Effects of technology complexity on the emergence and evolution of wind industry manufacturing locations along global value chains

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Wind energy can contribute to national climate, energy, and economic goals by expanding clean energy and supporting economies through new manufacturing industries. However, the mechanisms for achieving these interlinked goals are not well understood. Here we analyze the wind energy manufacturing global value chain (GVC), using a dataset on 389 component supplier firms (2006-2016) that work with 13 original equipment manufacturers (OEMs). We assess how technology complexity, i.e., the knowledge intensity and difficulty of manufacturing components, shapes the location of suppliers. For countries without existing wind industries, we find evidence of the emergence of suppliers only for low complexity components (e.g., towers and generators). For countries with existing wind industries, we find that suppliers' evolution, i.e., changes in their international supply relationships, is less likely for high complexity components (e.g., blades and gearboxes). Our findings show the importance of understanding technologies along with firms and countries within GVCs for achieving policy goals.

MAIN

The global market for wind power technology is large and growing. Installed wind capacity has grown worldwide from 73 GW in 2006 to 623 GW in 2019[1]. Mid-century projections expect continued expansion[2] for two reasons: first, the increasing ambition for clean energy deployment by the governments of many countries and second, the cost decreases driven by, among other factors, technological advances and manufacturing improvements at the component level[3–5]—such as in blades, towers, gearboxes, and bearings.

This expanding market for wind power has created co-benefit opportunities for policymakers interested in coupling energy and economic development goals. The ability to develop a domestic manufacturing component supply chain and generate employment is particularly attractive. Examples of governments explicitly trying to advance energy, climate, and industrial goals in the wind sector include the Offshore Wind Sector Deal (United Kingdom)[6] and local content requirement for onshore wind deployment (in Brazil, and previously in China)[7]. Articulating these co-benefits for improving domestic energy technology industries has been instrumental in the political dialogue on, and public support for, energy policy[8–10].

Despite growing research and policy interest in clean energy manufacturing and global value chains (GVCs)[11–14], there is a lack of understanding of the global manufacturing patterns of wind energy technologies (and other clean energy technologies). In the last two decades, changes in the manufacturing (and deployment) location of a few, large original equipment manufacturers (OEMs)—i.e., lead companies that assemble, and occasionally manufacture, components for wind turbines—have reshaped the global industry with countries like China and India catching up to first movers in Europe and the United States[15–18]. But there is an absence of comprehensive datasets or analyses to understand these changes at the industry-specific firm-level, i.e., comprising both component manufacturers and the OEMs that constitute the manufacturing GVC. This gap is present not only in wind energy but also more broadly for clean energy technologies and other manufacturing industries where GVCs are increasingly the subject of policy discussions on globalization and manufacturing[19–21]. With limited evidence on the firm-level, tensions have been prevalent as countries try to promote or protect domestic manufacturing, especially in clean energy industries[9].

This paper examines in-depth the manufacturing GVC of the wind energy industry to understand the technological drivers behind location of manufacturing. We operationalize this inquiry by focusing on what we call the technology complexity—i.e., the combination of design, processes, skills, resources, and institutions required to manufacture, transport, and integrate individual components (such as towers, blades, gearboxes, control systems, and more) into a wind turbine[3,22]. We analyze the link between technology complexity and two key factors: where and why new manufacturing companies emerge over time; and how existing companies evolve in response to the international changes in the GVC. The emphasis on components is critical for a global analysis of the wind industry because wind turbines are customized engineering-intensive goods where technology innovation and cost reductions occur mainly at the individual component- rather than the final product-level[23,24].

The full manufacturing global value chain for wind energy

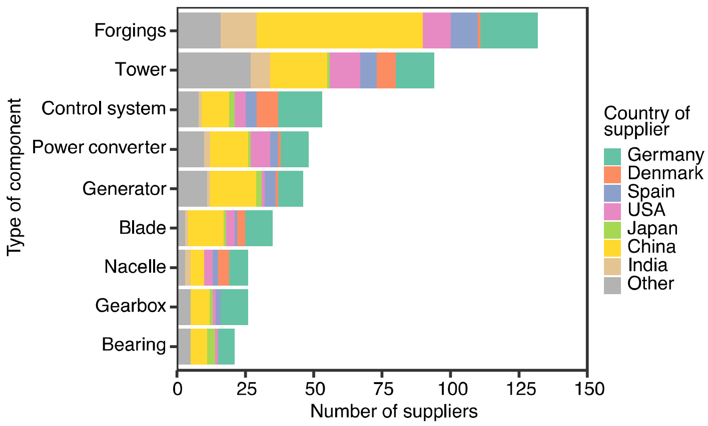
The focus on components compels an assessment of the full manufacturing GVC, comprising around 13 large OEMS and the hundreds of supplier firms that manufacture components for the OEMs.

Thus far, research has focused on public policies and technology strategies using the final wind turbine or the OEM as the unit of analysis, often examining how OEMs emerged in new countries or evolved with changing global markets (e.g., refs.[15–17,25]). Hundreds of supplier firms manufacture components for the large OEMs and play a pivotal, but often neglected role, in shaping the industry and the GVC[11,13,14]. Suppliers are often small and medium enterprises (SMEs)—the main employers that often constitute the backbone of many economies[26]—who must develop competences or strategies to stay competitive in rapidly changing local and international markets. Yet, there is limited evidence on where suppliers emerge or how they respond to the broader changes in global wind industry markets, with some case-study-based exceptions pointing to the importance of technology characteristics in determining supplier activity[11]. Given the importance of suppliers in the clean energy industry, understanding their behavior is key to coupling energy, climate, and industry policy goals.

We developed a database of the component suppliers in the wind energy technology GVC (see Methods for details). Our dataset builds on industry reports[27] and captures data on 389 suppliers involved in over 2,000 supplier-OEM market relationships with 13 major OEMs occurring between 2006 and 2016 for 9 key components identified in industry reports (see Figure 1)[27]. The

OEMs are located in Europe (e.g., Siemens, Vestas), the United States (General Electric), Japan (Mitsubishi), and later in China (e.g., Goldwind) and India (Suzlon). We then combined this dataset with the technology complexity of components to assess the emergence and evolution of manufacturing locations of component suppliers.

Figure 1: Diversity in number and geographic spread of suppliers by wind turbine component. The figure shows the total number and country of suppliers for each component that were active at least once in the period between 2006 and 2016 in our dataset, including OEMs' in-house suppliers. There are 389 suppliers in our dataset, but because some suppliers manufacture multiple components (see Methods), they are listed under each component in this Figure.



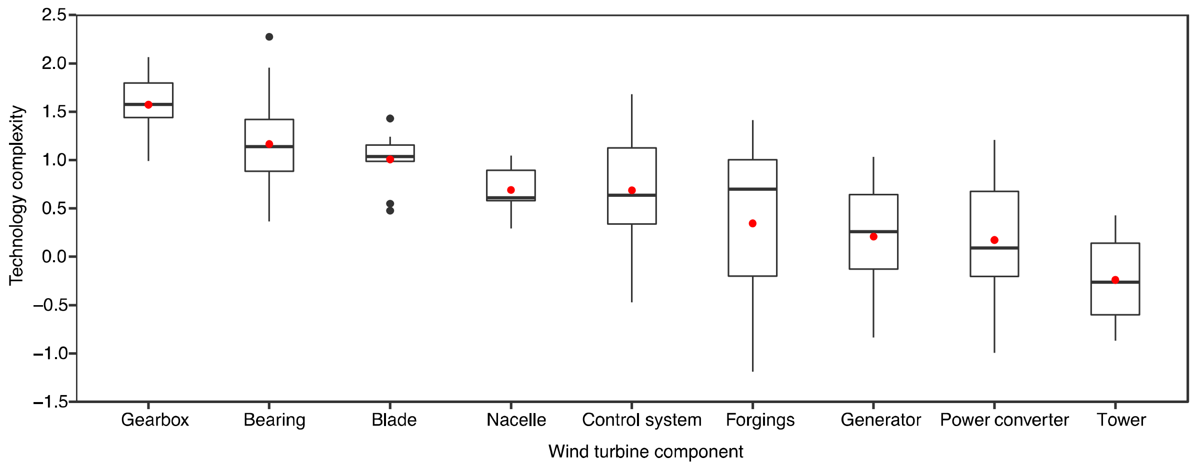
Technology complexity variation in wind turbine components

Our analysis takes into account the inherent technological differences across the different turbine components, instead of treating the end-product, i.e., the wind turbine as a technology black box as in most prior research focused on countries or OEMs (exceptions include, for e.g., ref.[24]).

To capture differences in the components, we quantify the variability in the technology complexity of each of the 9 components in our dataset (Figure 2). Complexity can be measured in different ways but there is no universal consensus metric or terminology (example refs. [28–34]) We use the Product Complexity Index (PCI) developed by Hausmann, Hidalgo, et al[28] as a measure of technology complexity. We found that compared to most other approaches to measure complexity that focus on knowledge competences, the PCI better reflects the broad set of real-world perspectives—including country economy and contexts, knowledge requirements, manufacturing skills, resources, and costs—for manufacturing, transporting, and integrating wind components[35] (see Methods for comparison of different complexity metrics, how they compare with insights specific to wind turbine technologies, and why we chose the PCI). We continue to refer to technology complexity rather than product complexity in the rest of this paper, because wind turbine technology is the end-product and includes multiple components or products, which in turn comprise other sub-components or products.

The PCI is based on the hypothesis that more complex technologies with greater knowledge intensity are manufactured and exported by countries that have higher knowledge intensity, and that these countries are also able to manufacture and export other high complexity technologies (i.e., with a higher PCI[28]). We calculate the PCI metric indicating technology complexity by assigning to each wind turbine component a relevant Harmonized System (HS) code(s). We then calculate the average PCI of that component based on PCI estimates derived from Hausmann, Hidalgo, et al's approach using global trade data on the component-level[36] (see Methods, Supplementary Table 1-3, Supplementary Figure 1).

Figure 2: Technology complexity estimates of wind turbine components. Wind turbine components have differences in technology complexity, as estimated using the product complexity index (PCI) method based on Hausmann, Hidalgo, et al (2014)[28]. For each component, in the box plot, the thick horizontal line indicates the median and the red dots indicate the mean from 2006 to 2016 (full dataset available in Supplementary Data 1). The bottom line in the box indicates the 25th percentile and the top indicates the 75th percentile. The whiskers indicate the observations that lie within 1.5 times the inter quartile range (IQR) and the black dots indicate outliers.



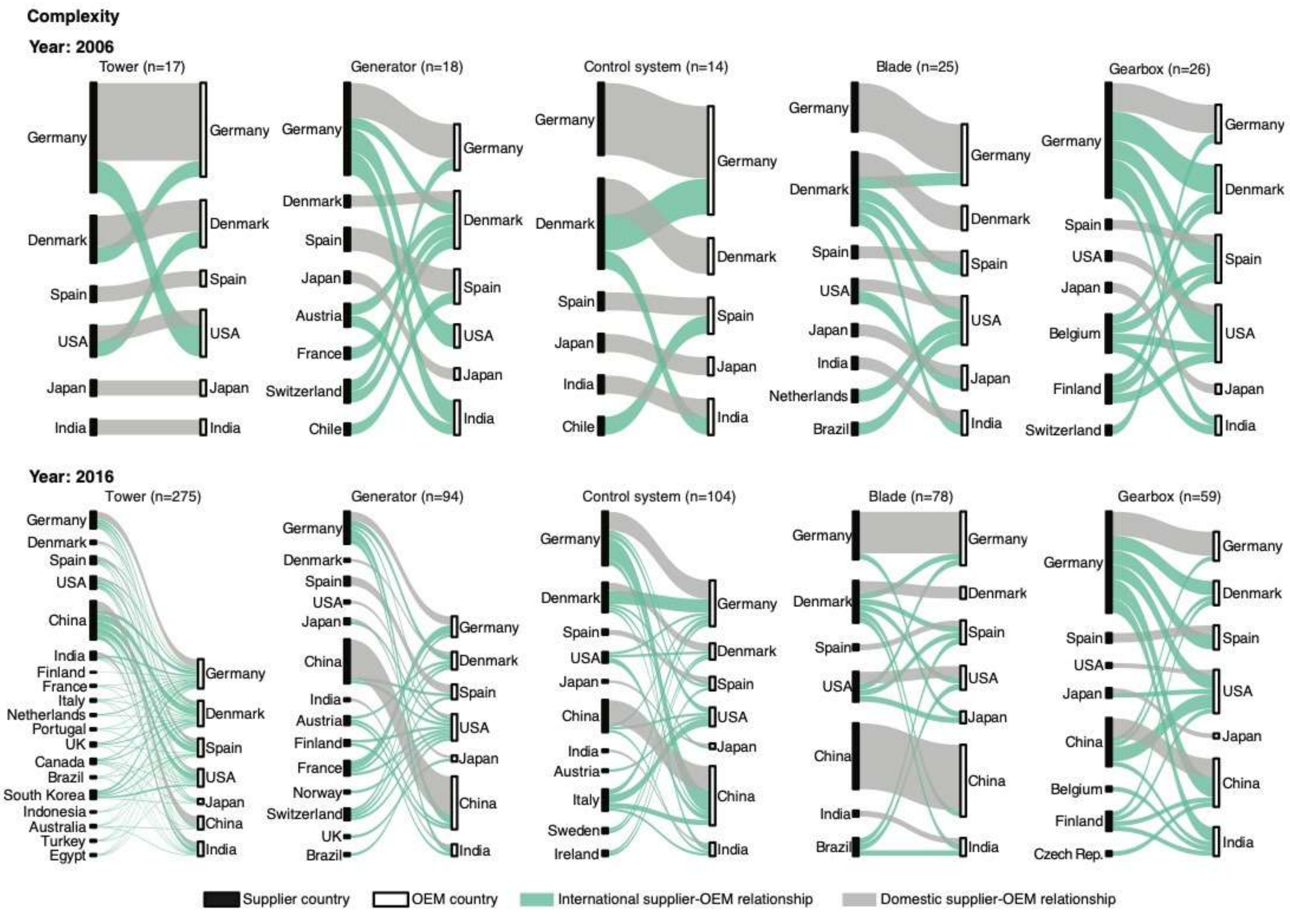
Under our assessment, blades and gearboxes are among the most complex technologies (PCI > 1), while towers are among the least complex (PCI < 0). For reference, using a similar methodology, solar photovoltaic cells have a relatively high PCI of 0.89, while biofuels have low complexity with a PCI of -1.1[37,38]. Our findings on the relatively high complexity of blades are consistent with the intensive requirements of blade manufacturing that require high technology equipment, more time, and advanced skills. Similarly, our findings on the low complexity of towers are consistent with research that indicates tower manufacturing involves more standard industrial processes[24,27] (See Supplementary Table 1).

The emergence of new component suppliers

Our analysis quantifies the relationships between wind component suppliers and their large OEMs partners in the GVC between 2006 and 2016. These interactions highlight three findings on the characteristics of the GVC and the emergence of wind component suppliers within our study period.

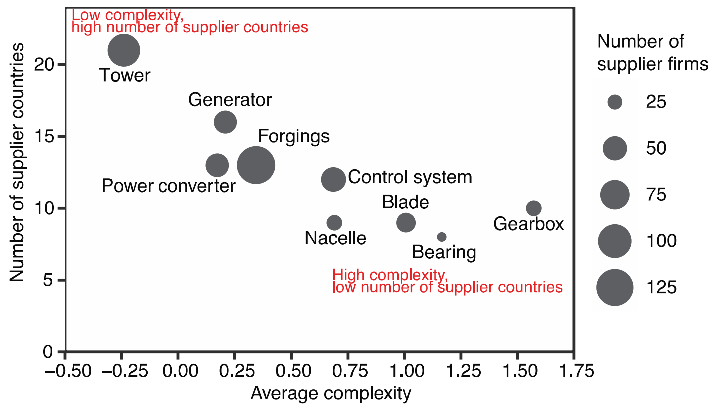
First, OEMs and suppliers were dispersed globally in 34 countries, but their relationships remained largely domestic, albeit with some exceptions discussed below. In our study period, 78% of suppliers (305 out of 389) were in countries that had a large OEM and 58% of relationships between OEMs and suppliers (1,239 out of 2,121) were domestic, i.e., involving suppliers and OEMs from the same country (see example, Figure 3). Our analysis, which starts in 2006, suggests that a domestic manufacturing supply chain initially developed in countries with large OEMs, which were the countries that also had the largest wind deployment markets in the study period (i.e. Germany, Denmark, Spain, United States, China, India, and Japan).

Figure 3: Change in international supplier-OEM relationships between 2006 and 2016 with increasing technology complexity. The figure shows the country (in the solid black rectangle) of the component suppliers that sold components to OEMs from specific countries (denoted by the white rectangles). The green bands denote an international relationship between component suppliers and OEMs (i.e., supplier and OEM from different countries) and the grey bands denote a domestic relationship between suppliers and OEMs (i.e., supplier and OEM from the same country). n represents the number of relationships in the dataset. The number of countries involved in the manufacturing of low complexity components increased substantially between 2006 and 2016. This was not the case for high complexity components. Low complexity components such as towers and generators experienced a greater diversification (or number) of supplier locations and more international relationships compared to high complexity components such as blades and gearboxes.



Second, the emergence of suppliers in new locations, especially in countries without an OEM, relates to the technology complexity of the components. Although new countries became part of the wind GVC over time, the extent of this emergence and the consequent global diversification of the GVC was inversely linked to the complexity of the component (Figure 3 and Figure 4). For low complexity components (i.e., towers and generators), suppliers from new locations in developing economies emerged (including countries in Africa, Latin America, and Asia-Pacific regions). For high complexity components (i.e., blades and gearboxes), the emergence of new supplier countries was significantly lower, potentially because more complex products required suppliers with skilled manufacturing, higher absorptive capacity, and tacit knowledge that may be more difficult for suppliers originating in developing and emerging economies[39]. Towers are large and their shipping costs are high, incentivizing manufacturing closer to demand, but such incentives may also be present for labor intensive components such as blades[40]. Our finding on the greater emergence of low complexity towers rather than of blades in most countries indicate the importance of transport as one of many factors, along with knowledge and skills[28], that shape costs and decisions in the location of manufacturing.

Figure 4: Relationship between the number of supplier countries of each component and the average complexity of the component. In this figure, suppliers include The dot size indicates the number of firms for each component in our dataset. Low complexity components experienced emergence of suppliers (including OEMs' in-house suppliers).



Third, a larger fraction of high complexity component suppliers interacted exclusively with OEMs from their own country or with OEMs from other industrialized countries. For example, we found that German OEMs primarily sourced blades from other German suppliers (or had subsidiaries or in-house production in Germany) or from suppliers in other industrialized countries (e.g., Denmark, US). This implies that higher complexity components that require more skills and expertise were likely manufactured only by a few specialized suppliers in industrialized countries (see Supplementary Figure 2). The emergence of a diverse and large number of countries with component suppliers for towers (a low complexity component) contrasts with the fewer specialized countries with suppliers working on gearboxes (a high complexity component) (Figure 3).

Overall, our analysis implies that, for most countries (and in particular developing countries that face institutional, financial and operational risks and uncertainties[17]), the emergence of suppliers manufacturing high complexity components with higher value add may be a challenging endeavor without active policy interventions, which we discuss later in this paper.

International evolution of suppliers

The globalization of the wind energy industry was evident in the shift of initial leadership of Europe and the United States in deployment and OEMs (in 2006) to increasing deployment and new OEMs in China and India (by 2016) with large and growing demand in those countries[15–18,41].

The changes in the broader industry affected the traditional or existing suppliers in countries with OEMs, as these suppliers faced increasing competition from new markets (and new suppliers). These existing suppliers had opportunities to work with both OEMs from the suppliers' countries (domestic or local OEMs) and those from other countries (international OEMs). But the most strategic and competitive suppliers likely delivered components to international OEMs and increased such international relationships over time[42–44], in what we refer to as evolution. We estimate this evolution by calculating the change (over a two-year time lag) in the fraction of each supplier's market or contractual relationships with international OEMs (see Methods).

We assessed the relationship between technology complexity and evolution with a detailed statistical analyses using Ordinary Least Squares (OLS) regressions (Model 1 and Model 2, see Methods, Table 1, and Supplementary Table 4), where we controlled for various factors that may affect evolution such as firm characteristics and firm strategic decisions[43,45–48]. These characteristics include wind specialization (activities only in wind and not in any other sectors), component diversification (supply of multiple wind components), age (number of years since company founding), size (number of employees), knowledge stock (measured through international and home country patents). We also controlled for the governance of the GVC[49]—i.e., whether suppliers supply to individual OEMs or have been acquired by them (e.g., 'captive' suppliers or those that are part of vertically integrated OEMs) or whether they supply to multiple OEMs in a more competitive market by estimating the supplier dependence on OEMs through in-house or outsources relationships. In addition, we use fixed effects to account for any firm-, country-, and time- specific features (see Methods for details on the variables).

The OLS regression analysis demonstrates that, as technology complexity increases by one unit, the likelihood of international evolution (i.e., increase in fraction of relationships with international OEMs) decreases by 12%, even after controlling for other important characteristics (Model 1, in Table 1). To give a sense of the size of the effect in our sample of components, a one unit increase in technology complexity is the difference in complexity measured using the PCI separating a low complexity component like towers (-0.24) from a higher complexity component like control systems (0.69) or blades (1.00) (see Supplementary Table 2).

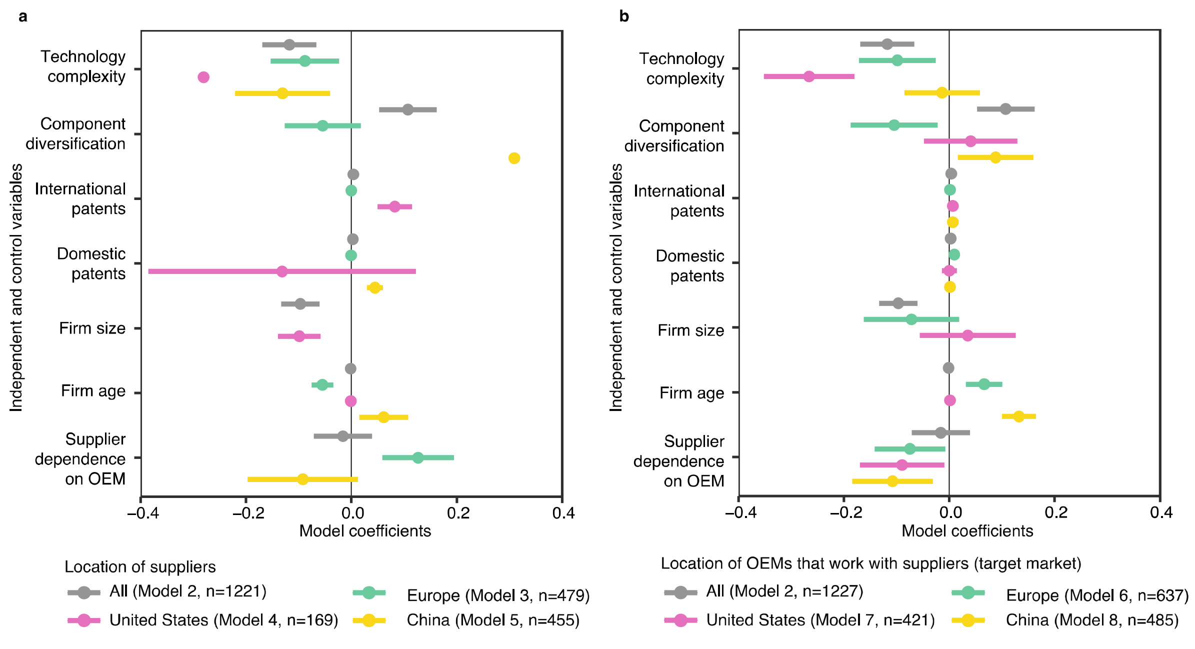
Additionally, the international evolution of supplier firms may be associated with their own country or with the OEMs that they work with (e.g., differences in countries' incentives for manufacturing or the OEMs' strategy)[11,49,50]. We developed two separate sets of models distinguishing our results based on the origin country of suppliers (see Figure 5a, Models 3-5) and the countries of their target OEMs (in Europe, the US, and China, see Figure 5b, Models 6-8). We note that while in many cases target OEMs are associated with the deployment markets in the countries of those OEMs, such assumptions may not always be true as, for example, several international OEMs were also present in India and China[17].

We found that the additional and statistically-significant firm-level predictors of international evolution, i.e., low specialization in wind and smaller size (in Model 1, Table 1), seem to be primarily driven by Chinese suppliers (see Model 5). This is potentially because larger state-owned firms may have established relationships with Chinese OEMs[17] whereas smaller firms in China may work more with international OEMs. Additionally, with the large manufacturing base in China, many firms may not specialize in wind energy, but rather manufacture components that have applications in multiple industries (e.g., generators, power converters) and supply these to international OEMs.

Even after accounting for the OEM- or country-related factors that could affect suppliers' behavior (as seen in the automotive sector, for example[50]), we find continued evidence of the negative relationship between technology complexity and international evolution. Distinguishing the origin countries of suppliers, we find that high technology complexity decreases the likelihood of international evolution by 13% for suppliers from China, 9% for suppliers from Europe (i.e., Germany, Denmark, and Spain), and 28% for suppliers from the United States (the latter two are not significant) (see Figure 5a and Table 1, Models 3-5). Distinguishing the OEM countries that suppliers have market relationships with, we find that high technology complexity decreases the likelihood of international evolution by up to 27% when suppliers work with OEMs from different countries, most notably the United States (see Figure 5b, Table 1, Models 6-8). Our results are robust across different model specifications and additional robustness checks, such as time-lags of one and three years and using different complexity metrics (see Methods and Supplementary Tables 5-6).

Together, our quantitative findings on the evolution of suppliers show that international competitiveness (proxied with increase in suppliers' relationships with international OEMs) increased for low complexity components for suppliers from all countries. Overall, this is consistent with the findings on the emergence of manufacturing.

Figure 5: Coefficient plots showing the relationship between international evolution, technology complexity and other control variables. The figures show results from OLS regressions, where the size of the regression coefficients is represented as dots and standard errors as bars. (a) Models with relationships grouped by location of the suppliers. (b) Models with relationships grouped by location of the OEMs that suppliers work with (i.e., the primary target market). Some of the larger coefficients of the OEM or country related factors are not depicted due to their large values but are shown in Table 1.



Implications for wind component technology manufacturing

Our analysis provides a comprehensive view of the wind energy manufacturing GVC, with central emphasis on the technological characteristics of components and suppliers — as opposed to just the turbines and OEMs covered by previous research.

As countries expand wind turbine manufacturing and domestic supply chains for both onshore and offshore wind, our findings suggest that governments and private firms would benefit from developing targeted, technology-specific approaches to participate in the wind energy manufacturing GVC. This requires designing policies that consider the technology complexity of individual components and the domestic capabilities of the country rather than simply the end product (i.e., the turbine). In turn, it means tailoring local industry support, skills development, and national policies to the specific characteristics of component technologies[18,51].

To support expanded wind manufacturing in developing countries and newly industrialized economies, we find that low complexity towers are a promising entry point. Even in larger market countries like China and India, the majority of domestic suppliers that initially emerged manufactured low complexity components (Figure 3). Of course, many countries would like to support industries that upgrade beyond low complexity. To this end, over the decade we studied, we also find evidence that a base of lower complexity technologies may provide a gateway to upgrade to more complex technologies. This program of 'catching up' can be enhanced by policy efforts that target both emergence of new suppliers and, eventually, the evolution of existing ones (see Figure 6).

For example, in China, a local content requirement policy that started in 2003 mandated domestic manufacturing of some components until 2009 to make them eligible for deployment incentives[17]. Partly to meet this requirement, high complexity blade manufacturing began with the Danish OEM Vestas establishing a new manufacturing location in China. A large number of domestic suppliers emerged following the Renewable Energy Law of 2006 that supported rapid, large scale wind power deployment while parallel policies supported the domestic development of larger turbines[17]. With growing demand and because of the presence of other industries with relevant transferable knowledge and skills, our dataset shows that the manufacturing of high complexity components such as gearboxes quickly emerged, led by the China High Speed Transmission Equipment Group Company that supplied to both Chinese and international OEMs since 2008.

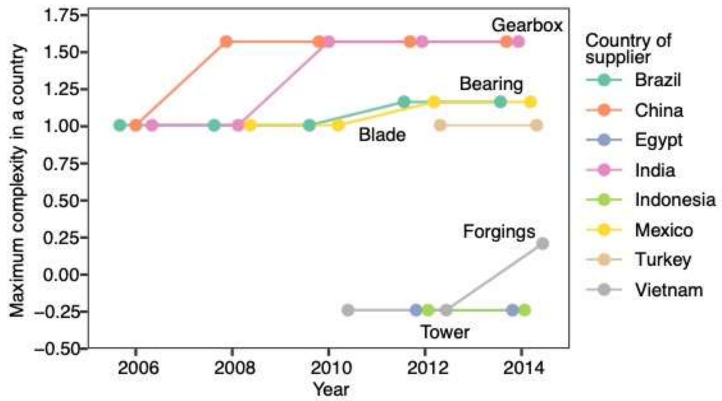
India provides a second example. A sizeable domestic market was already in place in 2006, along with some incentives for manufacturing, leading to the emergence of several domestic component suppliers for low complexity components[17]. Higher complexity components such as blades were manufactured in 2006 through Suzlon, a large Indian OEM, rather than through international suppliers. Although overall only a few high complexity domestic component manufacturers emerged in India, the existing low complexity base coupled with policies attracted the emergence of manufacturing for higher complexity gearboxes in 2010 through subsidiaries of European suppliers.

A third example is from Brazil, which developed higher-complexity component manufacturing even without a large domestic OEM. Brazil's domestic manufacturing expanded potentially because of its large market size, a local content requirement policy, and existing industry strengths as exemplified by companies like Tecsis, a blade manufacturer that emerged as a spin-off from the existing aviation industry[52].

Within countries, such opportunities for emergence and upgrading in the GVC have been possible over time through an overlapping system of domestic and international clean energy policies that spur market demand, incentivize domestic manufacturing, and catalyze existing industrial and knowledge bases or support new skills. In addition, from the examples of China and India, we also note that the emergence of manufacturing in more complex technologies may also be enabled through subsidiaries of suppliers from other countries who come in and exploit potential business opportunities in a large market.[16,17] Although we had limited data on suppliers' foreign subsidiaries to be included in our quantitative, statistical analysis, we found multiple examples where such approaches were used (these are included in Figure 6).

Our emphasis on 'domestically owned companies' is nevertheless valuable. Foreign firms with local manufacturing facilities may provide employment and tax revenues but not necessarily the same level of know-how, intellectual property, or support for local technology transfer.[40] In contrast, as domestic firms develop know-how and can meet standard manufacturing requirements (see Supplementary Table 1), even with the help of international firms, they can eventually get access to international markets, for example observed in blade manufacturing in China.[53]

Figure 6: The highest complexity of wind turbine components in a country in a given year. The Figure is based on data on a country's suppliers and the available data on any international subsidiaries. The data points are staggered around the year they represent to allow visualization of multiple countries for each component in a year. Developing countries and emerging economies have been able to manufacture more complex components over time. We cannot rule out the possibility that China, India, and Brazil—all appearing in the top part of the graph as manufacturing higher complexity components—started manufacturing lower complexity components well before 2006, as shown by the current state of manufacturing complexity in wind in Indonesia, Vietnam and Egypt.



For wind manufacturing in more industrialized countries, we observed a larger emergence of high complexity component manufacturing and lower evolution in high complexity component supply, even as emerging economies suppliers emerged and evolved. Our finding that suppliers are more likely to work with international OEMs for low complexity components suggests that the continued domestically-owned manufacturing of such components would need additional policy incentives to be competitive in international markets. This means that for countries trying to retain existing manufacturing in low complexity components (e.g., some countries in Europe or the US) through the evolution of existing firms, policies would need to be targeted towards specific technologies or components. While protectionist policies such as the US considering imposing trade tariffs on tower imports are one such near-term approach[54], they may not be effective in the long-term given that many other countries are already able to successfully produce low complexity towers at competitive costs. The high labor costs in the US mean that high tariffs may help US producers of low complexity components only for the domestic market but are unlikely to be helpful in expanding the reach of US manufacturing to sell such components internationally. Instead, a more effective, long-term strategy may be to support domestic innovation and industry in more complex components since the lead time for other countries to enter the competition can be longer and may require more systematic efforts on their part as well.

Implications for global value chains

The evidence provided in this paper on how technology complexity shapes the emergence and evolution of the full manufacturing value chain (i.e., both suppliers and OEMs) is valuable for understanding the interactions of domestic energy and industrial policies. It specifically underscores the importance of supporting an initial base of manufacturing, usually through a low complexity manufacturing entry point in latemover countries, to provide a gateway for upgrading to higher-complexity manufacturing in conjunction with carefully scoped policies.

As countries try to develop clean energy industries and meet climate and energy goals, it has become increasingly evident that effective and lasting policies will depend on simultaneously addressing economic development goals, including manufacturing[8,10]. By including technology and GVC perspectives in clean energy policy design, countries can take the opportunity to develop clean energy industries that will likely expand both manufacturing and deployment over time. From this perspective, our work on wind turbines can be extended to other similar clean energy industries that require high design capabilities for innovation but relatively low manufacturing capabilities[51] and involve 'lumpy' investments[55]. Such technologies include geothermal, concentrated solar, large hydropower stations, offshore wind, grid infrastructures, electric vehicles, and large buildings (as consumers of energy technologies)[51,55].

Our findings also underscore the central role of component technology characteristics at the supplier level—in addition to firms and countries—in understanding GVCs. We found that technology complexity shapes both the emergence and evolution of suppliers and the location of manufacturing, even as industries develop globally over time. To incentivize the development of new manufacturing opportunities in the clean energy industry or upgrading along the GVC, our findings imply that policies should have a targeted focus on manufacturing that considers existing local industrial strengths and suppliers, global value chain dynamics, and the technology complexity of components. Without such an integrated approach, countries may need to temper expectations for moving from lower complexity to higher complexity components.

We note three needs for future research that also address some of the limitations of our work. First, future work needs to remedy the absence of detailed industry datasets. Such datasets should capture granularity on the full location of the GVC, over an extended set of components, and a longer period of time. This includes a global network of multi-national companies and their subsidiaries, small businesses, and downstream firms and the quantity of supply between different firms and of different component. Our own approach was limited in using the location of component suppliers rather than the location of manufacturing (e.g., supplier subsidiaries in other countries) and lacked details on supply quantities because of limited data availability. Second, more mixed-methods research is needed to understand the relationships between technology complexity, governance of GVCs, and upgrading of supplier firms in different country contexts, especially for developing countries. Third, given that location of manufacturing may be influenced by technology complexity, but can also affect technology innovation, future research needs to analyze the direction of research and development and technology transfer in the GVC and its implications for developing countries (see for example ref. [53]).

Finally, GVC research and policy need to be specifically developed for knowledge-intensive clean energy industries. Evidence-based insights that capture technology, along with supplier firm and country characteristics within are needed to inform policy design that couples energy, climate, and economic development goals.

Competing interests: The authors declare no competing interests.

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Author contributions: K.S, C.D., and L.D.A developed the research idea and concept. K.S. and C.D collected and analyzed the data. K.S., C.D., L.D.A., and N.H. interpreted the results and conducted policy analysis. K.S. and C.D. wrote the manuscript. L.D.A. and N.H. edited the manuscript. K.S., L.D.A, and N.H. secured project funding.

METHODS

Wind supplier database development

We developed an original global database of component suppliers to major OEM for wind turbines. The database was manually developed by analyzing, in detail, text-based industry reports on the wind GVC and tabulating relevant information at the firm-level[27]. We obtained time series data using biennial reports from Navigant Consulting (2006, 2008, 2010, 2012, and 2014), with each relationship reported for a 3-year horizon—for example, the 2014 industry report identified supplier-OEM relationships from 2014 through 2016. In this step, we tabulated information on all major component suppliers (active between 2006 and 2014), the OEMs they supply to (and are expected to supply to until 2016), the outsourcing strategies of the OEM firms (either in-house development of components or outsourced to external supplier), and the geographical location of the supplier firms.

Our dataset captures nearly a decade of rapid advancements and international changes in wind energy manufacturing and deployment (e.g., refs. [16,17,42]) – however, it does not capture the emergence of suppliers before 2006 in the formative stages of the wind energy industry in countries worldwide (e.g., ref. [25]). It also does not capture more recent advancements—such as the merger between two large OEMs, Siemens and Gamesa in 2016—or new technological challenges related to grid integration and storage that suppliers and OEMs now work on[56]. Nonetheless, our dataset also includes part of the period before onshore wind was highly commoditized and is relevant for many other clean energy industries that are still at a formative stage, trying to establish domestic suppliers and to participate in GVCs.

After an initial cleaning of this dataset and excluding missing or incomplete data points, we had information on 389 suppliers and 9 components (i.e., towers, blades, nacelle, gearboxes, generators, control systems, power converters including transformers, bearings, and forgings) including information on which of the 13 OEMs the suppliers worked with for in-house or outsourced manufacturing. All analyses in this study were conducted on this dataset.

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), USA (General Electric), Japan (Mitsubishi), China (Goldwind, Mingyang, Dongfang, United Power), India (Suzlon). Additionally in some cases, suppliers also had multiple subsidiaries with manufacturing locations outside of their home country—for example ABB from Switzerland manufactured in the US and Rothe Erde from Germany manufactured in India, France, China, UK, and others—but a complete dataset on such additional subsidiaries or locations is not publicly available or verifiable and was not used for this assessment. Overall, the suppliers represent a global distribution of firms from major countries home to OEMs as well as others that are trying to develop domestic wind manufacturing capabilities in components and/or OEMs (e.g., France, UK).

Database expansion

We obtained additional data on each supplier firm from additional datasets and company website searches (Bloomberg, Orbis, Amadeus) on firm size, founding year, and specialization—i.e., whether the firm supplies to industries beyond the wind industry, or whether the firm supplies multiple components. Wind companies experienced multiple mergers and acquisitions in the timeframe of our study (e.g., Suzlon, REPower, and Senvion) and following prior research we considered them as individually operating companies if they were not integrated and continued to operate under a different brand.

We also estimated the knowledge stock, i.e. prior research and development (R&D) activity of each firm for each component domestically (i.e., in its home country) and internationally using patent information. We first searched for wind technology patents for each supplier firm (i.e., where the supplier was an assignee on the patent) based on a detailed and previously tested keyword search of the patent text and its Cooperative Patent Classification (CPC)[24,35] from the Derwent World Patent Index database. We extracted patent information (e.g., title, abstract including translated abstracts, technology classification, priority country where patent was first filed, and date of application) on each of the firms. Our search methodology limits patent results to wind energy technologies and components and minimizes influences from those suppliers and OEMs that are involved in multiple industries (e.g., large conglomerates like Siemens and GE). Although our approach may not yield patenting activity in components that are not unique to wind energy, we expect our approach to be thorough as our analysis emphasizes on the content of the patent in its linkages to wind-specific R&D.

The patents were then classified by the component they most closely relate to using a machine learning approach in R (version 3.6.2), as described in the following. The patent information was prepared for text-based analysis using the text mining package tm[57] 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 then used probabilistic topic modeling with latent Dirichlet allocation in the R topicmodels package[58]. The topicmodels package allowed us to differentiate the technological focus of innovation in the patent as we generated 26 topics or categories of patents by clubbing together those with similar word occurrences[59,60]. We first estimated a probability for patents to be related to each topic. We then mapped each of the 26 topics to the 9 components (and an additional category "other") to identify which component a patent most closely links to. Our results were robust to changes in the number of topics.

Technology complexity of components

Researchers have developed multiple approaches to quantify technology complexity (examples in ref. [28,31,33,34]). Many of these approaches are based on the concepts of knowledge diversity and technology interfaces and few approaches take into account the skills, capabilities, or costs associated with manufacturing (e.g., comparing the production of bulky and heavy components like blades or towers with gearboxes).

Wind energy industry reports[27] suggest that gearbox and blades are likely to have high complexity while towers are the least complex (Supplementary Table 1). These industry perspectives have also been reflected in empirical literature on wind turbine components' design hierarchy.[35]

Since there is no single or consensus metric in the literature that uniquely captures technology complexity, we tested three approaches to identify a quantitative metric that would most closely match the real-world challenges of designing, manufacturing, integrating, and transporting each of the 9 wind turbine components analyzed in this paper and their complexity over time (2006 to 2016).

First, we used the product complexity index (PCI) developed by Hausmann, Hidalgo et al[28,36]. The PCI quantifies the knowledge intensity of a technology by considering the knowledge intensity of its exporting countries (thus also capturing countries' economic and institutional contexts). We estimate the products or technologies associated with wind components by mapping each wind component with the Harmonized System (HS) code that they are globally exported under and averaging the reported PCIs in the database across all our mapped codes for each year. As components may be exported under different codes, we compiled these codes from literature and from a deeper review of code descriptions that were verified by two technical experts (see Supplementary Table 2 for the mapping of component codes)[38]. Technologies with higher complexity are manufactured in (and exported by) fewer countries with diversified manufacturing and reflect higher levels of skills and knowledge. Conversely, technologies with lower complexity are manufactured in and exported by a larger number of countries that may not necessarily be diversified in their manufacturing capabilities. This metric also captures the fact that while some technologies with higher complexity may be bulkier and have higher transportation costs resulting in more countries tempted to manufacture them locally, they would still require the domestic skills for manufacturing[28]. We estimated the PCI from the 2002 HS trade classification (HS02) as well as the 2007 HS trade classification (HS07). HS07 values were available in and after 2008 (we assumed HS02 numbers for 2006 and 2007).

Second, we use an approach developed by Fleming and Sorenson[34] that quantifies technology as a complex adaptive system. This metric is based on the interdependence of technologies and modularity of interfaces as assessed by international patent classification (IPC) codes. We use the simple interpretation applied by Broekel[31], which evaluates the ratio of patent subclass co-occurrences (10-digit IPC codes) of patents in a given year (with a 3 year moving average) to the cumulative patent subclass co-occurrences in all prior years (starting from 1994). To find the complexity of each of the 9 components, we averaged these ratios over all patents of each component.

Third, structural diversity is a metric developed by Broekel[31], inspired by the notion that technologies are combinatorial networks of technology and knowledge. This complexity metric intends to capture the diversity of a technology's sub-networks, captured through patents. We apply a simplified interpretation of Broekel's structural diversity approach. We use the probability of patents association with each component (as explained earlier) and assume that this probability reflects technology design and knowledge, in that it captures when components are closely related with other components in a patent description by assigning a probability to each component. We estimated the sub-networks of each component in a year by extracting all the patents for a given component in that year (with a 3-year moving average). In this component sub-network, we use social network analysis (weighted degree centrality) to estimate the co-occurrence of each component pair (where components are nodes and their co-occurrences are edges) weighted by the intensity of association between the component pair[61]. The edge-weight is the product of the probability of each component in a patent, relative to the maximum probability of any component in that patent. To find the complexity of each of the 9 components across the patent dataset, we averaged the degree of all components and divided it by the total patents for each component to account for the differences in the number of patents. We used the igraph[62] package in R for the social network analysis.

In comparing these metrics, we found that the Hausmann, Hidalgo et al's PCI best captures actual challenges of manufacturing and integrating wind components as reflected by technology roadmaps and the broader literature on wind power technologies[35,27] (see Supplementary Figure 1 and Supplementary Data 1). A correlation analysis of these metrics across our study period (Supplementary Table 3) reveals that all of them are positively correlated, however, the PCI-based metric has the strongest correlation with international evolution (which we describe in the following). Although our interpretation of Fleming and Sorenson's approach demonstrates similar trends as the PCI approach, it assigns a slightly higher complexity to towers which contrasts with the insights from the literature on wind turbine manufacturing. Our interpretation of Broekel's structural diversity index differed from the understanding of complexity reflected by the specific academic literature on knowledge transfer and manufacturing in wind. This could be because of differences specific to the wind sector and/or because of limitations in our simplified approach for estimating the index. For these reasons, we used the PCI-based approach as the main measure of technology complexity in our analysis. Our primary results report HS02 values as these were reported for each year from 2006 to 2016.

We note that the PCI has two main caveats. One, the PCI relies on international trade (and export) data and may not fully capture what is produced for local use – but it is likely that countries only export what they are good at producing, for both domestic and international use[28]. Two, resulting from the dependence on trade flows, the PCI values for individual components may see variations over time. However, we found that data on the different complexity metrics was correlated and the PCI was still the best suited for our study. For the purposes of our research, the PCI provides a suitable estimate of manufacturing wind turbine components, and of how technology characteristics that capture more than technology- or knowledge-competences determine the location of manufacturing.

Mixed-methods analysis of emergence of suppliers

We used network analysis techniques to visualize the relationships between OEM and component supplier firms over different reported time periods (i.e., 2006 and 2014). The networks-based approach is increasingly used to visualize and quantify GVCs as scholars recognize that GVCs are better represented by multi-dimensional networks rather than linear chains[63]. We use the term 'relationships' to describe inter-firm linkages (e.g., Vestas (OEM) with Titan Wind (supplier) for towers in 2014) and intra-firm linkages (e.g., Vestas (OEM) with Vestas (in-house manufacturing) for nacelles)). We use a Sankey (alluvial) diagram to visualize the proportional flow between nodes of the network (i.e., the location of the supplier and the location of the OEM) using R (version 3.6.2) package ggforce[64].

Statistical analysis for evolution of suppliers

To estimate the links between technology complexity and suppliers' ability to be strategic and competitive in international markets, we conduct a set of Ordinary Least Squares (OLS) regression analyses from 2006 to 2016 using statistical modeling in R (version 3.6.2) and output using the stargazer package[65].

The dependent variable is the evolution, estimated as the difference over two years (i.e., a two-year time lag) in the fraction of supplier's market relationships with OEMs from a different country (international OEMs), as a proxy for suppliers' ability to compete in international markets. We used the network analysis technique (as described in the previous section) to first quantify the market relationships between suppliers with OEMs. In a given year t, a value of 0 reflects that suppliers work only with OEMs from the same country while 1 reflects that suppliers only work with OEMs from a different country (international OEM). Then, to estimate the change over time, where an increase in international relationships indicates an increase in competitiveness, we calculated the difference with year t+2. The final variable for evolution ranges from -1 to 1, where a negative value indicates a decrease in the fraction of international relationships, 0 indicates no change, and 1 indicates an increase in the fraction of international relationships.

We combined the data on supplier-OEM relationships with home-country information of the suppliers and OEMs. We manually collected the addresses of each supplier and OEM by searching databases such as Orbis, Amadeus, or Bloomberg and verified and extended this information with a manual search on the suppliers' webpages. We used headquarter addresses in case of larger companies with multiple facilities. We calculated changes in the fraction of international relationships on a two-year basis, and also on a yearly basis as a robustness check. While the results using two-year and one-year changes revealed robust estimates, we decided to focus on two-year changes that are likely to capture actual strategic changes of suppliers' evolution to a greater extent.

The main independent variable is technology complexity (x_1), measured using the product complexity index as described above for each component and year.

In addition, we used the following supplier-specific control variables:

- wind specialization (x_2), which is a binary variable that measures whether the supplier specialized in wind energy (=1) or was active in other sectors outside of the wind industry (=0). We obtained this information during our efforts of expanding the original dataset by manually coding all suppliers based on an analysis of their webpages and databases such as Bloomberg.
- component diversification (x_3) is a variable that measures the number of wind components supplied by a firm to wind OEMs, which we derived from our original dataset. In our database, 279 (90.9%) suppliers only offered one component, 23 (7.5%) offered two, and 5 (1.6%) firms offered three components. Those 5 firms offered 8 of the 9 distinct components, so there is no bias in a certain direction.
- patenting international (x_4), which captures the cumulative number of international patents per component by each supplier, depreciated by 15% annually[41]. We used the patent data and classification as described above and mapped whether the country where each patent was first registered matches the country of origin of the supplier.
- patenting domestic (x_5), similarly captures the cumulative number of home-country patents applied for by each supplier.
- size (x_6), which estimates the number of employees (logged). This information was obtained from during the database expansion from Orbis, Amadeus, Bloomberg and the suppliers' webpages. We used the last available number of full-time employees (or equivalents) given that many of the covered supplier are private firms where time varying data is not available.
- age (x_7), which represents the time interval since the founding year of the supplier. This information was also obtained during the database expansion.
- supplier dependence on OEM (x_8), which captures the different outsourcing or insourcing strategies applied by the OEMs and indicates how dependent each supplier is on the OEM. The importance of including this variable as a control stems from the fact that OEMs have different approaches for procuring components from suppliers, i.e., the governance of the value chain: some suppliers are in-house or through acquired companies, some are outsourced to international suppliers who, despite being part of an OEM, continued to brand their products differently. This is a continuous variable ranging from 0 (only in-house relationships) to 1 (only outsourced relationships).

In the regression results, the change in international evolution (Y_i) for supplier i is estimated using the following OLS model:

$$(Y_i) = \beta_0 + \beta_1 x_{1i} + \beta_2 x_{2i} + \beta_3 x_{3i} + \beta_4 x_{4i} + \beta_5 x_{5i} + \beta_6 x_{6i} + \beta_7 x_{7i} + \beta_8 x_{8i} + \varphi_i + \gamma_i + t \quad (1)$$

where β_1 is the coefficient of interest on technology complexity, and $\beta_{2\text{-}8}$ the coefficients of the control variables. φ_i , γ_i and t are fixed effects for the supplier (φ_i), the country of the supplier (γ_i), and year (t).

The same set of explanatory and control variables in Equation 1 are used in all cases. Table 1 reports values of (β) and Supplementary Table 4 shows the descriptive statistics and correlations. In total, we have an unbalanced panel of 1,227 observations of 318 suppliers from Denmark, Germany, Spain, US, Japan, China, and India (out of the 389 global suppliers, from 2006-2016). Model 1 measures the impact of all control variables on international evolution, and Model 2 adds the effect of our main independent variable technology complexity, suggesting a significant negative impact on international evolution (β = -0.118, p-value =0.029). Model 3 includes the same variables but limits the firms to the 114 suppliers from Germany, Denmark and Spain (excluding US and Chinese suppliers). Model 4 captures the same for 37 US suppliers, and Model 5 for 138 Chinese suppliers. Given the low number of suppliers from India (21) and Japan (8), we did not calculate separate models for these countries. Model 6 limits the dataset to only capture relationships of suppliers with OEMs from EU, Model 7 to OEMs from the USA and Model 8 from China.

In addition, we conducted several robustness checks for our model specifications. These include different complexity metrics, time lags, and interaction effects (Supplementary Tables 5-6). Our results are robust to all model specifications.

Finally, we undertook a three-step approach to address endogeneity concerns that the complexity will shape how countries export and internationalize, while the PCI based complexity measure is also calculated based on countries that are able to manufacture and export a technology. First, complexity (the independent variable) is measured at the component-level based on broader mapping of HS codes from Hausmann, Hidalgo, et al.'s PCI approach (where other components unrelated to wind may also be traded under a particular component code). International evolution (our dependent variable) is estimated on the supplier-component level of the wind energy industry. This eliminates the use of same data and unit of analysis for the two variables. Second, we use other complexity metrics that are based on patent data and do not rely on country information. Our results are again robust to these other complexity metrics (Supplementary Table 5). Third, we use time lags of two years in our main model (Model 1 and Model 2) and multiple other time lags for robustness checks (See Supplementary Table 6). This reduces the relationship in a particular year between the dependent variable and the complexity independent variable. Our results are robust under different specifications.

Table 1: Regression results on the relationship between technology complexity and evolution i.e., change in fraction of relationships with international OEMs. Suppliers of high complexity components are likely to have low evolution. The model results are from Ordinary Least Squares (OLS) regressions. Numbers in parentheses indicate robust standard errors.

International evolution (change in the fraction of supplier relationships with international OEMs)	Controls	All suppliers	European suppliers	US suppliers	Chinese suppliers	Suppliers to European OEMs	Suppliers to US OEMs	Suppliers to Chinese OEMs
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
technology complexity		-0.118**	-0.088	-0.281	-0.131*	-0.099	-0.266***	-0.014
		(0.054)	(0.066)	(0.239)	(0.075)	(0.078)	(0.089)	(0.062)
		t = -2.191	t = -1.337	t = -1.175	t = -1.752	t = -1.263	t = -2.993	t = -0.222
		p = 0.029	p = 0.182	p = 0.240	p = 0.080	p = 0.207	p = 0.003	p = 0.825
wind specialization	-1.141***	-1.105***	0.307	0.011	-1.943***	0.291*	-12.733***	-0.381
	(0.390)	(0.390)	(0.368)	(0.299)	(0.649)	(0.173)	(4.602)	(1.550)
	t = -2.927	t = -2.836	t = 0.834	t = 0.036	t = -2.995	t = 1.682	t = -2.767	t = -0.246
	p = 0.004	p = 0.005	p = 0.405	p = 0.972	p = 0.003	p = 0.093	p = 0.006	p = 0.806
component diversification	0.136**	0.107	-0.055	0.449***	0.309***	-0.105	0.04	0.088
	(0.069)	(0.068)	(0.081)	(0.148)	(0.119)	(0.097)	(0.120)	(0.093)
	t = 1.984	t = 1.572	t = -0.676	t = 3.027	t = 2.588	t = -1.079	t = 0.337	t = 0.946
	p = 0.048	p = 0.116	p = 0.500	p = 0.003	p = 0.010	p = 0.281	p = 0.737	p = 0.345
patenting international	0.003	0.003	-0.0004	0.082**	0.627**	0.001	0.007**	0.007***
	(0.003)	(0.003)	(0.002)	(0.041)	(0.280)	(0.004)	(0.003)	(0.002)
	t = 1.101	t = 1.132	t = -0.148	t = 2.011	t = 2.241	t = 0.267	t = 2.200	t = 2.813
	p = 0.271	p = 0.258	p = 0.883	p = 0.045	p = 0.026	p = 0.790	p = 0.028	p = 0.005
patenting home	-0.001	0.003	-0.001	-0.132	0.045***	0.009	-0.0002	0.001
	(0.005)	(0.005)	(0.005)	(0.244)	(0.014)	(0.011)	(0.016)	(0.009)
	t = -0.116	t = 0.505	t = -0.166	t = -0.539	t = 3.091	t = 0.874	t = -0.015	t = 0.142
	p = 0.908	p = 0.614	p = 0.868	p = 0.590	p = 0.002	p = 0.383	p = 0.989	p = 0.888
size	-0.547**	-0.516**	0.156**	-0.396	-1.977***	0.064	10.710***	-0.343
	(0.216)	(0.214)	(0.078)	(0.281)	(0.635)	(0.110)	(3.303)	(1.342)
	t = -2.534	t = -2.408	t = 2.016	t = -1.409	t = -3.111	t = 0.578	t = 3.243	t = -0.255
	p = 0.012	p = 0.017	p = 0.044	p = 0.159	p = 0.002	p = 0.564	p = 0.002	p = 0.799
age	0.008***	0.008***	0.002	-0.057***	-0.031	0.001	-0.680***	-0.01
	(0.002)	(0.002)	(0.001)	(0.011)	(0.023)	(0.001)	(0.228)	(0.033)
	t = 3.736	t = 3.697	t = 1.079	t = -4.958	t = -1.367	t = 1.053	t = -2.989	t = -0.293
	p = 0.0002	p = 0.0003	p = 0.281	p = 0.00000	p = 0.172	p = 0.293	p = 0.003	p = 0.770
supplier dependence on OEM	-0.018	-0.016	0.127		-0.092	-0.075	-0.09	-0.108
	(0.067)	(0.067)	(0.077)		(0.130)	(0.072)	(0.083)	(0.083)
	t = -0.266	t = -0.240	t = 1.640		t = -0.708	t = -1.034	t = -1.076	t = -1.300
	p = 0.791	p = 0.810	p = 0.102		p = 0.479	p = 0.302	p = 0.283	p = 0.194
Constant	4.703***	4.551***	-0.940**	4.457***	14.883***	-0.046	-50.519***	3.054
	(1.604)	(1.595)	(0.447)	(1.691)	(4.896)	(0.635)	(15.602)	(10.390)
	t = 2.931	t = 2.853	t = -2.103	t = 2.637	t = 3.039	t = -0.072	t = -3.238	t = 0.294
	p = 0.004	p = 0.005	p = 0.036	p = 0.009	p = 0.003	p = 0.943	p = 0.002	p = 0.769
Country FE	YES	YES	NO	NO	NO	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES	YES	YES
Observations	1,227	1,227	479	169	455	637	421	485
R^2	0.426	0.429	0.456	0.548	0.487	0.457	0.449	0.509
Adjusted R^2	0.288	0.291	0.319	0.397	0.338	0.307	0.297	0.362

Note: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Data availability

The database on the global manufacturing value chain developed for this study was built on third-party reports published by Navigant Consulting, with additional details obtained from Orbis, Amadeus, Bloomberg, and Derwent World Patents Index. Restrictions apply to the availability of these third-party data and so the dataset is not publicly available. Data are however available upon reasonable request from the corresponding author. Supplier data (without the supplier company name) are available at [https://github.com/kavsurana/tech-complexity-project/] along with the source and code to replicate the analysis. The source data underlying Figs. 1–6 and Supplementary Figs. 1–2 are provided as a Source Data file.

References

1. IRENA. Renewable Capacity Statistics 2020. https://www.irena.org/publications/2020/Mar/Renewable-Capacity-Statistics-2020 (2020).
2. IEA. World Energy Outlook 2019. https://www.iea.org/reports/world-energy-outlook-2019 (2019).
3. GLWN (Global Wind Network). U.S. Wind Energy Manufacturing and Supply Chain: A Competitiveness Analysis. https://energy.gov/sites/prod/files/2014/09/f18/U.S.%20Wind%20Energy%20Manufacturing%20and%20Supply%20Chain%20Competitiveness%20Analysis_0.pdf (2014).
4. Wiser, R. et al. Expert elicitation survey on future wind energy costs. Nature Energy **1**, 16135 (2016).
5. Wiser, R. et al. 2018 Wind Technologies Market Report. 103 (2018).
6. HM Government. Industrial Strategy: Offshore Wind Sector Deal. https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/790950/BEIS_Offshore_Wind_Single_Pages_web_optimised.pdf (2019).

7. Hansen, U. E., Nygaard, I., Morris, M. & Robbins, G. The effects of local content requirements in auction schemes for renewable energy in developing countries: A literature review. Renewable and Sustainable Energy Reviews **127**, 109843 (2020).
8. Schmidt, T. S., Schmid, N. & Sewerin, S. Policy goals, partisanship and paradigmatic change in energy policy – analyzing parliamentary discourse in Germany over 30 years. Climate Policy **19**, 771–786 (2019).
9. Lewis, J. I. The Rise of Renewable Energy Protectionism: Emerging Trade Conflicts and Implications for Low Carbon Development. Global Environmental Politics **14**, 10–35 (2014).
10. Stokes, L. C. & Warshaw, C. Renewable energy policy design and framing influence public support in the United States. Nature Energy **2**, 17107 (2017).
11. Haakonsson, S. J. & Kirkegaard, J. K. Configuration of technology networks in the wind turbine industry. A comparative study of technology management models in European and Chinese lead firms. International Journal of Technology Management **70**, 281–299 (2016).
12. Binz, C. & Truffer, B. Global Innovation Systems—A conceptual framework for innovation dynamics in transnational contexts. Research Policy **46**, 1284–1298 (2017).
13. Pietrobelli, C. & Rabellotti, R. Global Value Chains Meet Innovation Systems: Are There Learning Opportunities for Developing Countries? World Development **39**, 1261–1269 (2011).
14. Jurowetzki, R., Lema, R. & Lundvall, B.-Å. Combining Innovation Systems and Global Value Chains for Development: Towards a Research Agenda. Eur J Dev Res **30**, 364–388 (2018).
15. Lema, R. & Lema, A. Technology transfer? The rise of China and India in green technology sectors. Innovation and Development **2**, 23–44 (2012).
16. Lewis, J. I. Building a national wind turbine industry: experiences from China, India and South Korea. International Journal of Technology and Globalisation **5**, 281–305 (2011).
17. Surana, K. & Anadon, L. D. Public policy and financial resource mobilization for wind energy in developing countries: A comparison of approaches and outcomes in China and India. Global Environmental Change **35**, 340–359 (2015).

18. Binz, C., Gosens, J., Hansen, T. & Hansen, U. E. Toward technology-sensitive catching-up policies: insights from renewable energy in China. World Development **96**, 418–437 (2017).
19. World Bank. World Development Report 2020: Trading for development in the age of global value chains. (World Bank, 2020).
20. OECD. Multinational enterprises in the global economy - Heavily debated but hardly measured. https://www.oecd.org/industry/ind/MNEs-in-the-global-economy-policy-note.pdf (2018).
21. Antràs, P. Conceptual Aspects of Global Value Chains. http://www.nber.org/papers/w26539 (2019) doi:10.3386/w26539.
22. AWEA. Wind Energy Industry Manufacturing Supplier Handbook. (2011).
23. Hobday, M. Product complexity, innovation and industrial organisation. Research Policy **26**, 689–710 (1998).
24. Huenteler, J., Schmidt, T. S., Ossenbrink, J. & Hoffmann, V. H. Technology life-cycles in the energy sector — Technological characteristics and the role of deployment for innovation. Technological Forecasting and Social Change **104**, 102–121 (2016).
25. Garud, R. & Karnoe, P. Bricolage versus breakthrough: distributed and embedded agency in technology entrepreneurship. Research Policy **32**, 277–300 (2003).
26. OECD. OECD SME and Entrepreneurship Outlook 2019. (2019).
27. Navigant Research. Supply Chain Assessment 2014 – Wind Energy 2014-2018. (2014).
28. Hausmann, R. et al. The atlas of economic complexity: Mapping paths to prosperity. vol. 51 (MIT Press, 2014).
29. McNerney, J., Farmer, J. D., Redner, S. & Trancik, J. E. Role of design complexity in technology improvement. PNAS **108**, 9008–9013 (2011).
30. Novak, S. & Eppinger, S. D. Sourcing By Design: Product Complexity and the Supply Chain. Management Science **47**, 189–204 (2001).
31. Broekel, T. Using structural diversity to measure the complexity of technologies. PLOS ONE **14**, e0216856 (2019).

32. Mealy, P., Farmer, J. D. & Teytelboym, A. Interpreting economic complexity. Science Advances **5**, eaau1705 (2019).
33. Balland, P.-A. & Rigby, D. The Geography of Complex Knowledge. Economic Geography **93**, 1–23 (2017).
34. Fleming, L. & Sorenson, O. Technology as a complex adaptive system: evidence from patent data. Research Policy **30**, 1019–1039 (2001).
35. Huenteler, J., Ossenbrink, J., Schmidt, T. S. & Hoffmann, V. H. How a product's design hierarchy shapes the evolution of technological knowledge—Evidence from patent-citation networks in wind power. Research Policy **45**, 1195–1217 (2016).
36. MIT Media Lab. Observatory of Economic Complexity - Product Complexity Rankings. https://atlas.media.mit.edu/en/rankings/product/hs07/?year_range=2011-2016.
37. Paisemi, F. EU energy technology trade: Import and export. https://setis.ec.europa.eu/sites/default/files/reports/eu_energy_technology_trade.pdf (2017).
38. Wind, I. HS Codes and the Renewable Energy Sector. Research and Analysis, International Centre for Trade and Sustainable Development (ICTSD) (2008).
39. Asheim, B. T. & Coenen, L. Knowledge bases and regional innovation systems: Comparing Nordic clusters. Research Policy **34**, 1173–1190 (2005).
40. Lewis, J. I. & Wiser, R. H. Fostering a renewable energy technology industry: An international comparison of wind industry policy support mechanisms. Energy Policy **35**, 1844–1857 (2007).
41. Qiu, Y. & Anadon, L. D. The price of wind power in China during its expansion: Technology adoption, learning-by-doing, economies of scale, and manufacturing localization. Energy Economics **34**, 772–785 (2012).
42. Awate, S., Larsen, M. M. & Mudambi, R. Accessing vs sourcing knowledge: A comparative study of R&D internationalization between emerging and advanced economy firms. Journal of International Business Studies **46**, 63–86 (2015).

43. Nieto, M. J. & Rodríguez, A. Offshoring of R&D: Looking abroad to improve innovation performance. Journal of International Business Studies **42**, 345–361 (2011).
44. Dunning, J. H. & Lundan, S. M. The Internationalization of Corporate R&D: A Review of the Evidence and Some Policy Implications for Home Countries1. Review of Policy Research **26**, 13–33 (2009).
45. Doblinger, C., Dowling, M. & Helm, R. An institutional perspective of public policy and network effects in the renewable energy industry: enablers or disablers of entrepreneurial behaviour and innovation? Entrepreneurship & Regional Development **28**, 126–156 (2016).
46. Cox Pahnke, E., McDonald, R., Wang, D. & Hallen, B. Exposed: Venture Capital, Competitor Ties, and Entrepreneurial Innovation. AMJ **58**, 1334–1360 (2014).
47. Doblinger, C., Surana, K. & Anadon, L. D. Governments as partners: The role of alliances in U.S. cleantech startup innovation. Research Policy **48**, 1458–1475 (2019).
48. Schilling, M. A. & Phelps, C. C. Interfirm collaboration networks: The impact of large-scale network structure on firm innovation. Management Science **53**, 1113–1126 (2007).
49. Gereffi, G., Humphrey, J. & Sturgeon, T. The governance of global value chains. Review of International Political Economy **12**, 78–104 (2005).
50. Sturgeon, T., Van Biesebroeck, J. & Gereffi, G. Value chains, networks and clusters: reframing the global automotive industry. J Econ Geogr **8**, 297–321 (2008).
51. Schmidt, T. S. & Huenteler, J. Anticipating industry localization effects of clean technology deployment policies in developing countries. Global Environmental Change **38**, 8–20 (2016).
52. Brauch, H. G., Spring, Ú. O., Grin, J. & Scheffran, J. Handbook on sustainability transition and sustainable peace. vol. 10 (Springer, 2016).
53. Haakonsson, S., Kirkegaard, J. K. & Lema, R. The decomposition of innovation in Europe and China’s catch-up in wind power technology: the role of KIBS. European Planning Studies **0**, 1–19 (2020).

54. USITC. Utility Scale Wind Towers from Canada, Indonesia, Korea, and Vietnam. Investigation Nos. 701-TA-627-629 and 731-TA-1458-1461 (Preliminary). https://www.usitc.gov/publications/701_731/pub4952.pdf (2019).
55. Wilson, C. et al. Granular technologies to accelerate decarbonization. Science **368**, 36–39 (2020).
56. IRENA. Future of wind: Deployment, investment, technology, grid integration and socio-economic aspects. https://www.irena.org/-/media/Files/IRENA/Agency/Publication/2019/Oct/IRENA_Future_of_wind_2019.pdf (2019).
57. Feinerer, I., Hornik, K. & Meyer, D. Text Mining Infrastructure in R. Journal of Statistical Software **25**, 1–54 (2008).
58. Grün, B. & Hornik, K. topicmodels: An R Package for Fitting Topic Models. Journal of Statistical Software **40**, 1–30 (2011).
59. Chan, G. The Commercialization of Publicly Funded Science: How Licensing Federal Laboratory Inventions Affects Knowledge Spillovers. http://isites.harvard.edu/fs/docs/icb.topic1459278.files/CHAN-Gabriel_11-21-14_JMP%20-%20National%20Lab%20Patent%20Licensing.pdf (2015).
60. Kim, G., Park, S. & Jang, D. Technology Analysis from Patent Data Using Latent Dirichlet Allocation. in Soft Computing in Big Data Processing (eds. Lee, K. M., Park, S.-J. & Lee, J.-H.) 71–80 (Springer International Publishing, 2014).
61. Barrat, A., Barthélemy, M., Pastor-Satorras, R. & Vespignani, A. The architecture of complex weighted networks. PNAS **101**, 3747–3752 (2004).
62. Csardi, G. & Nepusz, T. The igraph software package for complex network research. InterJournal **Complex Systems**, 1695 (2006).
63. Taglioni, D. & Winkler, D. Making Global Value Chains Work for Development. (The World Bank, 2016). doi:10.1596/978-1-4648-0157-0.
64. Pedersen, T. L. ggforce: Accelerating ‘ggplot2’. R package version 0.1 **2**, (2019).

65. Hlavac, M. Stargazer: Well-formatted regression and summary statistics tables. R package version **5**, (2015).