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Catching up in clean energy technologies: a patent analysis

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Abstract
How we can accelerate the diffusion of new clean energy technologies worldwide is a highly relevant topic for energy and climate policies, as well as industrial policies. We trace the time lag between the introduction and the diffusion of breakthroughs in solar photovoltaic technology and wind power technology. Our results show that both domestic knowledge base and organizational proximity to the country introducing breakthroughs, help latecomer countries catch up by actively innovating in these technologies on their own. Moreover, we find that there are more opportunities for latecomer countries with stronger domestic knowledge base to catch up in solar photovoltaic technology than wind power technology. The results of this paper provide systematic evidence of the technology-sensitive catching-up process in the clean energy technological paradigm.

Keywords Catching-up · Solar photovoltaic technology · Wind power technology · Diffusion · Relatedness · Proximity · Multinational companies

JEL Classification O14 · O25 · O31 · O33 · Q55

1 Introduction

The decarbonisation of our current energy systems to meet climate change mitigation goals is crucial and urgent, requiring a faster diffusion of new clean energy technologies worldwide. This challenge is especially acute in latecomer countries where the demands for energy grow rapidly (Grubler et al., 2016; Sovacool, 2016). Besides the goal of climate change mitigation, the emerging clean energy technological paradigm offers latecomer countries windows of opportunity to catch up with countries on the technological frontier of these radically new technologies (Lema et al., 2020; Mathews, 2013; Pegels & Altenburg, 2020; Perez, 2016).

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Although latecomer countries can deploy clean energy technologies relatively easy relying on imported clean energy products (Bento et al., 2018; Grubler et al., 2016), their ability to innovate in clean energy technologies up is another matter. To catch up with countries on the technology frontier, latecomer countries need to acquire advanced technological capabilities for innovating in radically new technologies on their own by learning about the technology, its production and its deployment (Perez & Soete, 1988). Moreover, recent studies show that successful catching-up is mainly driven by a country's ability to move into new technologies at an early stage (Alshamsi et al., 2018; Hartmann et al., 2021; Lee & Lim, 2001; Lee & Malerba, 2017).

Recent studies in evolutionary economic geography highlight that technological development is a path-dependent process, with new technological capabilities building on existing ones [for systematic reviews: see Boschma (2017) and Hidalgo (2021)]. Using patent data, these studies found that countries tend to diversify into new technologies that are related to technologies that they already master. Moreover, besides domestic capabilities in related technologies, the ability to catch up in a new technology also depends on a country's access to knowledge residing in other countries, in particular, where new technologies originate (Balland & Boschma, 2021; Boschma, 2017).

The present study deals with the catching-up process in clean energy technologies by investigating how fast latecomer countries can start innovating in radically new technologies on their own. We conceive of this process as a technological diffusion process. Following a recent methodology to identify radically new technologies (we will use radically new technologies and breakthroughs interchangeably in the remaining part of the paper) as new combinations between patent classes (Verhoeven et al., 2016), we trace the spatial-temporal diffusion of breakthroughs in solar photovoltaic technology and wind power technology, and quantify the impacts of domestic knowledge base and international access to the new knowledge on the speed of diffusion. The comparison between the spatial-temporal diffusion patterns of solar photovoltaic technology and wind power technology further allows us to shed light upon the technology-sensitive catching-up process in clean energy technologies as suggested by recent literature (Binz et al., 2017; Malhotra & Schmidt, 2020; Schmidt & Huenteler, 2016).

The remainder of the paper is structured as follows. In Sect. 2, we review the relevant literature on the temporal and spatial diffusion of new technologies. In Sect. 3, we describe the data, econometric model and variables. In Sect. 4, we present the results of descriptive analysis and econometric analysis. We conclude by discussing the implications of our findings in Sect. 5.

2 Theoretical background

2.1 Windows of opportunity and the entry timing

The diffusion of new technology is inherently a spatial process that new technologies originate in certain places, often technology centres, and diffuse to other places if they are successful (Hägerstrand, 1973). The spatial diffusion process from technology centres to the periphery is through a hierarchy of sub-centres. In this process, industrialized countries often enter early on, with the comparative advantage later shifting to latecomer countries as a new technology reaches maturity (Perez & Soete, 1988).

The emergence of new technologies opens windows of opportunity for latecomers to catch up through imitating and improving upon them (Perez & Soete, 1988; Lee & Malerba, 2017) extended the notion of windows of opportunity to various building blocks of sectoral innovation systems. They explain that, besides technological breakthroughs, other forces such as major shifts in market structures and large shifts in politics, could also open such windows of opportunity. Yap and Truffer (2019) further argued that the latter two processes are especially important for the catching-up process in clean energy technologies.

Although the conventional spatial diffusion process of technologies suggests that it might be easier for latecomer countries to enter a new technology at a more mature stage, the right timing of entry is key to the catching-up process of latecomer countries when windows of opportunity emerge (Perez & Soete, 1988). The evolutionary view of technological change suggests that new technologies develop path-dependently following well-defined technological trajectories (Dosi, 1982). Later entry indicates a larger gap with the technological frontier due to the accumulation of experience and skills in the incremental improvements of a new technology along the diffusion process (Dosi, 1991; Metcalfe, 1981; Rosenberg, 1982). Furthermore, later entry also implies less technological opportunities because most technological opportunities might have already been exhausted when a new technology matures (Dosi, 1982; Perez & Soete, 1988).

The importance of early entry in new technologies is corroborated by recent studies of the search behaviour of inventors and firms showing that the utilization of emerging knowledge correlates with a higher technological impact of inventions (Capaldo et al., 2017; Kok et al., 2019; Mukherjee et al., 2017). Moreover, higher utilization rates of recent technologies are associated with the improvement in performance, or the cost reduction of new technologies (Benson & Magee, 2014, 2015).

Recent case studies in catching-up literature also confirm that mid- to long-run economic catch-up is mainly driven by a country's ability to move into new sectors at an early stage (Hartmann et al., 2021; Lee & Lim, 2001; Lee & Malerba, 2017). However, these empirical insights on the timing of entry and catching-up remain largely qualitative. Kwon et al. (2017) were the first to systematically quantify the catching-up process by investigating the time needed for inventors of a particular country to cite an invention from technological frontier. They showed that Korea, Israel and Taiwan managed to narrow the gap with technological frontier, whereas similar progress could not be observed in China and India. Nevertheless, we still lack a systematic understanding of the determinants of the early entry of latecomer countries in new technologies since their study only focused on the overall technological progress of specific countries instead of in particular new technologies.

2.2 Local capabilities and the temporal dimension in evolution economic geography

The earlier version of windows of opportunity concept suggested that the diffusion of radically new technologies is rather independent of the pre-existing technology structure in the receiving country or region (Perez & Soete, 1988; Storper & Walker, 1989). The reasoning here was that radically new technologies are fundamentally different from previous technologies. Hence, what is learnt in the past would be less relevant for understanding and institutionalising the new technologies.

However, new technologies do not diffuse automatically nor in isolation from other technologies (Grubler et al., 2016). Latecomer countries need the capacities to absorb and assimilate the new technology, and overcome the costs of entry (Cohen & Levinthal, 1990; Maskell & Malmberg, 1999; Perez & Soete, 1988). In this context, recent studies in evolutionary economic geography highlighted the role of related capabilities in the development of new technologies (see an extensive review in Hidalgo (2021)). Building on an seminal study of the diversification in exports by Hidalgo et al., (2007), these studies show that countries are more likely to diversify into new technologies that are related to their existing knowledge bases (Li et al., 2020; Perruchas et al., 2020; Petralia et al., 2017).

However, as pointed out by Henning (2019), these studies only compare the new technology emerging in a country with the pre-existing technology structure of the focal country in the past. It ignores whether the focal technology is already established globally and only new to the country, or is also new to the world (Boschma et al., 2017; Heimeriks & Boschma, 2014). Put differently, studies in evolutionary economic geography focused only on the introduction of novelty in a local context, while neglecting diffusion of technology as a process at the global level. The temporal dimension thus remained rather abstract (Henning, 2019).

In this study, we focus on technologies that are new to the world and investigate to what extent the existing related capabilities in countries matter for the speed at which countries become actively innovating in these new technologies on their own. Radically new technologies or breakthroughs are considered the results from the combination of existing knowledge, technologies and artefacts in novel ways (Arthur, 2007; Arts & Veugelers, 2015; Fleming, 2001; Henderson & Clark, 1990; Strumsky & Lobo, 2015; Verhoeven et al., 2016). Building on this view, Pezzoni et al. (2022) traced the diffusions of radically new technologies, and found that they can diffuse faster if their components were familiar to the inventors' community. We therefore expect that the local related capabilities of countries can facilitate early entry in the radically new technologies.

2.3 Clean energy technologies and technology-sensitive catching-up processes

Clean energy technologies are considered radical and disruptive in the energy sector because of their distinct knowledge base and potential to replace fossil fuel technologies (Geels, 2018; Markard & Truffer, 2008; Wilson, 2018). These technologies rely on diverse knowledge inputs from largely unrelated technologies (Barbieri et al., 2020), and can thus be considered more complex than dirty technologies. However, knowledge and skills accumulated in related technologies, even in fossil fuel technologies, can still help countries diversify into clean energy technologies (Li et al., 2020; Perruchas et al., 2020; van den Berge et al., 2020). Furthermore, the increased global interdependence in clean energy transitions allows countries to engage in the global value chains and global innovation networks of clean energy technologies (Binz & Truffer, 2017; Meckling & Hughes, 2018). The technology transfer and learning through these international linkages play an important role in the development of clean energy technologies, especially for the catching-up of latecomer countries (Binz & Anadon, 2018; Gosens et al., 2015; Haakonsson & Slepniov, 2018; Lema & Lema, 2012, 2016; Quitzow, 2015; Zhang & Gallagher, 2016).

Lee & Malerba (2017) suggested that there are heterogeneities in the catching-up processes of different technologies. This also holds for clean energy technologies. The technological characteristics of different clean energy technologies may have important impacts on the spatial-temporal diffusion of breakthroughs in these technologies (Binz et al., 2017;

Binz & Truffer, 2017; Malhotra & Schmidt, 2020; Schmidt & Huenteler, 2016). In the recent conceptual framework of the Global Innovation Systems, solar photovoltaic technology is categorized as more footloose, whereas wind power technology is categorized as spatially more sticky (Binz & Truffer, 2017; Schmidt & Huenteler, 2016). This is related to the dominant design in wind turbine technology, which appeared earlier than the dominant design of solar photovoltaic technology (Huenteler et al., 2016b). The innovation focus of wind turbine has consequently shifted to its components and grid connection (Huenteler et al., 2016a), whereas inventors in photovoltaic technology are still researching alternative solar photovoltaic cells with better performance (Kalthaus, 2019; Leydesdorff, 2015). The continuing technological dynamism in the solar photovoltaic technology may thus offer continuing windows of opportunity for latecomer countries to catch-up.

Solar photovoltaic technology is further considered to follow mostly the STI (science-technology-innovation) innovation model and standardized mass production which requires more manufacturing capabilities, whereas wind turbine technology is considered to follow more the DUI (doing, using and interacting) innovation mode which requires more design capabilities (Binz & Truffer, 2017; Schmidt & Huenteler, 2016). Knowledge transfer in solar photovoltaic technology is often embodied in capital goods like manufacturing equipment which can be relatively easily transferred across globalized markets, whereas the knowledge transfer in wind turbine technology is more dependent on the transfer of tacit knowledge (Binz & Truffer, 2017; Schmidt & Huenteler, 2016). Thus, it is more difficult for countries without previous knowledge accumulation to catch up in wind turbine technology.

3 Research design

3.1 Sample and data

The data used in this paper are patent applications filed at European Patent Office (EPO), United States Patent and Trademark Office (USPTO) and through the Patent Cooperation Treaty (PCT) from 1980 to 2015. Patent applications are extracted from European Patent Office Worldwide Patent Statistics Database PATSTAT 2018 Autumn Version. We only focus on patents assigned to companies and institutions following Mancusi (2008) because patents assigned only to individuals are usually considered less innovative. The type and the unique identifier of applicants are extracted from the PATSTAT Standardized Name table developed by ECOOM in KU Leuven (Du Plessis et al., 2009; Magerman et al., 2009).

Since multiple equivalent patent applications can be filed at EPO, USPTO and PCT to protect the intellectual property rights of the same invention, we use IPC codes of all patent applications in the same PATSTAT simple patent family as the technological classifications of the invention under consideration (Martínez, 2011). The year of a PATSTAT simple patent family is based on the application year of its first patent application.

Patent classification codes in which a patent is assigned are considered as proxies for the specific technology components associated with the patented invention (Fleming, 2001). Although some studies also use the backward citations to proxy the knowledge recombination (see the review by Jaffe & de Rassenfosse (2017)), technological codes are determined by patent examiners; thus, unlike patent citations, they are not biased by firms' strategic considerations. For that reason, co-occurrences of technology codes at the patent level are ideal for determining the technological combinations that led to a patented innovation (Fleming, 2001; Fleming et al., 2007).

We identify the breakthroughs by assessing the new combinations of patent technology codes at the main group level of the International Patent Classifications (IPC) following Verhoeven et al. (2016). A pairwise combination of IPC main groups is considered new if they appear for the first time in (recent) history. We use all the patents applied between 1980 and 1992 to find the already existing combinations and track the emergence of breakthroughs from 1993.

We assign each patent to the country of residence of the first named inventor in the earliest patent document in a patent family following Mancusi (2008). There are increasing numbers of patents of which applicants and inventors are located in different countries. This phenomenon is mostly driven by the internationalization of R&D activities in multinational corporations (Alkemade et al., 2015; de Rassenfosse & Seliger, 2020). Consider, as an example, patent application number US20140248123A1 filed on 28 November 2012 at the USPTO. The sole applicant was the Danish wind turbine manufacturer Vestas Wind Systems AS, while all three inventors were located in United Kingdom. We consider the first inventor's address to best identify where the R&D was performed (Mancusi, 2008). However, the innovation network of a multinational corporation with inventors active in different countries does contain relevant information about possible international channels of knowledge diffusion (Phene et al., 2005). We thus also take into account the embeddedness of inventors in latecomer countries in the innovation network of multinational corporations in the empirical analysis.

We focus on the diffusion of breakthroughs in two leading clean energy technologies, solar photovoltaic and wind power. Patents in these two technologies are identified using the Y02E10/5 code (solar photovoltaic) and Y02E10/7 code (wind power) in the newly launched Cooperative Patent Classification (CPC). The Y02 class is developed by EPO experts by combining existing International Patent Classifications (IPC) and European Patent Classifications with a lexical analysis of abstracts or claims in identifying cross-sectoral technologies with potential in climate change mitigations (Veefkind et al., 2012).

3.2 Econometric model

In order to trace the determinants of the speed in the spatial-temporal diffusion of breakthroughs in clean energy technologies that are new to the world, we applied the Cox proportional hazard model (Cox, 1972), in which the hazard is assumed to be as follows:

$$h(t) = h_0(t)(\beta_1 x_1 + \cdots + \beta_k x_k)$$

The Cox model has the advantage of estimating the hazard ratios ($\beta_1 \ldots \beta_k$) without specifying baseline hazards $h_0(t)$. Furthermore, the Cox model allows group specific baseline hazards. This can be operationalized using stcox command with strata() option in Stata. The hazard at time t for a subject in group i is assumed to be as follows:

$$h(t) = h_{0i}(t)(\beta_1 x_1 + \cdots + \beta_k x_k)$$

Our dependent variable is the number of days between the introduction of a breakthrough (new to the world) and the date at which a country adopts the breakthrough by patenting on its own (new to the country). Countries that did not adopts the breakthrough are treated as right-censored. Positive hazard ratios indicate that independent variables will facilitate earlier adoptions of breakthroughs. We report the coefficients instead of hazard ratios (exponentiated coefficients) in the regression tables.

We consider all breakthroughs introduced between 1993 and 2007 to leave an 8-year window forward to this last cohort. We only focus on breakthroughs which are adopted more than 20 times in solar photovoltaic or wind power patents as to be able to apply a threshold for the impacts of new technologies following Pezzoni et al. (2022). Here, 20 times corresponds to top 2% of new combinations adopted in solar photovoltaic patents, and top 4% of new combinations adopted in wind power patents. However, new combinations introduced in earlier years are more likely to be included in the sample when we use the number of times as a threshold. In the robustness check, we include only new combinations that are among top 1% of new combinations introduced in the same year in terms of the number of times being adopted by solar photovoltaic or wind power patents. The results remain consistent.

We focus on breakthroughs introduced by inventors from United States to proxy new technologies developed at the technology frontier following Kwon et al. (2017). As a robustness check, we also use breakthroughs introduced by inventors from Germany and Japan separately, and three countries together. The number of breakthroughs introduced by these three countries accounts for 70% of all breakthroughs introduced during the period 1993–2007. Leydesdorff et al. (2015) also shows that these three countries are in fact at the technological frontier of solar photovoltaic technology.

Our main interest is the impacts of independent variables on the diffusion speed of breakthroughs. As emphasised by Griffith et al. (2011), it is crucial to control for unobserved heterogeneity at the breakthrough level since some breakthroughs diffuse more quickly than others, for example, due to their level of codification or usefulness. The Cox model allows estimating different hazard ratios across groups. We include four variables to stratify our breakthroughs to control the different diffusion speeds across breakthroughs.

First, we include the *technological distance* between technological components being recombined in the breakthrough inventions by exploring the hierarchical structure of the IPC codes following Pezzoni et al. (2022). We include a *same field* dummy (stating whether the IPC main groups in the new combination are from the same technological field) and a *same sector* dummy (stating whether the pairwise IPC main groups are from different technological fields but the same sector). The IPC main groups are linked to technological fields and sectors based on the concordance table developed by Schmoch (2008). Second, we include the *intra-technology* dummy (stating whether the breakthrough is introduced by the same type of renewable energy technology that adopts it). Third, we also include the year in which the focal breakthrough is introduced.

As pointed out by Jaffe et al. (1993), and Griffith et al. (2011), new technologies are more likely to diffuse locally. Thus, we only focus on the international diffusion of breakthroughs to avoid the home bias. We include all OECD countries, EU 28 countries and BRICS countries (Brazil, Russia, India, China and South Africa) as the potential adopting country. The list of countries included in our regressions is shown in the Appendix. Finally, we cluster the standard errors at the country level to control for the unobserved heterogeneity in adopting breakthroughs across countries.

The main explanatory variable we are focusing on in this paper is the familiarity of inventors in a country with the technology components being used in a new combination. *Familiarity* takes the minimum value of the number of patents in a country among the IPC main groups of the breakthrough invention, in the past five years, following Clancy (2018). A larger value of *Familiarity* indicates that inventors in the country have a larger knowledge stock in both technological components used in the new combination, thus more likely to adopt breakthroughs earlier.

Apart from the domestic knowledge base, we are also interested in the role of proximity of a country vis-à-vis the country of origin. Proximity, in what ever sense, is expected to enhance the diffusion of technological knowledge (Hägerstrand, 1973) as for example shown in research using patent citations (Breschi & Lissoni, 2009; Jaffe et al., 1993). Here, we distinguish between geographical proximity and organizational proximity (Boschma, 2005). The impact of geographical proximity on the speed of spatial diffusion is assessed using the distance between the capital of United States, Germany and Japan, respectively, and the capital of the adopting country. The *Distance* variable is constructed from data are extracted from the CEPII database (Mayer & Zignago, 2011).

The impact of organizational proximity is assessed by the embeddedness of latecomer countries in the innovation network of the company introducing the breakthrough. We construct the variable *Same assignee* by including the number of patents invented by inventors in the focal country while assigned to the same multinational company who introduced the new combination in the previous 5 years before the adoption. These patents are usually innovations from subsidiaries of the multinational company in the focal country (de Rassenfosse & Seliger, 2020). The higher value of *Same assignee* indicates that the focal country is more important or better embedded in the global innovation network of the focal multinational company (Phene & Almeida, 2008; Phene & Tallman, 2018). Given the fact that these patents could also include co-patenting with inventors from the same company in other countries, this variable captures benefits from international co-patenting as well as benefits from knowledge transfer within multinational companies.

We add three control variables to control for the country-level factors which may affect the speed of technology diffusion. First, we include *GDP per capita* to control for the level of economic development of a country using data extracted from the Penn States Table 9.1 (Feenstra et al., 2015). Second, we take into account whether the adopting country specializes in solar photovoltaic technology (wind power technology) using the *Revealed Technology Advantage* index *(RTA)* following Soete & Wyatt (1983). The *RTA* takes the value 1 if the share of the solar photovoltaic patents (wind power patents) of a focal country in its total number of patents is larger than the share of solar photovoltaic patents (wind power patents) worldwide, and 0 otherwise. Third, we include the amount of electricity generated from solar photovoltaic (wind power) to control for the impact of domestic market development *(Market)* on the development of new technologies. We expect positive impacts from *GDP, RTA*, and *Market*.

Finally, in order to trace whether latecomer countries are closing the gap with countries at the technological frontier, we include the interactions of *Familiarity* with *GDP per capita* and *RTA* to test whether the impact of *Familiarity* differs across countries. Here, we expect that being familiar with the technologies recombined in breakthroughs will help countries at lower levels of economic development and countries with a lack of specialisations in solar (wind), to compensate for their lack of a more generic knowledge base and other unfavourable conditions (Petralia et al., 2017).

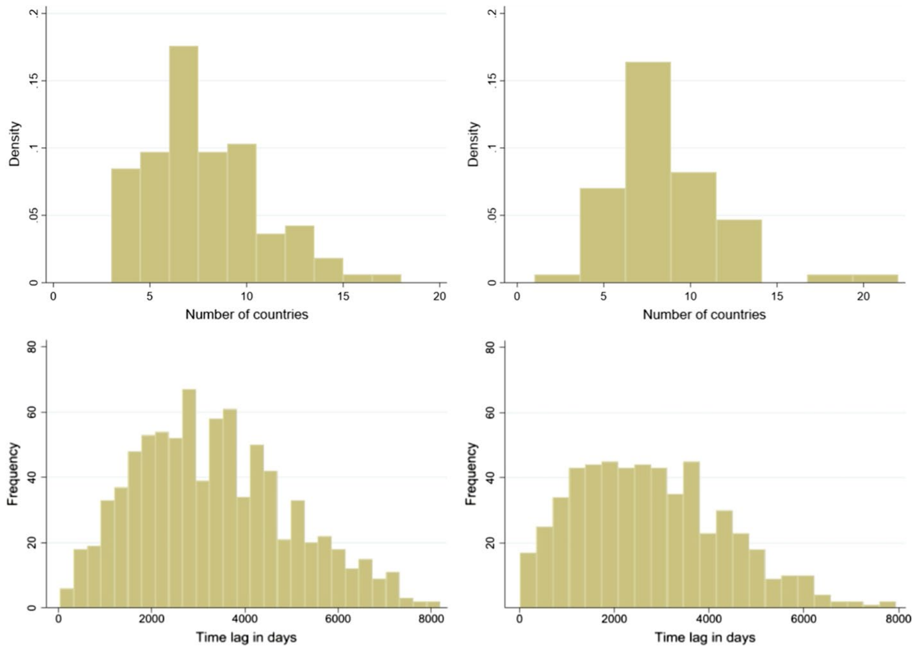

Fig. 1 Descriptive analysis of number of adopting countries and time-lag of adoption (solar photovoltaic technology in the left panels, and wind power technology in the right panels)

4 Results

4.1 Descriptive results

We focus on the spatial-temporal diffusions of 110 breakthrough inventions in solar photovoltaic technology and 65 breakthrough inventions in wind power technology introduced by US inventors among 47 countries, therefore 5170 observations for solar photovoltaic and 3055 observations for wind power. Figure 1 shows the distributions of the number of countries adopting breakthroughs and time lags of adoption in solar photovoltaic (left panels) and wind power (right panels). Most of breakthroughs in both technologies are only adopted by less than 15 countries, and most of the diffusion happen within 4000 days.

Tables 1 and 2 show the summary statistics and the correlation between the explanatory variables for solar photovoltaic and wind power technology respectively. The correlation between independent variables is not high.

4.2 Econometric results

Table 3 shows the econometric results of solar photovoltaic technology using new combinations introduced by inventors from United States. We divide our sample into pre-2000 and post-2000 subsamples following Conti et al. (2018). They observed the acceleration in EU renewable energy patenting at the turn of the century.

Table 1 Summary statistics: solar photovoltaic

Variable	Obs	Mean	SD	Min	Max						
Familiarity	5170	23.08	107.23	0.00	2766.00	1.000					
GDP pc	5170	32,117.08	13,925.11	2004.19	81,911.47	0.042	1.000				
Market	5170	2311.56	6094.85	0.00	44,782.00	0.139	−0.117	1.000			
Distance	5170	7894.57	2794.95	737.04	15,961.95	0.101	−0.199	0.115	1.000		
Same assignee	5170	7.22	65.21	0.00	1442.00	0.100	−0.012	0.069	0.026	1.000	
RTA	5170	0.31	0.46	0.00	1.00	0.176	0.205	0.004	0.176	− 0.006	1.000

Table 2 Summary statistics: wind power

Variable	Obs	Mean	SD	Min	Max						
Familiarity	3055	8.49	27.23	0.00	408.00	1.000					
GDP	3055	32,108.71	13,887.88	3399.05	83,851.23	0.082	1.000				
Market	3055	9134.77	21,821.66	0.00	18,5766.00	0.237	−0.199	1.000			
Distance	3055	7894.57	2795.13	737.04	15,961.95	0.055	−0.184	0.060	1.000		
Same assignee	3055	13.23	74.29	0.00	979.00	0.189	−0.108	0.216	0.075	1.000	
RTA	3055	0.58	0.49	0.00	1.00	−0.064	−0.208	−0.038	−0.164	−0.001	1.000

Table 3 Econometric results: Solar photovoltaic

	1993-2007		Pre-2000		Post-2000	
	(1)	(2)	(3)	(4)	(5)	(6)
Familiarity	0.211***	1.576***	0.213***	1.889***	1.007***	2.426***
	(0.04)	(0.20)	(0.04)	(0.23)	(0.16)	(0.37)
RTA	0.675	0.560	0.665	0.568	0.543	0.488
	(0.44)	(0.44)	(0.47)	(0.45)	(0.43)	(0.42)
GDP	0.034	0.053	−0.044	−0.017	0.139	−0.079
	(0.18)	(0.17)	(0.19)	(0.18)	(0.17)	(0.13)
Market	−0.220	−0.537*	−0.392	−0.882	−0.086	−0.200
	(0.20)	(0.32)	(0.37)	(0.78)	(0.10)	(0.12)
Distance	0.139	0.160	0.126	0.149	0.184	0.150
	(0.22)	(0.22)	(0.24)	(0.23)	(0.19)	(0.20)
Same assignee	0.081***	0.075***	0.050	0.032	0.533***	0.530***
	(0.03)	(0.03)	(0.04)	(0.04)	(0.11)	(0.11)
*Familiarity*GDP*		0.210*		0.341*		−1.254***
		(0.12)		(0.18)		(0.35)
*Familiarity*RTA*		−1.425***		−1.774***		−0.927***
		(0.19)		(0.23)		(0.23)
Observations	5170	5170	2961	2961	1739	1739
Log likelihood	−3889.248	−3799.358	−2118.874	−2039.937	−1367.174	−1342.662

The coefficients of *Familiarity* are significantly positive in all six models, indicating that countries adopt new combinations earlier if they are familiar with the technology components used in the new combinations. Although the coefficients of *GDP* are not significant, the coefficients of *Familiarity*GDP* are significantly positive in the full sample, and in the sub-sample of pre-2000 new combinations, and significantly negative in the sub-sample of post-2000 new combinations. The results indicate that the impacts of *Familiarity* before 2000 are larger for high-income countries, and after 2000 for low-income countries. This suggests that domestic knowledge base is more important for the countries with lower income in catching-up in solar photovoltaic technology as it matures.

The coefficients of *RTA* are not significant. However, after the introduction the interaction term *Familiarity*RTA*, the coefficients of *RTA* are positive in the full sample and sub-sample of pre-2000 model, while the coefficients of *Familiarity*RTA* are significantly negative in all three models. The results show that familiarity with the technological components used in the new combination is more important for countries without a specialization in solar photovoltaic technology. This can be explained by the dynamic inventive pattern of solar photovoltaic technologies that several new types of solar photovoltaic cells emerged during the focal period opening up windows of opportunities (Kalthaus, 2019), as well as the rapid international transfer of codified knowledge concerning solar photovoltaic technology (Binz & Truffer, 2017), allowing latecomer countries to catch-up.

Concerning the two proximity variables, the coefficients of *Same assignee* are significantly positive in the full sample and in the sub-sample of new combinations introduced after 2000. This result indicates that diffusion is faster when latecomer countries are well embedded in the global innovation network of the multinational company that introduces the breakthrough, underscoring the importance of organizational proximity for technology

Table 4 Econometric results: Wind power

	1993–2007		Pre-2000		Post-2000	
	(1)	(2)	(3)	(4)	(5)	(6)
Familiarity	0.256***	0.422***	0.221***	0.445***	0.263***	0.461***
	(0.04)	(0.08)	(0.05)	(0.13)	(0.04)	(0.09)
RTA	0.471	0.495	0.341	0.413	0.636	0.621
	(0.41)	(0.43)	(0.42)	(0.42)	(0.40)	(0.45)
GDP	0.216	0.110	0.229	0.136	0.233	0.099
	(0.17)	(0.16)	(0.16)	(0.17)	(0.17)	(0.16)
Market	0.069	−0.185	0.155	−0.157	0.041	−0.258
	(0.11)	(0.22)	(0.11)	(0.35)	(0.12)	(0.22)
Distance	−0.006	−0.054	−0.032	−0.091	0.026	−0.032
	(0.16)	(0.18)	(0.20)	(0.23)	(0.16)	(0.19)
Same assignee	0.073**	0.038	0.013	−0.041	0.078**	0.036
	(0.04)	(0.04)	(0.10)	(0.09)	(0.04)	(0.04)
Familiarity*GDP		−0.462**		−0.403		−0.594***
		(0.18)		(0.30)		(0.20)
Familiarity*RTA		0.173*		0.093		0.216**
		(0.10)		(0.16)		(0.09)
Observations	3055	3055	893	893	1786	1786
Log likelihood	−2444.059	−2424.017	−781.850	−775.303	−1351.962	−1335.566

diffusion. This result is in line with the previous findings reported in Phene et al. (2005). The coefficients of *Distance* are however insignificant, which is unexpected. We do not find any effect of geographical proximity between countries on the speed of technology diffusion. Finally, *Market* variable is not significant [with the exception that *Market* is significant and negative in column (2)].

Table 4 shows the econometric results of wind power technology. Similar to solar photovoltaic technology, the coefficients of *Familiarity* are significantly positive in all six columns, indicating the importance of domestic knowledge base in the catching-up process. Although the coefficients of *GDP* are not significant, the coefficients of *Familiarity*GDP* are significantly negative in the full sample and in the sub-sample of post-2000 new combinations. Similar to the results in solar photovoltaic technology, the results show that the impacts of *Familiarity* on the time of entry becomes more important for low-income countries in wind power technology as it matures in recent years.

The coefficients of *RTA* are not significant. However, the coefficients of *Familiarity*RTA* are significantly positive in the full model and the sub-sample of the post-2000 model. The results show that the familiarity with technological components used in the new combination is more important for countries already specialized in wind power technology, indicating a strong path-dependent process.

Of the proximity variables, the effect of *Same assignee* is positive and significant in the full sample and the sub-sample of post-2000, while no effect of *Distance* is found. And, again, no effect of *Market* size was found.

Table 5 Robustness check: Solar photovoltaic

	Japan			Germany		
	Full sample		Post-2000	Full sample		Post-2000
	(1)	(2)	(3)	(4)	(5)	(6)
Familiarity	0.298***	0.369***	1.480***	0.145***	1.775***	5.680***
	(0.03)	(0.10)	(0.46)	(0.04)	(0.24)	(1.06)
RTA	– 0.293	– 0.278	– 0.212	0.565	0.474	0.225
	(0.67)	(0.64)	(0.65)	(0.52)	(0.49)	(0.54)
GDP	0.160	0.154	– 0.001	0.141	– 0.038	– 0.473**
	(0.19)	(0.19)	(0.19)	(0.21)	(0.20)	(0.20)
Market	– 0.320	– 0.355	– 0.348	– 0.617	– 0.721*	– 1.326***
	(0.22)	(0.24)	(0.30)	(0.58)	(0.37)	(0.47)
Distance	– 0.649**	– 0.631*	– 0.543*	0.337**	0.331**	0.306*
	(0.31)	(0.35)	(0.30)	(0.16)	(0.16)	(0.18)
Same assignee	0.024**	0.025*	0.026**	0.303***	0.201***	0.189**
	(0.01)	(0.01)	(0.01)	(0.03)	(0.02)	(0.08)
*Familiarity*GDP*		– 0.063	– 0.999***		– 1.075***	– 4.286***
		(0.09)	(0.36)		(0.16)	(0.89)
*Familiarity*RTA*		– 0.039	– 0.208		– 1.317***	– 3.014***
		(0.27)	(0.37)		(0.17)	(0.83)
Observations	5875	5875	1833	2397	2397	470
Log likelihood	– 3985.301	– 3983.446	– 1219.283	– 1732.007	– 1672.767	– 256.738

4.3 Robustness check

In order to check the robustness of our results, we first focus on the spatial-temporal diffusions of new combinations introduced by inventors from Japan and Germany. Tables 5 and 6 show the results from the robustness check for solar photovoltaic and wind power respectively. Most results are consistent with the results in Tables 3 and 4. One interesting finding is the different impacts of *Distance* on the diffusion speed of new combinations introduced by inventors from Japan and Germany in solar photovoltaic technology. The impacts of *Distance* are negative on the diffusion of new combinations introduced by Japanese inventors (as expected), whereas these are positive on the diffusion of new combinations introduced by German inventors (not as expected). The results may be explained by the rise of Asian economies like South Korea, Taiwan and China in solar photovoltaic technology (Binz & Anadon, 2018; Nemet, 2019; Quitzow, 2015; Wu & Mathews, 2012). The adoptions in these three countries account for approximately 25% of all adoptions of breakthroughs in solar photovoltaic technology introduced by German or Japanese inventors. However, these countries are geographically much closer to Japan than Germany.

Second, we re-estimated the model by calculating the hazard rate for each new combination instead of using stratified groups. This allows further specification of baseline hazards for each new combination instead of baseline hazards for each group of new combinations categorized by *technological distance, intra-technology and year of introduction*. The results shown in column (1)–(3) in Tables 7 and 8 are consistent with the results in

Table 6 Robustness check: wind power

	Japan			Germany		
	Full sample		Post– 2000	Full sample		Post-2000
	(1)	(2)	(3)	(4)	(5)	(6)
Familiarity	0.445***	0.368***	− 0.012	0.309***	0.333***	0.286***
	(0.09)	(0.07)	(0.19)	(0.05)	(0.06)	(0.05)
RTA	0.560	0.493	0.557	0.383	0.371	0.479
	(0.49)	(0.49)	(0.46)	(0.42)	(0.42)	(0.46)
GDP	0.200	0.180	0.130	0.230	0.225	0.224
	(0.17)	(0.18)	(0.18)	(0.16)	(0.16)	(0.17)
Market	0.029	0.028	0.048	− 0.029	− 0.028	0.009
	(0.11)	(0.11)	(0.16)	(0.07)	(0.07)	(0.07)
Distance	− 0.266	− 0.284	− 0.335*	0.037	0.039	0.101
	(0.19)	(0.20)	(0.20)	(0.17)	(0.17)	(0.16)
Same assignee	0.184*	0.205***	0.533***	0.090***	0.095***	0.084***
	(0.11)	(0.08)	(0.09)	(0.01)	(0.01)	(0.01)
*Familiarity*GDP*		− 0.006	− 0.178		− 0.059	0.002
		(0.05)	(0.15)		(0.04)	(0.05)
*Familiarity*RTA*		0.187	0.810***		0.173	0.150
		(0.13)	(0.18)		(0.13)	(0.12)
Observations	846	846	376	4747	4747	2538
Log likelihood	− 582.500	− 580.423	− 279.338	− 5102.293	− 5089.371	− 2458.478

Tables 2 and 3, suggesting that the patterns we observed are robust regardless of the baseline hazards we assumed for new combinations.

Third, we only focus on the Top 1% of the new combinations introduced each year in terms of the times of them being adopted in solar photovoltaic patents or wind power patents to test whether the results are sensitive to the change of threshold for breakthroughs. The results are shown in column (4)–(6) in Tables 7 and 8. The results are consistent with the results in Tables 2 and 3.

5 Conclusions

Catching-up by latecomer countries is generally achieved through a process of imitation followed by improvements upon new technologies on their own to seize the windows of opportunity offered by emerging technological paradigms (Hartmann et al., 2021; Perez & Soete, 1988). In this paper, we focused on the determinants of early entry in clean energy technologies by tracing the spatial-temporal diffusions of breakthroughs in solar photovoltaic technology and wind power technology using patent data. Following the view of breakthroughs as new combinations of existing technological components, our results suggest that latecomer countries' familiarity with the technological components recombined in the breakthroughs can facilitate early entry, especially in countries with lower levels of economic development.

Table 7 Robustness check: Solar photovoltaic

	Stratify by new combination			Top 1% new combination		
	Full sample		Post-2000	Full sample		Post-2000
	(1)	(2)	(3)	(4)	(5)	(6)
Familiarity	0.508***	1.851***	2.788***	0.424***	1.493***	1.696***
	(0.13)	(0.29)	(0.50)	(0.07)	(0.23)	(0.25)
RTA	0.592	0.525	0.479	0.392	0.400	0.476
	(0.42)	(0.41)	(0.40)	(0.41)	(0.40)	(0.40)
GDP	0.034	0.047	– 0.110	0.044	0.026	– 0.061
	(0.17)	(0.17)	(0.12)	(0.18)	(0.16)	(0.13)
Market	– 0.294*	– 0.597**	– 0.240*	– 0.376*	– 0.639**	– 0.140
	(0.18)	(0.30)	(0.13)	(0.21)	(0.26)	(0.12)
Distance	0.128	0.138	0.142	0.167	0.150	0.215
	(0.21)	(0.21)	(0.20)	(0.20)	(0.20)	(0.19)
Same assignee	0.137***	0.150***	0.552***	0.122***	0.132***	0.438***
	(0.05)	(0.05)	(0.15)	(0.03)	(0.03)	(0.09)
*Familiarity*GDP*		0.164	– 1.441***		– 0.067	– 0.929***
		(0.11)	(0.35)		(0.16)	(0.26)
*Familiarity*RTA*		– 1.445***	– 0.839***		– 1.053***	– 0.637***
		(0.28)	(0.25)		(0.25)	(0.14)
Observations	5170	5170	1739	2350	2350	1222
Log likelihood	– 2893.843	– 2820.006	– 1071.575	– 1747.197	– 1698.668	– 845.854

Our analysis provides the first systematic, quantitative evidence of the catching-up process of latecomer countries in clean energy technological paradigm (Lema et al., 2020; Mathews, 2013; Pegels & Altenburg, 2020; Perez, 2016). Although our theoretical reasoning is similar to the original concept of related diversification (Boschma, 2017; Hidalgo et al., 2007), our analysis extends earlier studies on technological diversification in two ways. First, we look exclusively at new-to-the-world technologies by analysing their spatial-temporal diffusion, whereas most existing studies did not differentiate between new-to-the-country and new-to-the-world technologies (Boschma et al., 2017). Second, we go beyond the typical research question of whether or not a country diversifies into a particular technology by analysing how fast a country is able to diversify into radically new technologies, contributing to a better understanding of temporal dimension in evolutionary economic geography (Henning, 2019).

On a methodological note, our study design also has the advantage that we measure diversification in a straightforward way by simply observing the date that a country first adopts a radically new technology. Hence, our approach differs from previous studies

Table 8 Robustness check: wind power

	Stratify by new combination			Top 1% new combination		
	Full sample		Post-2000	Full sample		Post-2000
	(1)	(2)	(3)	(4)	(5)	(6)
Familiarity	0.292***	0.445***	0.495***	0.309***	0.512***	0.511***
	(0.04)	(0.10)	(0.10)	(0.04)	(0.09)	(0.09)
RTA	0.478	0.496	0.620	0.433	0.403	0.547
	(0.41)	(0.43)	(0.43)	(0.38)	(0.41)	(0.47)
GDP	0.220	0.113	0.093	0.260	0.105	0.052
	(0.17)	(0.16)	(0.16)	(0.17)	(0.16)	(0.17)
Market	0.069	− 0.185	− 0.269	0.020	− 0.199	− 0.213
	(0.12)	(0.22)	(0.21)	(0.11)	(0.19)	(0.16)
Distance	− 0.012	− 0.056	− 0.035	0.030	− 0.025	− 0.040
	(0.16)	(0.18)	(0.18)	(0.15)	(0.17)	(0.18)
Same assignee	0.086*	0.051	0.042	0.109**	− 0.014	− 0.031
	(0.04)	(0.04)	(0.05)	(0.05)	(0.06)	(0.05)
*Familiarity*GDP*		− 0.462**	− 0.626***		− 0.759***	− 0.791***
		(0.19)	(0.21)		(0.28)	(0.24)
*Familiarity*RTA*		0.181*	0.249***		0.332***	0.336***
		(0.09)	(0.09)		(0.13)	(0.10)
Observations	3055	3055	1786	752	752	517
Log likelihood	− 1968.447	− 1950.222	− 1018.529	− 603.324	− 595.868	− 354.310

that measure diversification as becoming specialised in a particular technology relative to all other countries based on the Revealed Technological Advantage index with its known disadvantages (Laursen, 2015; van Dam et al., 2020).

Our empirical comparison of the two clean energy technologies shows that for solar photovoltaic technology, the knowledge base of countries is more important for countries without specialisation, whereas for wind power technology, the knowledge base of countries is more important for countries with specialisation. These findings provide systematic evidence of the technology-sensitive catching-up process in clean energy technologies (Binz et al., 2017; Binz & Truffer, 2017; Lee & Malerba, 2017; Schmidt & Huenteler, 2016).

Several questions remain for future research. First, as our results show that the embeddedness of latecomer countries in the global networks is important for the early entry of new technologies, more actor-level analyses are required to understand how latecomer countries can engage in the global value chains and global innovation networks, and the structural change processes that may follow (Boschma, 2017; Hausmann & Neffke, 2019; Henning, 2019; Neffke et al., 2018). Second, although we find that the knowledge base of countries can facilitate early entry, institutional and organizational changes might be necessary for the better mobilisation local capabilities for scaling up new clean energy technologies faster (Grubler et al., 2016; Hughes & Meckling, 2018). Third, it is important to focus on the impacts of the spatial-temporal diffusion of breakthroughs on the cost reduction and performance improvement of clean energy

Table 9 List of countries and regions included in our analysis

Country	
Australia	Japan
Austria	Korea
Belgium	Latvia
Brazil	Lithuania
Bulgaria	Luxembourg
Canada	Malta
Chile	Mexico
Chinese Taipei/Taiwan	Netherlands
Croatia	New Zealand
Cyprus	Norway
Czech Republic	People's Republic of China
Denmark	Poland
Estonia	Portugal
Finland	Romania
France	Russian Federation
Germany	Slovak Republic
Greece	Slovenia
Hong Kong (China)	South Africa
Hungary	Spain
Iceland	Sweden
India	Switzerland
Ireland	Turkey
Israel	United Kingdom
Italy	United States

technologies to better understand the role of technological change in sustainability transitions (Benson & Magee, 2014, 2015; Kavlak et al., 2018; Nemet, 2019).

Appendix

See Appendix Table 9.

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