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Recombinant invention in solar photovoltaic technology: can geographical proximity bridge technological distance?

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ABSTRACT

This paper explores the emergence of new combinations of unrelated technologies at the regional level. The analyses show that for solar photovoltaic inventions, such unrelated technologies are more likely to be recombined when they strongly co-locate in the same region rather than in different regions. Furthermore, we show that this pattern is common to renewable energy inventions, although different dynamics are observed in different types of renewable energy technology. The results highlight the importance of place-based capabilities in facilitating breakthrough inventions in renewable energy technologies.

KEYWORDS

recombinant invention; solar photovoltaic; geographical proximity; technological distance; renewable energy technologies

JEL B15, O33, Q55, R11

HISTORY Received 22 March 2019; in revised form 24 September 2020

INTRODUCTION

New inventions result from the recombination of existing technologies, knowledge and capabilities in new and often more complex ways (Arthur, 2007; Henderson & Clark, 1990). Cognitive capabilities play an important role in this recombination process (Cohen & Levinthal, 1990; Galunic & Rodan, 1998; Kogut & Zander, 1992; Nooteboom, 2000). Thus, one expects that the recombination of related technologies occurs more often than the recombination of unrelated technologies (Caviggioli, 2016). This effect of technological distance has indeed been shown repeatedly for the effect of related variety on patenting (Castaldi et al., 2015; Miguelez & Moreno, 2018; Tavassoli & Carbonara, 2014).

The processes behind the recombination of unrelated technologies are less clear. Assuming that breakthrough inventions often stem from new combinations of unrelated technologies, the occurrence of breakthrough inventions can be associated with the presence of 'unrelated variety' within a region. Indeed, Castaldi et al. (2015) found that breakthrough inventions, as measured by highly cited patents, occurred more often in regions with more unrelated variety. However, these earlier studies have not investigated whether the breakthrough inventions were indeed the result of the recombination of unrelated technologies strongly present in the same region. If this is the case, cross-specialization or the promotion crossovers between these unrelated technologies strongly present in a region, as suggested by Janssen and Frenken (2019), may be an effective technology policy.

The objective of this paper is therefore to investigate empirically whether breakthrough inventions are place dependent in the sense of building mostly on the local knowledge base rather than on the global knowledge base. We focus on renewable energy technologies, specifically on solar photovoltaic (PV) inventions, because these complex technologies require knowledge input from various unrelated technologies (Barbieri et al., 2020a; Nemet, 2012).

We operationalize the research question by testing how likely unrelated technologies are to be recombined when they are both strongly present in the same region, using patent applications at the United States Patent and Trademark Office (USPTO), the European Patent Office (EPO) and the Patent Cooperation Treaty (PCT) route.

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We first focus on the new combinations in solar PV technology from regions in Organisation for Economic Co-operation and Development (OECD) countries and the BRICS (Brazil, Russia, India, China and South Africa) during the period 1998–2012. We then compare solar PV with other renewable energy technologies to assess whether our results are specific to solar PV or common to other renewable energy technologies.

This paper contributes to the existing literature in two ways. First, we provide the first empirical test of the 'cross-specialization' policy framework proposed by Janssen and Frenken (2019) which extends recent Smart Specialisation strategies by highlighting the importance of linking strong but unrelated technologies in an economy in order to facilitate breakthrough inventions. Second, we discuss how the results can be relevant for supporting a regional perspective on innovation policy aimed at solving societal challenges such as climate change (Coenen et al., 2015; Foray, 2018a; Wanzenböck & Frenken, 2020).

The remainder of the paper is structured as follows. The next section reviews the literature on the path and place dependencies of technological change, and how they interact in recombinant innovations. The third section describes the data, econometric model and variables. The fourth section presents the results of the descriptive and econometric analyses. The paper concludes by discussing the implications of the findings.

LITERATURE REVIEW

Recombinant inventions and renewable energy technology

In the combinatorial view of technological change, new inventions are either new combinations of existing or new technological components or refinements of previous combinations of technological components (Fleming, 2001; Strumsky & Lobo, 2015; Verhoeven et al., 2016). Although most inventions build on existing combinations, recombining existing technologies in novel ways can increase the likelihood of achieving high-impact inventions (Arts & Veugelers, 2015; Strumsky & Lobo, 2015; Verhoeven et al., 2016).

The recombination of unrelated technologies is risky and uncertain because inventors need the cognitive capabilities to understand how technologies interact with each other (Cohen & Levinthal, 1990; Galunic & Rodan, 1998; Kaplan & Tripsas, 2008; Nooteboom et al., 2007). Ferguson and Carnabuci (2017), for example, showed that patents that combine knowledge from unrelated technologies are less likely to be granted. Consequently, new combinations of related technologies occur more frequent than new combinations of unrelated technologies (Caviggioli, 2016).

However, the recombination of unrelated technologies is found to be especially important in the earlier development stage of new technologies, whereas in the later stage the recombination of related technologies is more prominent (Krafft et al., 2011). Barbieri et al. (2020b) observed a similar pattern in renewable energy technologies which are considered more complex than non-green technology because they rely on diverse knowledge inputs from unrelated technologies (Barbieri et al., 2020a; Nemet, 2012).

Although recent studies by Barbieri et al. (2020b) and Sbardella et al. (2018) suggested that the renewable energy technologies might have entered a more mature phase based on the more prominent role of related variety they observed, there is a trade-off between the short- and long-term benefits in such recombinant inventions (Zeppini & van den Bergh, 2011). The recombination of related technologies can facilitate immediate technology improvement. The recent, rapid growth of innovative activities in renewable energy technologies results from private sector activities incentivized by growing markets supported by government demand–pull policies (Bettencourt et al., 2013; Trancik et al., 2015). Private sector activities tend to focus on incremental refinements to technology and manufacturing (Hoppmann et al., 2013; Trancik et al., 2015). Without the recombination of unrelated technologies to facilitate the convergence of unrelated technologies and offer new opportunities for future technology development, the limits to incremental improvements may soon be reached (Safarzyńska & van den Bergh, 2013).

Path dependence and place dependence

Although technological opportunities increase as the number of technological components increases, the difficulty and uncertainty of the recombinant search process also increase along with the opportunity (Baldwin & Clark, 2000). Inventors and decision-makers in firms have limited cognitive capabilities, limiting their abilities to identify potentially fruitful combinations of technologies that seem unrelated to their existing knowledge bases or to each other (Cohen & Levinthal, 1990; Nooteboom, 2000). Thus, innovation patterns are myopic, cumulative and path dependent in that inventors typically explore new combinations of related rather than unrelated technologies (Dosi, 1982; Nelson & Winter, 1982).

This path dependence can be also observed at the regional level: the growth trajectories of regions are simultaneously the outcome of the path-dependent process of economic evolution, and a major determinant of future development (Henning et al., 2013; Martin, 2010; Martin & Sunley, 2006). Inspired by the seminal work of Hidalgo et al. (2007), recent systematic empirical studies of regional diversification find that regions indeed tend to develop new technologies which are related to the technologies in their current portfolios (Boschma et al., 2015; Colombelli et al., 2014; Feldman et al., 2015; Kogler et al., 2017; Li et al., 2020; Rigby, 2015; Tanner, 2016, 2014; van den Berge et al., 2020). Thus, the path-dependent process of regional development is, to a large extent, conditioned by the past economic structure and knowledge base of regions, and hence also place dependent (Heimeriks & Boschma, 2014; Martin & Sunley, 2006).

Despite this place- and path-dependence regions may still develop new technologies that are less related or even unrelated to their existing knowledge bases

(Heimeriks & Boschma, 2014; Li et al., 2020; Montresor & Quatraro, 2020; Perruchas et al., 2020; Petralia et al., 2017). Following the combinatory view of inventions, such novelty may result from a recombination of locally present, but previously unrelated, technologies. Indeed, several authors have found that a region's capability of introducing such new combinations is associated with the diversity of its knowledge base (Breschi & Lenzi, 2015; Castaldi et al., 2015; Desrochers & Leppälä, 2011; Miguelez & Moreno, 2018). However, the question whether these new combinations, especially the new combinations of unrelated technologies, are indeed building on the locally available technologies remains open.

Cross-specialization: interaction of path dependence and place dependence

Path dependence and place dependence interact with each other in the knowledge-production process and place dependence may help to break path dependence through the recombination of locally available, unrelated technologies. Though technological distance can indeed be a challenge in the recombination process, it can most easily be bridged through frequent face-to-face interactions of individuals, which is easier if they are located in close geographical proximity (Desrochers & Leppälä, 2011; Storper & Venables, 2004). The joint learning processes between actors with different backgrounds in the same region can increase their cognitive proximity (Balland et al., 2015). The creation of a new combination requires a minimum level of knowledge in both technological components to reduce the uncertainty in the inventive process (Clancy, 2018; Fleming, 2001; Perez & Soete, 1988). Thus, the presence of a critical mass of unrelated technologies in a region can facilitate the learning process between them, a logic that has been referred to as 'cross-specialization' (Janssen & Frenken, 2019).

Geographical proximity can facilitate the learning process between unrelated technologies in two ways. First, co-location in close geographical proximity enables cooperating actors to monitor each other constantly, closely and almost without effort or cost (Malmberg & Maskell, 2002). Such local knowledge spillovers can increase the cognitive proximity between two cooperating actors, and as a result the knowledge bases of the two actors become more similar (Balland et al., 2015). This increases their capacity to identify and test potential new combinations (Desrochers & Leppälä, 2011; Galunic & Rodan, 1998), which is especially useful in immature technological environments, where the effects of interactions are uncertain or unknown and alternative technological options compete (Sbardella et al., 2018).

Second, geographical proximity can also facilitate cognitive proximity through other forms of proximity (Balland et al., 2015; Boschma, 2005; Torre & Rallet, 2005). For example, geographical proximity can facilitate social proximity. Most of the carriers of social proximity tend to be geographically bounded, such as spin-off processes, inventive collaborations and labour mobilities (Breschi & Lissoni, 2009; Eriksson, 2011; Klepper, 2007). The formal or informal collaboration of individuals possessing different skills and backgrounds is important for the creation of new combinations (Desrochers & Leppälä, 2011). Moreover, individuals working on unrelated technologies might nonetheless be using similar skills and thus benefit from learning from each other (Desrochers & Leppälä, 2011).

In sum, we expect that unrelated technologies are more likely to be recombined when they are both strongly present in the same region. That is, we expect that geographical proximity can bridge technological distance in creating new combinations.

RESEARCH DESIGN

Sample

For our empirical analyses we focus on new combinations in solar PV technology for the period 1998–2012. Solar PV is an interesting technology to analyse for three reasons. First, it is the leading renewable energy technology and has long-term potential (Trancik et al., 2015). Both electricity production capacities and patenting activities of solar PV have grown the fastest among all renewable sources since 1997 when the Kyoto Protocol was signed (Bettencourt et al., 2013). Solar PV is selected by many countries as the main solution to achieve their carbon-reduction goals (Trancik et al., 2015).

Second, although the existing literature suggests renewable energy technologies might enter a mature phase because of the observed relative dominance of related variety, we also observe novel developments (Fraunhofer Institute, 2019; National Renewable Energy Laboratory, 2019). Whereas crystalline silicon PV modules have a long history and dominant market share in PV technologies, new generations of solar PV technologies emerged during the period of investigation (Fraunhofer Institute, 2019; National Renewable Energy Laboratory, 2019). These new generations of solar PV technologies differ from current dominant crystalline silicon PV technology in terms of efficiency, material use, and manufacturing complexity and cost (Jean et al., 2015). However, given the fact that most of these new generations of PV technologies are still far from commercialization, continuous innovation efforts are required to improve these technologies (Schmalensee, 2015).

Third, considering the growth potential of the solar PV market under the commitments of The Paris Agreement, both the material scalability and the intermittency of solar resources require additional innovation efforts (Trancik et al., 2015). Reaching the full growth potential of solar PV requires finding more abundant active cell materials for some emerging PV technologies and substituting a more abundant material for the silver electrodes for current dominant crystalline silicon PV technology (Trancik et al., 2015). Also, further development of system integration and interoperability between solar PV technology and technologies such as storage technologies and long-distance transmission technology is required (Sbardella et al., 2018).

Data

Technological classifications capture the technological components and principles of an invention, and are widely used to assess the recombination of technologies (Fleming, 2001; Strumsky & Lobo, 2015). We use the pairwise combinations of subclass-level International Patent Classification (IPC) codes assigned to a patent to proxy recombination following Verhoeven et al. (2016). More specifically, for each pair of IPC subclasses, we assess its previous existence in the body of solar PV patents filed before the application date of the patent under consideration.

We use all patent applications filed at the USPTO, the EPO and the PCT route between 1980 and 2012. The patent applications are extracted from the EPO Worldwide Patent Statistics Database PATSTAT (2017 Spring Version). Since non-granted USPTO patent applications are only partly present from 2001 onwards, we excluded non-granted EPO patents and PCT-route patents which are not granted by any patent office.

In order to remedy the issue of multiple equivalent patent applications protecting the intellectual property rights of the same invention in different patent offices, we use the residence address of inventors, and IPC codes of all patents in the same PATSTAT simple patent family to identify the location and technological classification of the invention under consideration (Martínez, 2011). The year assigned to a PATSTAT simple patent family is the application year of the first patent application in the patent family.

The solar PV patents are identified using the Y02E10/5 code in the Cooperative Patent Classification (CPC). The Y02 classes are developed by EPO experts by combining existing IPC and European Patent Classifications with lexical analyses of abstracts or claims in the patent documents (Veefkind et al., 2012), and have been widely adopted by researchers to study the technology change of climate change-mitigation technologies (Haščič & Migotto, 2015; Leydesdorff et al., 2015; Sbardella et al., 2018).

Patents, and their combination of IPC subclasses, are assigned to regions based on the residential addresses of inventors listed in the patent documents. Inventors' addresses of the EPO patents and the PCT-route patents are extracted from the OECD's REGPAT database (March 2018). Inventors' addresses of the USPTO patents are extracted from the PatentsView database (2018 May Version) and assigned to regions based on their geographical coordinates. We use the Territorial Level 2 regions in the REGPAT database for OECD countries, and the highest administrative breakdowns for the BRICS. Overall, there are 599 regions in the OECD and BRICS countries.

Variables

Dependent variable

In order to explore the emergence of new combinations at the regional level, we use the binary variable $NC_{r,ij}$ to indicate whether region r recombines IPC subclass i and j for the first time in history in the body of solar PV patents. Although assessing new combinations in the body of all patents can better capture the novelty of inventions (Verhoeven et al., 2016), a combinations of technologies might function differently in different technology fields (Boschma et al., 2017). Therefore, we measure novelty new to the solar PV technology instead of new to the world in this paper.

For the construction of the dependent variable, we only consider patents with inventors located in the focal region following Breschi and Lenzi (2015). Cross-region collaborations can also facilitate the creation of new combinations by bringing together individuals with different backgrounds in different locations (Breschi & Lenzi, 2015; Giuliani et al., 2016). By excluding new combinations that are the outcome of such cross-region collaboration, this variable can be considered as a measure of a region's indigenous combinatorial and inventive capabilities. New combinations introduced by inventors from the same region account for 66% of all new combinations introduced between 1998 and 2012.

Independent variables

As independent variables we use the technological relatedness between IPC subclasses i and j, TR_{ij}, as a measure of path dependence, and the level of cross-specialization of region r in IPC subclasses i and j $CS_{r,ij}$ to measure place dependence. We describe each variable in more detail:

- TR_{ij} measures the technological relatedness between IPC subclasses i and j at the time when they are recombined. Two IPC subclasses are considered related if they cite each other frequently (Caviggioli, 2016; Rigby, 2015), a widely used measure of the relatedness between technologies (Jaffe & de Rassenfosse, 2017). We first calculate the share of patents in IPC subclass j citing patents in IPC subclass i over the total number of patents in IPC subclass j (P_{ji}) in the five years before they were recombined. The TR_{ij} then takes the average value of P_{ji} and P_{ij}.
- $CS_{r,ij}$ captures whether the IPC subclasses being recombined are strongly co-present in the region. It takes the minimum value of the number of internal patents in IPC subclass i and the number of internal patents in IPC subclass j in region r in the five years before the recombination following Clancy (2018). We exclude patents with inventors external to the region to capture the scale effects associated with the agglomeration of inventive activities at the regional level (Breschi & Lenzi, 2015; Lobo & Strumsky, 2008). The larger value of $CS_{r,ij}$ indicates regions have larger knowledge stock in both IPC subclasses.

Control variables

In order to control the regional factors' impacts on the recombination of IPC subclasses, we include three regional level variables in the econometric model:

Table 1. Summary statistics.

Variable	Observations	Mean	SD	Minimum	Maximum
$CS_{r,ij}$	1,568,182	1.633	16.534	0	5362.98
TR_{ij}	1,568,182	0.087	0.101	0	0.764
$Variety_r$	1,568,182	2.914	1.760	0	5.477
$External_r$	1,568,182	0.373	0.835	0	40
$Count\_field_r$	1,568,182	4.402	30.623	0	969

- $Variety_r$ captures the variety of the knowledge base in region r. We calculate this variable using the entropy index following Castaldi et al. (2015):

$$Variety_r = \sum_k P_{k,\,r} * \ln(1/P_{k,r}) \tag{1}$$

where $P_{k,\,r}$ is share of internal patents in IPC subclass k in region r over the total number of internal patents in region r in the five years before the recombination of IPC subclass i and IPC subclass j.
- $Extrenal_r$ captures the extent of external network connections following Lobo and Strumsky (2008). It is the ratio of the number of patents with inventors from outside the focal region over the number of internal patents. We use this variable to control the potential impacts of extra-regional knowledge spillovers.
- $Count\_field_r$ captures the knowledge stock of region r in solar PV technology. It takes the number of internal solar PV patents in region r in the five years before IPC subclass i and IPC subclass j were recombined.

Empirical model

Our estimation strategy is based on a conditional logit model that is similar to those used in studies on the location choice of firms (Schmidheiny & Brülhart, 2011). More specifically, at each point in time t, the probability of a new combination of IPC subclass i and IPC subclass j emerging in a region r is a function of the observable characteristics of region r described by equation (2):

$$P(NC_{r,ij}) = \beta_1 CS_{r,ij} + \beta_2 Variety_r + \beta_3 External_r + \beta_4 Count\_field_r + Country + NC_{ij} + \varepsilon \tag{2}$$

where β_1 captures the impact of cross-specialization of regions on introducing new combinations. We expect the positive value of β_1 due to the place dependence of technological change. β_2, β_3 and β_4 capture the impacts of regional factors on recombining IPC subclasses i and j. We also include country dummies to control for the unobserved heterogeneities of regions in different countries since the inventive patterns of solar PV technology differ significantly across countries (Kalthaus, 2019).

In order to test whether geographical proximity can indeed bridge technological distance, we add the interaction term of cross-specialization $CS_{r,ij}$ and technological relatedness TR_{ij} to the model. As the fixed effect of new combinations is already included in the conditional logit model, technological relatedness TR_{ij} is not introduced in the model individually because TR_{ij} is invariable across regions, thus correlating with the error term. We estimate equation (3) as follows:

$$P(NC_{r,ij}) = \beta_1 CS_{r,ij} + \beta_2 Variety_r + \beta_3 External_r + \beta_4 Count\_field_r + \beta_5 CS_{r,ij} * TR_{ij} + Country + NC_{ij} + \varepsilon \tag{3}$$

where β_5 measures whether the impact of cross-specialization differs across new combinations with different levels of technological relatedness. We expect a negative coefficient of β_5, as we expect that the impact of cross-specialization is larger for new combinations of unrelated technologies than for related technologies. Tables 1 and 2 present summary and correlation statistics. The correlations between independent variables are not high.

RESULTS

Descriptive results

Figure 1 shows the number of solar PV patents (left y-axis), the number of solar PV patents with new combinations of IPC subclasses (left y-axis) and the share of patents with new combinations among all solar PV patents (right y-axis) over time. The share of patents with new combinations among all solar PV patents starts to decrease after 2004 because of the rapid growth of the number of solar PV patents and the relatively stable growth of the

Table 2. Correlation statistics.

	$CS_{r,ij}$	TR_{ij}	$Variety_r$	$External_r$	$Count\_field_r$
$CS_{r,ij}$	1				
TR_{ij}	0.037	1			
$Variety_r$	0.105	0.001	1		
$External_r$	0.018	0.038	0.292	1	
$Count\_field_r$	0.341	0.001	0.146	0.020	1

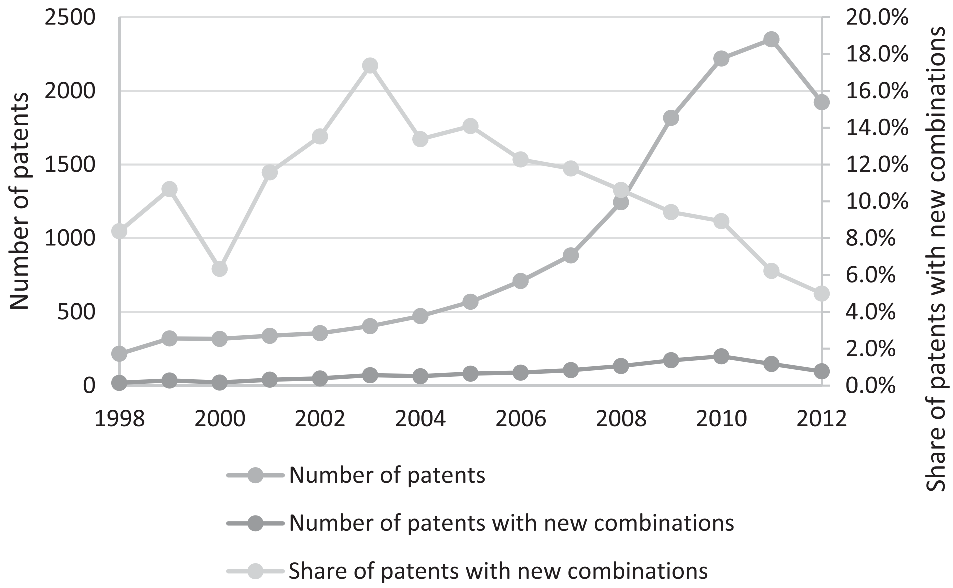

Figure 1. Evolution of the number of solar photovoltaic (PV) patents (left *y*-axis), number of solar PV patents with new combinations of International Patent Classification (IPC) subclasses (left *y*-axis) and share of patents with new combinations among all solar PV patents (right *y*-axis).

number of solar PV patents with new combinations. The rapid growth of incremental inventions is driven by private sector activities that mostly focus on the refinement of existing technology and manufacturing (Hoppmann et al., 2013; Trancik et al., 2015).

The number of solar PV patents with new combinations starts to decrease after 2010 in Figure 1. A possible explanation for this could be the industry shakeout that started in 2010 (Furr & Kapoor, 2018). On the one hand, there is a decrease in patenting activities in the solar PV industry because of the decreasing number of patenting firms during the industry shakeout (Carvalho et al., 2017; Furr & Kapoor, 2018). On the other hand, during the industry shakeout, the innovation focus of firms shifted from developing new products to reducing production costs, leading to a decrease of recombinant inventions (Carvalho et al., 2017).

Figure 2 shows the evolution of the average technological relatedness between new combinations of IPC subclasses and the average technological relatedness between IPC subclasses which are not recombined in solar PV technology. The average technological relatedness between new combinations of IPC subclasses is larger than the average technological relatedness between IPC subclasses which are not combined, indicating that technological change in solar PV technology is indeed path dependent and that related technologies are more likely to be recombined than unrelated technologies.

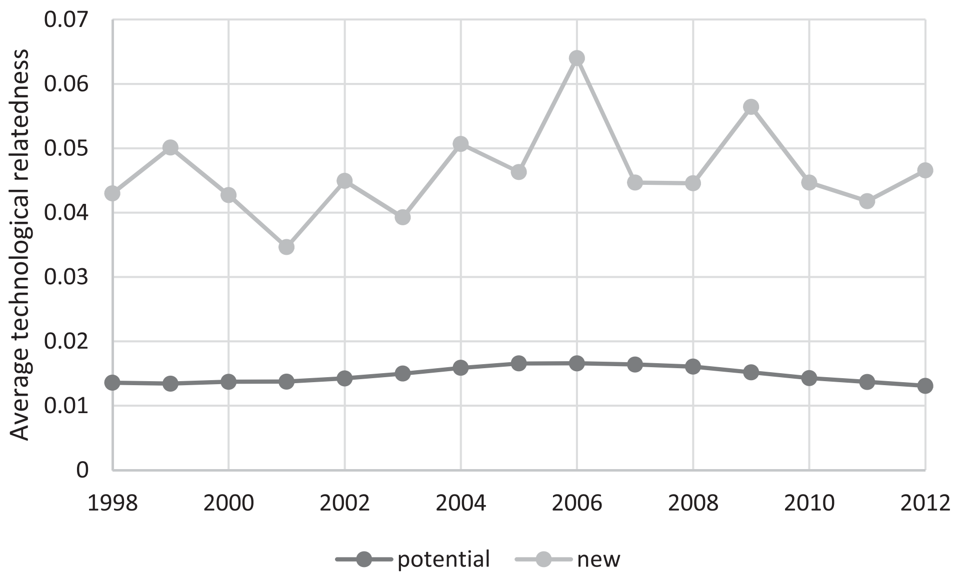

Figure 2. Average technological relatedness between new combination of International Patent Classification (IPC) subclasses and potential combination of IPC subclasses.

Table 3. Top regions in the number of patents with new combinations of International Patent Classification (IPC) subclasses.

Region	New combinations	Share (%)	Region	New combinations	Share (%)
California, United States	610	14.6%	Northern Kanto, Japan	90	2.1%
Southern Kanto, Japan	349	8.4%	Michigan, United States	82	2.0%
Texas, United States	205	4.9%	Hesse, Germany	79	1.9%
Massachusetts, United States	152	3.6%	New Jersey, United States	79	1.9%
Kansai region, Japan	143	3.4%	North Rhine-Westphalia, Germany	78	1.9%
Seoul region, South Korea	125	3.0%	Baden-Württemberg, Germany	72	1.7%
New York, United States	121	2.9%	Chinese Taipei	72	1.7%
Bavaria, Germany	102	2.4%	Top 15 regions in total	2360	56.4%

Table 3 shows the top 15 regions with new combinations in solar PV technology. Top regions are concentrated in Japan, Germany and the United States. The number of new combinations from the top 15 regions accounts for 56% of the total number of new combinations during the period 1998–2012.

Econometric results for solar PV

Table 4 presents the results of our econometric analysis. Column (1) reports the model with the $CS_{r,ij}$ and control variables. Column (2) adds the interaction term of $CS_{r,ij}$ and TR_{ij}. The coefficient of $CS_{r,ij}$ is positively significant in column (1), indicating that regions are more likely to recombine two technologies when they have a larger knowledge stock in both technologies. This shows that there is place dependence in the creation of new combinations: regions are more likely to recombine technologies strongly present in their technology portfolios. In column (2), the interaction term of $CS_{r,ij}$ and TR_{ij} is significantly negative, indicating that the impact of $CS_{r,ij}$ on creating a new combination is larger when the focal technologies are unrelated. This result suggests that geographical proximity can indeed bridge technological distance in the creation of new combinations, as we hypothesized.3

Regarding the control variables, the coefficients of $Variety_r$ and $Count\_field_r$ are significantly positive in both columns (1) and (2), indicating that new combinations are more likely to emerge in regions with a more diverse knowledge base or a larger knowledge stock in solar PV technology. However, the coefficient of $External_r$ is significantly negative in both columns (1) and (2), indicating that new combinations are less likely to emerge in regions which are more reliant on extra-regional knowledge flows.

Robustness check

We now move to testing whether the results from solar PV technology are common to renewable energy technologies. First, we re-estimate equations (2) and (3) for renewable energy inventions and all inventions, respectively. Second, we compare solar PV with other two leading renewable energy technologies, wind and biofuel. We identify inventions in six types of non-hydro-renewable energy technology using the Y02 classes: solar photovoltaic (Y02E10/5), solar thermal (Y02E10/4), wind (Y02E10/7), ocean (Y02E10/3), biofuel (Y02E50/1) and geothermal (Y02E10/1). The results from the robustness check are shown in Table 5.

The results from renewable energy inventions in columns (1) and (2) of Table 5 are consistent with the results in Table 4, whereas the coefficient of the interaction term $CS_{r,ij} * TR_{ij}$ in column (4) is significantly positive in the results from all inventions. These results suggest that the process of linking local unrelated strongholds to facilitate breakthrough inventions is specific to renewable energy technologies. For inventions in general the place dependence strengthens path dependence by mostly recombining related technologies.

The results from biofuels in columns (7) and (8) of Table 5 are consistent with the results from solar PV technology shown in Table 4. However, the negative coefficient of the interaction term $CS_{r,ij} * TR_{ij}$ in column (6) in wind technology is not significant. This result indicates that the effectiveness of linking local unrelated strongholds is technology sensitive. The different knowledge base of different technologies can lead to different dynamics (Heimeriks & Balland, 2016). Both solar PV and biofuel are characterized as highly dynamic technology that different

Table 4. Results of econometric regressions.

	(1)	(2)
$CS_{r,ij}$	0.002	0.004***
	(0.00)	(0.00)
$CS_{r,ij} * TR_{ij}$		−0.005***
		(0.00)
$Variety_r$	0.686 * * *	0.684***
	(0.05)	(0.05)
$External_r$	−0.303* * *	−0.294***
	(0.04)	(0.04)
$Count\_field_r$	0.006* * *	0.005***
	(0.00)	(0.00)
Country fixed effects	Yes	Yes
Observations	1,568,182	1,568,182
Log-likelihood	−11,812.867	−11,789.490

Note: *Significant at 0.1, **significant at 0.05 and ***significant at 0.01. Robust standard errors are reported in the parentheses.

Table 5. Robustness check.

	Renewables		All technologies		Wind		Biofuel	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$CS_{r,ij}$	0.008* * *	0.010***	0.030***	0.022***	0.002**	0.004**	0.008***	0.012***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
$CS_{r,ij}*TR_{ij}$		−0.015***		1.764***		−0.007		−0.021***
		(0.00)		(0.25)		(0.00)		(0.00)
$Variety_r$	0.763* * *	0.757***	1.189***	1.186***	0.908***	0.904***	0.642***	0.641***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.06)	(0.06)	(0.03)	(0.03)
$External_r$	−0.364* * *	−0.354***	−0.024*	−0.024*	−0.278***	−0.268***	−0.102*	−0.092*
	(0.02)	(0.02)	(0.01)	(0.01)	(0.04)	(0.04)	(0.04)	(0.04)
$Count\_field_r$					0.015***	0.015***	0.023***	0.023***
					(0.00)	(0.00)	(0.00)	(0.00)
Country fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4,721,318	4,721,318	17,412,063	17,412,063	1,231,544	1,231,544	1,304,622	1,304,622
Log-likelihood	−38,745.498	−38,719.690	−147,116.956	−147,027.895	−9828.229	−9820.885	−10,726.156	−10,705.494

Note: *Significant at 0.1, **significant at 0.05 and ***significant at 0.01. Robust standard errors are reported in the parentheses.

sub-trajectories with significantly different knowledge bases emerge over time (Carvalho et al., 2017; Costantini et al., 2015; Kalthaus, 2019), whereas the recent offshore wind technology partly builds on the onshore wind technology (Wieczorek et al., 2013). Given the numerous ways of recombining unrelated technologies, the cost and uncertainty of the search process for breakthrough inventions are high, especially in technologies with strong sub-trajectories dynamics such as solar PV and biofuel. Linking local unrelated strongholds is therefore more important in these technologies for addressing the uncertainties and seizing the opportunities in emerging sub-trajectories.

DISCUSSION AND CONCLUSIONS

The transformation of the current energy systems towards a new low-carbon paradigm requires breakthrough inventions in renewable energy technologies. Breakthrough inventions are considered the result from the novel combination of existing technologies, especially unrelated technologies. Hence, in this paper we study the emergence of new combinations in solar PV technology at the regional level of OECD and BRICS countries. The results show that for solar PV technology unrelated technologies are more likely to be recombined when they are strongly present in the same region, indicating that geographical proximity can bridge technological distance in facilitating breakthrough inventions.

Moreover, the pattern we observed in solar PV technology is common to renewable energy technologies. The process of place dependence breaking the path dependence that favours recombining related technologies has important implications for innovation policies aimed at promoting transformative change. Climate change mitigation requires novel technological solutions in renewables to break the current dominance of fossil fuels. The heterogeneous knowledge bases across regions can offer various new combinations of unrelated technologies to achieve such goal. At the same time, linking unrelated existing specialization in a regional economy can be viewed as a middle road for facilitating radical change (Janssen & Frenken, 2019). Because of the disruptive role of renewables in energy sector and energy intensive industries (Geels, 2018; Wilson, 2018), they face resistance and legitimacy problems (Weber & Rohracher, 2012). Building on the existing strengths in a region may increase the local support for the development of renewables (Frenken, 2017). This argument is supported by recent studies on the role of the fossil fuel knowledge base in the development of renewable energy technologies (Mäkitie et al., 2019; van den Berge et al., 2020; van der Loos et al., 2020).

This paper provides a first empirical test of the policy framework cross-specialization proposed by Janssen and Frenken (2019). The cross-specialization policy framework extends the recent Smart Specialisation strategies approach which has been integrated into the reformed Cohesion Policy of the European Union (Foray, 2018a, 2018b), and highlights the importance of linking strong but unrelated knowledge bases in the search for radical innovations. Our results suggest that the cross-specialization approach provides a bottom-up or place-based solution to facilitate breakthrough inventions in renewables, supporting a geographical perspective of innovation policies aimed at addressing societal challenges (Coenen et al., 2015; Foray, 2018a; Frenken, 2017; Wanzenböck & Frenken, 2020).

However, the heterogenous results we observed among different types of renewable energy technologies suggest that there is no universal mechanism for the cross-specialization approach. The fundamentally different characteristics of different technologies require different cross-specialization strategies. Some unrelated technologies might be recombined without any interventions while others require special coordination process (Foray, 2018b). Future research should therefore focus on how technology-specific support can facilitate the recombination of such local unrelated strongholds. An evaluation of the effectiveness of the cross-specialization approach must take into account the design and implementation of policies and their heterogeneous outcomes. One potential way forward is to explore, first, the channels through which local actors in unrelated technologies can learn from each other, after which how different policies can coordinate and allocate resources to facilitate the learning processes (Flanagan et al., 2011; Magro & Wilson, 2019; Uyarra et al., 2017).

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