		0.000				
	[1.827]	[1.256]		[1.017]				
% short-term Chinese patents					8.397**	8.525***		20.633***
					(0.016)	0.000		0.000
					[3.473]	[2.061]		[0.251]
lnalpha	0.606*	0.755***	0.077	−1.419***	1.057***	0.615***	1.272***	−0.645***
	(0.051)	(0.003)	(0.937)	0.000	(0.001)	(0.004)	0.000	0.000
	[0.310]	[0.250]	[0.964]	[0.229]	[0.308]	[0.212]	[0.309]	[0.166]
Constant	−4.522***	−6.361***	−15.842***	−4.757***	−6.128***	−6.213***	0.511	−19.247***
	(0.001)	0.000	0.000	0.000	0.000	(0.009)	(0.722)	0.000
	[1.329]	[1.612]	[2.765]	[1.346]	[1.338]	[2.370]	[1.439]	[1.077]
Observations	237	534	150	457	237	534	150	457
OEM Strategy FE	YES	YES	YES	YES	YES	YES	YES	YES
Pseudo R^2	0.264	0.28	0.382	0.503	0.177	0.271	0.122	0.396

p-value in parentheses *** $p<0.01$, ** $p<0.05$, * $p<0.1$; firm-clustered standard error in brackets.

Table A9
Results for 2SLS IV regression (instrument: Number of trade agreements).

	Long-term patenting activity		Short-term patenting activity	
	European suppliers before 2012	European suppliers after 2012	European suppliers before 2012	European suppliers after 2012
Main effect				
International relationship	6.128	3.438***	1.817	1.763**
	(0.418)	(0.000)	(0.643)	(0.018)
	[7.560]	[0.786]	[3.923]	[0.748]
Local relationship	−0.730	−0.352	0.821	0.293
	(0.811)	(0.164)	(0.604)	(0.223)
	[3.048]	[0.253]	[1.582]	[0.241]
Constant	0.016	−2.150***	−0.519	−1.113**
	(0.990)	(0.000)	(0.445)	(0.029)
	[1.307]	[0.535]	[0.678]	[0.509]
Observations	237	534	237	534
Durbin (score) $chi^2(1)$	0.756 ($p =$ 0.385)	22.675 ($p =$ 0.000)	0.002 ($p =$ 0.969)	1.260 ($p =$ 0.262)
Wu-Hausman F (1,1963)	0.745 ($p =$ 0.389)	23.503 ($p =$ 0.000)	0.002 ($p =$ 0.970)	1.253 ($p =$ 0.263)
Minimum eigenvalue statistic	2.20	25.21	2.20	25.21

p-value in parentheses *** $p<0.01$, ** $p<0.05$, * $p<0.1$; standard error in brackets.

References

Ahuja, G., Lampert, C.M., 2001. Entrepreneurship in the large corporation: a longitudinal study of how established firms create breakthrough inventions. Strat. Mgmt. J. 22, 521–543. https://doi.org/10.1002/smj.176.

Ambos, B., Ambos, T.C., 2011. Meeting the challenge of offshoring R&D: an examination of firm- and location-specific factors. R&D Manag. 41, 107–119. https://doi.org/10.1111/j.1467-9310.2010.00625.x.

Ambos, B., Brandl, K., Perri, A., Scalera, V.G., Van Assche, A., 2021. The nature of innovation in global value chains. J. World Bus. 56, 101221 https://doi.org/10.1016/j.jwb.2021.101221.

Anadón, L.D., 2012. Missions-oriented RD&D institutions in energy between 2000 and 2010: a comparative analysis of China, the United Kingdom, and the United States. Res Policy 41, 1742–1756. https://doi.org/10.1016/j.respol.2012.02.015.

Anadón, L.D., Baker, E., Bosetti, V., 2017. Integrating uncertainty into public energy research and development decisions. Nature Energy 2, 1–14. https://doi.org/10.1038/nenergy.2017.71.

Arthur, W.B., 2007. The structure of invention. Res. Policy 36, 274–287. https://doi.org/10.1016/j.respol.2006.11.005.

Arts, S., Hou, J., Gomez, J.C., 2021. Natural language processing to identify the creation and impact of new technologies in patent text: code, data, and new measures. Res. Policy 50, 104144. https://doi.org/10.1016/j.respol.2020.104144.

Awate, S., Larsen, M.M., Mudambi, R., 2015. Accessing vs sourcing knowledge: a comparative study of R&D internationalization between emerging and advanced economy firms. J. Int. Bus. Stud. 46, 63–86. https://doi.org/10.1057/jibs.2014.46.

Awate, S., Larsen, M.M., Mudambi, R., 2012. EMNE catch-up strategies in the wind turbine industry: is there a trade-off between output and innovation capabilities? Global Strat. J. 2, 205–223. https://doi.org/10.1111/j.2042-5805.2012.01034.x.

Baldwin, R., Venables, A.J., 2013. Spiders and snakes: offshoring and agglomeration in the global economy. J. Int. Econ. 90, 245–254. https://doi.org/10.1016/j.jinteco.2013.02.005.

Barradale, M.J., 2010. Impact of public policy uncertainty on renewable energy investment: wind power and the production tax credit. Energy Policy, Special Sec. 38, 7698–7709. https://doi.org/10.1016/j.enpol.2010.08.021.

Bettencourt, L.M.A., Trancik, J.E., Kaur, J., 2013. Determinants of the Pace of Global Innovation in Energy Technologies. PLoS One 8, e67864. https://doi.org/10.1371/journal.pone.0067864.

Binz, C., Truffer, B., 2017. Global Innovation Systems—A conceptual framework for innovation dynamics in transnational contexts. Res. Policy 46, 1284–1298. https://doi.org/10.1016/j.respol.2017.05.012.

Breakthrough Energy, 2021. Policy Solutions [WWW Document]. URL. https://www.breakthroughenergy.org/us-policy-overview (accessed 2.21.21).

BTM Consult, 2001. World Marktet Update 2000 - International Wind Energy Development. BTM Consult.

Buciuni, G., Pisano, G., 2021. Variety of innovation in global value chains. J. World Bus. 56, 101167 https://doi.org/10.1016/j.jwb.2020.101167.

Cattaneo, O., Gereffi, G., Miroudot, S., Taglioni, D., 2013. Joining, Upgrading and Being Competitive in Global Value chains: a Strategic Framework (Policy Research working Paper No. WPS 6406). World Bank, Washington DC.

Chan, G., 2015. The Commercialization of Publicly Funded Science: How Licensing Federal Laboratory Inventions Affects Knowledge Spillovers. Harvard Kennedy School, Harvard University. Working Paper.

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. https://doi.org/10.1016/j.techfore.2013.06.002.

Corredoira, R.A., Banerjee, P.M., 2015. Measuring patent's influence on technological evolution: a study of knowledge spanning and subsequent inventive activity. Res. Policy 44, 508–521. https://doi.org/10.1016/j.respol.2014.10.003.

Dahlin, K.B., Behrens, D.M., 2005. When is an invention really radical?: defining and measuring technological radicalness. Res. Policy 34, 717–737. https://doi.org/10.1016/j.respol.2005.03.009.

Dechezleprêtre, A., Glachant, M., 2014. Does foreign environmental policy influence domestic innovation? Evidence from the wind industry. Environ. Res. Econ. 58, 391–413. https://doi.org/10.1007/s10640-013-9705-4.

Deveaud, R., SanJuan, E., Bellot, P., 2014. Accurate and effective latent concept modeling for ad hoc information retrieval. Document numérique 17, 61–84. https://doi.org/10.3166/dn.17.1.61-84.

Doblinger, C., Surana, K., Anadón, L.D., 2019. Governments as partners: the role of alliances in U.S. cleantech startup innovation. Res. Policy 48, 1458–1475. https://doi.org/10.1016/j.respol.2019.02.006.

Enevoldsen, P., Xydis, G., 2019. Examining the trends of 35 years growth of key wind turbine components. Energy Sustain. Dev. 50, 18–26. https://doi.org/10.1016/j.esd.2019.02.003.

European Commision, 2021. SME definition.

European Commission, 2021. A European Green Deal.

Feinerer, I., Hornik, K., Meyer, D., 2008. Text Mining Infrastructure in R. J. Stat. Softw. 25, 1–54.

Fifarek, B.J., Veloso, F.M., Davidson, C.I., 2008. Offshoring technology innovation: a case study of rare-earth technology. J. Oper. Manage. 26, 222–238. https://doi.org/10.1016/j.jom.2007.02.013.

Fleming, L., 2001. Recombinant uncertainty in technological search. Manage Sci. 47, 117–132. https://doi.org/10.1287/mnsc.47.1.117.10671.

Foray, D., Mowery, D.C., Nelson, R.R., 2012. Public R&D and social challenges: what lessons from mission R&D programs? Research Policy, The need for a new generation of policy instruments to respond to the Grand Challenges 41, 1697–1702. https://doi.org/10.1016/j.respol.2012.07.011.

Fuchs, E.R.H., 2014. Global manufacturing and the future of technology. ScienceScience 345, 519–520. https://doi.org/10.1126/science.1250193.

Fuchs, E.R.H., Field, F.R., Roth, R., Kirchain, R.E., 2011. Plastic cars in China? The significance of production location over markets for technology competitiveness in the United States versus the People's Republic of China. Int. J. Prod. Econ. 132, 79–92. https://doi.org/10.1016/j.ijpe.2011.03.008.

Fuchs, E.R.H., Kirchain, R., 2010. Design for location? The impact of manufacturing offshore on technology competitiveness in the optoelectronics industry. Manage. Sci. 56, 2323–2349. https://doi.org/10.1287/mnsc.1100.1227.

Funk, R.J., Owen-Smith, J., 2017. A dynamic network measure of technological change. Manage. Sci. 63, 791–817. https://doi.org/10.1287/mnsc.2015.2366.

Gao, X., Rai, V., 2019. Local demand-pull policy and energy innovation: evidence from the solar photovoltaic market in China. Energy Policy 128, 364–376. https://doi.org/10.1016/j.enpol.2018.12.056.

Garud, R., Karnoe, P., 2003. Bricolage versus breakthrough: distributed and embedded agency in technology entrepreneurship. Res. Policy 32, 277–300. https://doi.org/10.1016/S0048-7333(02)00100-2. Special Issue on Technology Entrepreneurship and Contact Information for corresponding authors.

Gereffi, G., Humphrey, J., Sturgeon, T., 2005. The governance of global value chains. Rev. Int. Political Econ. 12, 78–104. https://doi.org/10.1080/09692290500049805.

Gosens, J., Lu, Y., 2014. Prospects for global market expansion of China's wind turbine manufacturing industry. Energy Policy 67, 301–318. https://doi.org/10.1016/j.enpol.2013.12.055.

Griliches, Z., 1990. Patent statistics as economic indicators: a survey. J. Econ. Lit. 28, 1661–1707. https://doi.org/10.2307/2727442.

Grubb, M., Drummond, P., Poncia, A., McDowall, W., Popp, D., Samadi, S., Penasco, C., Gillingham, K.T., Smulders, S., Glachant, M., Hassall, G., Mizuno, E., Rubin, E.S., Dechezleprêtre, A., Pavan, G., 2021. Induced innovation in energy technologies and systems: a review of evidence and potential implications for CO2 mitigation. Environ. Res. Lett. 16, 043007 https://doi.org/10.1088/1748-9326/abde07.

Grün, B., Hornik, K., 2011. topicmodels: an R Package for Fitting Topic Models. J Stat Softw 40, 1–30. https://doi.org/10.18637/jss.v040.i13.

Haakonsson, S.J., Kirkegaard, J.K., 2016. Configuration of technology networks in the wind turbine industry. A comparative study of technology management models in European and Chinese lead firms. Int. J. Technol. Manage. 70, 281–299. https://doi.org/10.1504/IJTM.2016.075892.

Haakonsson, S.J., Slepniov, D., 2018. Technology transmission across national innovation systems: the role of Danish suppliers in upgrading the wind energy industry in China. Eur J Dev Res 30, 462–480. https://doi.org/10.1057/s41287-018-0128-5.

Hall, B.H., Jaffe, A., Trajtenberg, M., 2005. Market value and patent citations. RAND J. Econ. 36, 16–38.

Hargadon, A.B., 2002. Brokering knowledge: linking learning and innovation. Res Organ Behav 24, 41–85. https://doi.org/10.1016/S0191-3085(02)24003-4.

Helveston, J., Nahm, J., 2019. China's key role in scaling low-carbon energy technologies. ScienceScience 366, 794–796.

Hipp, A., Binz, C., 2020. Firm survival in complex value chains and global innovation systems: evidence from solar photovoltaics. Res. Policy 49, 103876. https://doi.org/10.1016/j.respol.2019.103876.

Hoppmann, J., Peters, M., Schneider, M., Hoffmann, V.H., 2013. The two faces of market support—How deployment policies affect technological exploration and exploitation

in the solar photovoltaic industry. Res. Policy 42, 989–1003. https://doi.org/10.1016/j.respol.2013.01.002.
Howell, S.T., 2017. Financing innovation: evidence from R&D grants. Am. Econ. Rev. 107, 1136–1164.
Huenteler, J., Ossenbrink, J., Schmidt, T.S., Hoffmann, V.H., 2016a. How a product's design hierarchy shapes the evolution of technological knowledge—Evidence from patent-citation networks in wind power. Res. Policy 45, 1195–1217. https://doi.org/10.1016/j.respol.2016.03.014.
Huenteler, J., Schmidt, T.S., Ossenbrink, J., Hoffmann, V.H., 2016b. Technology life-cycles in the energy sector — technological characteristics and the role of deployment for innovation. Technol. Forecast. Soc. Change 104, 102–121. https://doi.org/10.1016/j.techfore.2015.09.022.
IEA, 2020. Clean Energy Innovation. IEA, Paris.
IEA Wind, 2013. Long-term Research and Development Needs for Wind Energy for the Time Frame 2012 to 2030, Ad Hoc Group Report to the Executive Committee of the International Energy Agency Implementing Agreement for Co-operation in the Research and Development of Wind Turbine Systems.
IEA Wind, 2001. Long-term Research and Development Needs for Wind Energy for the Time Frame 2000 to 2020, Ad Hoc Group Report to the Executive Committee of the International Energy Agency Implementing Agreement for Co-operation in the Research and Development of Wind Turbine Systems.
IRENA, 2021. Renewable Capacity Statistics 2021.
Jaffe, A.B., Rassenfosse, G.de, 2017. Patent citation data in social science research: overview and best practices. J. Assoc. Inf. Sci. Technol. 68, 1360–1374. https://doi.org/10.1002/asi.23731.
Johnstone, N., Haščič, I., Popp, D., 2010. Renewable energy policies and technological innovation: evidence based on patent counts. Environ. Res. Econ. 45, 133–155. https://doi.org/10.1007/s10640-009-9309-1.
Jurowetzki, R., Lema, R., Lundvall, B.-Å., 2018. Combining innovation systems and global value chains for development: towards a research agenda. Eur. J. Dev. Res. 30, 364–388. https://doi.org/10.1057/s41287-018-0137-4.
Kaplan, S., Vakili, K., 2015. The double-edged sword of recombination in breakthrough innovation. Strat. Mgmt. J. 36, 1435–1457. https://doi.org/10.1002/smj.2294.
Kelly, B., Papanikolaou, D., Seru, A., Taddy, M., 2018. Measuring technological innovation over the long run (Working Paper No. 25266), working paper series. Nat. Bureau Econ. Res. https://doi.org/10.3386/w25266.
Kim, G., Park, S., Jang, D., 2014. Technology Analysis from Patent Data Using Latent Dirichlet Allocation (Eds.). In: Lee, K.M., Park, S.-J., Lee, J.-H. (Eds.), Soft Computing in Big Data Processing, Advances in Intelligent Systems and Computing. Springer International Publishing, pp. 71–80.
Lam, L.T., Branstetter, L., Azevedo, I.M.L., 2017. China's wind industry: leading in deployment, lagging in innovation. Energy Policy 106, 588–599. https://doi.org/10.1016/j.enpol.2017.03.023.
Lema, R., Lema, A., 2012. Technology transfer? The rise of China and India in green technology sectors. Innov. Develop. 2, 23–44. https://doi.org/10.1080/2157930X.2012.667206.
Lewis, J.I., 2011. Building a national wind turbine industry: experiences from China, India and South Korea. Int. J. Technol. Globalisation 5, 281–305.
Lewis, J.I., Wiser, R.H., 2007. Fostering a renewable energy technology industry: an international comparison of wind industry policy support mechanisms. Energy Policy 35, 1844–1857. https://doi.org/10.1016/j.enpol.2006.06.005.
Li, D., Heimeriks, G., Alkemade, F., 2021. Recombinant invention in solar photovoltaic technology: can geographical proximity bridge technological distance? Reg. Stud. 55, 605–616. https://doi.org/10.1080/00343404.2020.1839639.
Malhotra, A., Schmidt, T.S., 2020. Accelerating Low-Carbon Innovation. Joule 4, 2259–2267. https://doi.org/10.1016/j.joule.2020.09.004.
Mazzucato, M., 2018. Mission-oriented innovation policies: challenges and opportunities. Ind. Corporate Change 27, 803–815. https://doi.org/10.1093/icc/dty034.
Mazzucato, M., Semieniuk, G., 2018. Financing renewable energy: who is financing what and why it matters. Technol. Forecast. Soc. Change 127, 8–22. https://doi.org/10.1016/j.techfore.2017.05.021.
Meckling, J., Hughes, L., 2018. Global interdependence in clean energy transitions. Bus. Politics 20, 467–491. https://doi.org/10.1017/bap.2018.25.
Meckling, J., Hughes, L., 2017. Globalizing solar: global supply chains and trade preferences. Int. Stud. Q. 61, 225–235. https://doi.org/10.1093/isq/sqw055.
Meng, J., Way, R., Verdolini, E., Anadon, L.D., 2021. Comparing expert elicitation and model-based probabilistic technology cost forecasts for the energy transition. Proc. Natl. Acad. Sci. 118 https://doi.org/10.1073/pnas.1917165118.
Navigant Research, 2014. Supply Chain Assessment 2014 – Wind Energy 2014-2018.
Nemet, G.F., 2009. Demand-pull, technology-push, and government-led incentives for non-incremental technical change. Res. Policy 38, 700–709. https://doi.org/10.1016/j.respol.2009.01.004.
Nieto, M.J., Rodríguez, A., 2011. Offshoring of R&D: looking abroad to improve innovation performance. J. Int. Bus. Stud. 42, 345–361.
Novak, S., Eppinger, S.D., 2001. Sourcing by design: product complexity and the supply chain. Manag. Sci. 47, 189–204. https://doi.org/10.1287/mnsc.47.1.189.10662.
OECD, 2018. Multinational Enterprises in the Global Economy - Heavily debated But Hardly Measured.
Peñasco, C., Anadón, L.D., Verdolini, E., 2021. Systematic review of the outcomes and trade-offs of ten types of decarbonization policy instruments. Nat. Clim. Chang. 11, 257–265. https://doi.org/10.1038/s41558-020-00971-x.
Phene, A., Fladmoe-Lindquist, K., Marsh, L., 2006. Breakthrough innovations in the U.S. biotechnology industry: the effects of technological space and geographic origin. Strat. Mgmt. J. 27, 369–388. https://doi.org/10.1002/smj.522.
Pietrobelli, C., Rabellotti, R., 2011. Global value chains meet innovation systems: are there learning opportunities for developing countries? World Dev. 39, 1261–1269. https://doi.org/10.1016/j.worlddev.2010.05.013.
Pisano, G.P., Shih, W.C., 2012. Does America really need manufacturing. Harv. Bus. Rev. 90, 94–102.
Pisano, G.P., Shih, W.C., 2009. Restoring american competitiveness. Harv. Bus. Rev. 87, 114–125.
Popp, D., 2019. Environmental Policy and Innovation: a decade of research. IRERE 13, 265–337. https://doi.org/10.1561/101.00000111.
Popp, D., 2004. ENTICE: endogenous technological change in the DICE model of global warming. J. Environ. Econ. Manage. 48, 742–768.
Popp, D., Haščič, I., Medhi, N., 2011. Technology and the diffusion of renewable energy. Energy Econ. 33, 648–662. https://doi.org/10.1016/j.eneco.2010.08.007. Special Issue on The Economics of Technologies to Combat Global Warming.
Probst, B., Touboul, S., Glachant, M., Dechezleprêtre, A., 2021. Global trends in the invention and diffusion of climate change mitigation technologies. Nat. Energy 6, 1077–1086. https://doi.org/10.1038/s41560-021-00931-5.
Qiu, Y., Anadón, L.D., 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, 772–785. https://doi.org/10.1016/j.eneco.2011.06.008.
Quitzow, R., Walz, R., Köhler, J., Rennings, K., 2014. The concept of "lead markets" revisited: contribution to environmental innovation theory. Environ. Innov. Soc. Transit., Global Diffus. Environ. Innov. 10, 4–19. https://doi.org/10.1016/j.eist.2013.11.002.
Ren21, 2017. 2017 Renewables global status report.
Sagar, A.D., van der Zwaan, B., 2006. Technological innovation in the energy sector: R&D, deployment, and learning-by-doing. Energy Policy 34, 2601–2608. https://doi.org/10.1016/j.enpol.2005.04.012.
Sandor, D., Keyser, D., Mann, M., Engel-Cox, J., Reese, S., Horowitz, K., Lantz, E., Weers, J., Roberts, B., Buchanan, S., Arent, D., Walker, B., Dixon, R., 2020. Clean energy manufacturing: renewable energy technology benchmarks (Ed.). In: Uyar, T. S. (Ed.), Accelerating the Transition to a 100% Renewable Energy Era, Lecture Notes in Energy. Springer International Publishing, Cham, pp. 195–206. https://doi.org/10.1007/978-3-030-40738-4_9.
Schilling, M.A., Phelps, C.C., 2007. Interfirm collaboration networks: the impact of large-scale network structure on firm innovation. Manage. Sci. 53, 1113–1126.
Schmidt, T.S., Huenteler, J., 2016. Anticipating industry localization effects of clean technology deployment policies in developing countries. Glob. Environ. Chang. 38, 8–20. https://doi.org/10.1016/j.gloenvcha.2016.02.005.
Schmidt, T.S., Schneider, M., Rogge, K.S., Schuetz, M.J.A., Hoffmann, V.H., 2012. The effects of climate policy on the rate and direction of innovation: a survey of the EU ETS and the electricity sector. Environ. Innov. Soc. Transit. 2, 23–48. https://doi.org/10.1016/j.eist.2011.12.002.
Sharma, A., Surana, K., George, M., 2022. Do clean energy trade duties generate employment benefits? Renewable Sustainable Energy Rev. 159, 112104 https://doi.org/10.1016/j.rser.2022.112104.
Singh, J., Fleming, L., 2010. Lone Inventors as Sources of Breakthroughs: myth or Reality? Manage Sci. 56, 41–56. https://doi.org/10.1287/mnsc.1090.1072.
Sivaram, V., Dabiri, J.O., Hart, D.M., 2018. The need for continued innovation in solar, wind, and energy storage. Joule 2, 1639–1642. https://doi.org/10.1016/j.joule.2018.07.025.
Stock, J., Watson, M., 2007. Introduction to Econometrics. Addison-Wesley, Boston.
Sun, B., Kolesnikov, S., Goldstein, A., Chan, G., 2021. A dynamic approach for identifying technological breakthroughs with an application in solar photovoltaics. Technol. Forecast. Soc. Change 165, 120534. https://doi.org/10.1016/j.techfore.2020.120534.
Surana, K., Anadón, L.D., 2015. Public policy and financial resource mobilization for wind energy in developing countries: a comparison of approaches and outcomes in China and India. Glob. Environ. Chang. 35, 340–359. https://doi.org/10.1016/j.gloenvcha.2015.10.001.
Surana, K., Doblinger, C., Anadón, L.D., Hultman, N., 2020. Effects of technology complexity on the emergence and evolution of wind industry manufacturing locations along global value chains. Nature Energy 5, 811–821. https://doi.org/10.1038/s41560-020-00685-6.
Taglioni, D., Winkler, D., 2016. Making global value chains work for development. World Bank. https://doi.org/10.1596/978-1-4648-0157-0.
Tang, T., Popp, D., 2016. The learning process and technological change in wind power: evidence from China's CDM wind projects. J. Policy Anal. Manage. 35, 195–222. https://doi.org/10.1002/pam.21879.
The World Bank, 2017. Global Value Chains Development Report: measuring and Analyzing the Impact of GVCs on Economic Development. International Bank for Reconstruction and Development/The World Bank.
Tushman, M.L., Anderson, P., 1986. Technological discontinuities and organizational environments. Adm. Sci. Q. 31, 439–465. https://doi.org/10.2307/2392832.
Tyre, M.J., von Hippel, E., 1997. The situated nature of adaptive learning in organizations. Organiz. Sci. 8, 71–83. https://doi.org/10.1287/orsc.8.1.71.
UNFCCC, 2021. Compilation of Good Practices and Lessons Learned on International Collaborative research, Development and Demonstration Initiatives of Climate technology. United Nations Framework Convention on Climate Change.
U.S. Department of Energy, 2021. National Blueprint for Lithium Batteries 2021-2030. U. S. Department of Energy.
Van Assche, A., 2017. Global Value Chains and innovation, in: The Elgar Companion to Innovation and Knowledge Creation. Edward Elgar Publishing.

van der Loos, A., Langeveld, R., Hekkert, M., Negro, S., Truffer, B., 2022. Developing local industries and global value chains: the case of offshore wind. Technol. Forecast. Soc. Change 174, 121248. https://doi.org/10.1016/j.techfore.2021.121248.

Verhoeven, D., Bakker, J., Veugelers, R., 2016. Measuring technological novelty with patent-based indicators. Res. Policy 45, 707–723. https://doi.org/10.1016/j.respol.2015.11.010.

Vernon, R., 1966. International Investment and International Trade in the Product Cycle. The Quarterly Journal of Economics 80, 190–207. https://doi.org/10.2307/1880689.

Verspagen, B., 2007. Mapping technological trajectories as patent citation networks: a study on the history of fuel cell research. Adv. Complex Syst. 10, 93–115.

Von Hippel, E., 1994. Sticky information" and the locus of problem solving: implications for innovation. Manage Sci. 40, 429–439.

Wilson, C., 2018. Disruptive low-carbon innovations. Energy Res. Soc. Sci. 37, 216–223. https://doi.org/10.1016/j.erss.2017.10.053.

Wilson, C., Grubler, A., Bento, N., Healey, S., Stercke, S.D., Zimm, C., 2020. Granular technologies to accelerate decarbonization. ScienceScience 368, 36–39. https://doi.org/10.1126/science.aaz8060.

WTO, 2021. Regional Trade Agreements.

Yang, C.-.H., Nugent, R., Fuchs, E.R.H., 2016. Gains from others' losses: technology trajectories and the global division of firms. Res. Policy 45, 724–745. https://doi.org/10.1016/j.respol.2015.12.005.

Zhang, F., Gallagher, K.S., 2016. Innovation and technology transfer through global value chains: evidence from China's PV industry. Energy Policy 94, 191–203. https://doi.org/10.1016/j.enpol.2016.04.014.

Zhou, Y., Li, X., Lema, R., Urban, F., 2016. Comparing the knowledge bases of wind turbine firms in Asia and Europe: patent trajectories, networks, and globalisation. Sci. Public Policy 43, 476–491. https://doi.org/10.1093/scipol/scv055.

Zhu, M., Qi, Y., Hultman, N., 2022. Low-carbon energy transition from the commanding heights: how state-owned enterprises drive China's wind power "miracle. Energy Res. Soc. Sci. 85, 102392 https://doi.org/10.1016/j.erss.2021.102392.