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

Deyu Li, Gaston Heimeriks & Floor Alkemade

Published online: 26 Nov 2020.

Submit your article to this journal ↗

Article views: 1886

View related articles ↗

View Crossmark data ↗

Routledge
Taylor & Francis Group

RSA **Regional Studies**
Association

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

Deyu Li[a] , Gaston Heimeriks[b] and Floor Alkemade[c]

**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

## 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.

## CONTACT

[a] (Corresponding author)  lideyu.theo@gmail.com
 Copernicus Institute of Sustainable Development, Utrecht University, Utrecht, the Netherlands; and Department of Land Economy, University of Cambridge, Cambridge, UK.
[b]  g.j.heimeriks@uu.nl
Copernicus Institute of Sustainable Development, Utrecht University, Utrecht, the Netherlands.
[c]  F.Alkemade@tue.nl
School of Innovation Sciences, Eindhoven University of Technology, Eindhoven, the Netherlands.

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 & Quataro, 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):

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

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):

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

where $\beta_1$ captures the impact of cross-specialization of regions on introducing new combinations. We expect the positive value of $\beta_1$ due to the place dependence of technological change. $\beta_2$, $\beta_3$ and $\beta_4$ 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:

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

where $\beta_5$ measures whether the impact of cross-specialization differs across new combinations with different levels of technological relatedness. We expect a negative coefficient of $\beta_5$, 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.
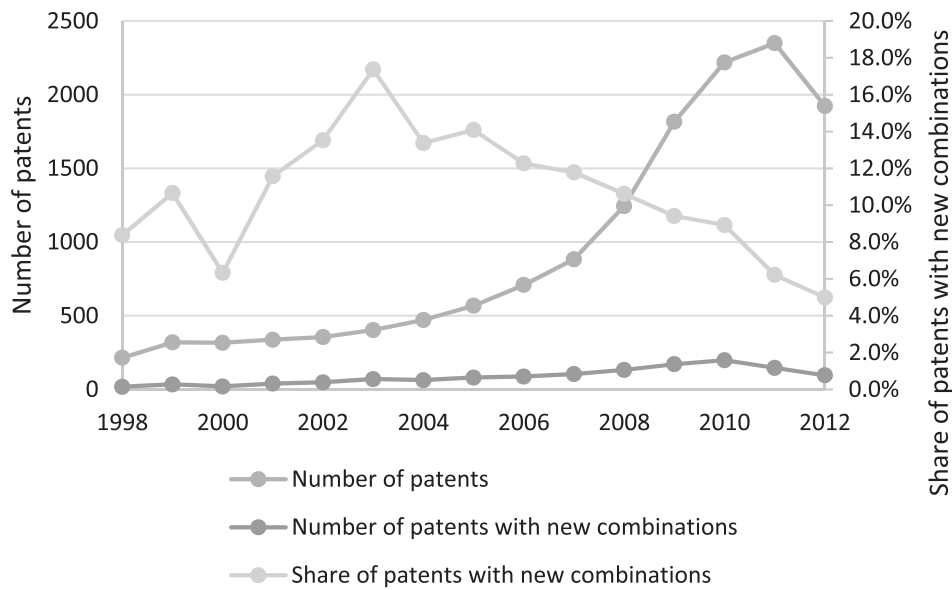
## RESULTS

### 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.
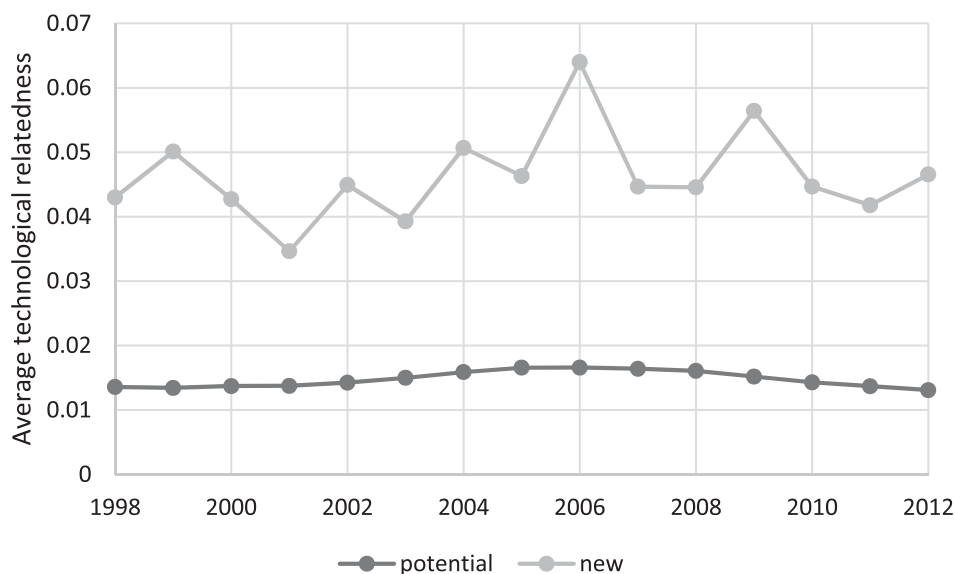


**Figure 2.** Average technological relatedness between new combination of International Patent Classification (IPC) subclasses and potential combination of IPC subclasses.

**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).

## ACKNOWLEDGEMENTS

## DISCLOSURE STATEMENT

## FUNDING

## ORCID

*Deyu Li* http://orcid.org/0000-0002-9154-6302
*Gaston Heimeriks* http://orcid.org/0000-0002-0577-6938
*Floor Alkemade* http://orcid.org/0000-0002-2231-1913

## REFERENCES

Arthur, W. B. (2007). The structure of invention. *Research Policy*, *36*(2), 274–287. https://doi.org/10.1016/j.respol.2006.11.005

Arts, S., & Veugelers, R. (2015). Technology familiarity, recombinant novelty, and breakthrough invention. *Industrial and Corporate Change*, *24*(6), 1215–1246. https://doi.org/10.1093/icc/dtu029

Baldwin, C. Y., & Clark, K. B. (2000). *Design rules: The power of modularity*. MIT Press.

Balland, P.-A., Boschma, R., & Frenken, K. (2015). Proximity and innovation: From statics to dynamics. *Regional Studies*, *49*(6), 907–920. https://doi.org/10.1080/00343404.2014.883598

Barbieri, N., Marzucchi, A., & Rizzo, U. (2020a). Knowledge sources and impacts on subsequent inventions: Do green technologies differ from non-green ones? *Research Policy*, *49*(2), 103901. https://doi.org/10.1016/j.respol.2019.103901

Barbieri, N., Perruchas, F., & Consoli, D. (2020b). Specialization, diversification, and environmental technology life cycle. *Economic Geography*, *96*(2), 161–186. https://doi.org/10.1080/00130095.2020.1721279

Bettencourt, L. M. A., Trancik, J. E., & Kaur, J. (2013). Determinants of the pace of global innovation in energy technologies. *PLoS One*, *8*(10), e67864. https://doi.org/10.1371/journal.pone.0067864

Boschma, R. (2005). Proximity and innovation: A critical assessment. *Regional Studies*, *39*(1), 61–74. https://doi.org/10.1080/0034340052000320887

Boschma, R., Balland, P.-A., & Kogler, D. F. (2015). Relatedness and technological change in cities: The rise and fall of technological knowledge in US metropolitan areas from 1981 to 2010. *Industrial and Corporate Change*, *24*(1), 223–250. https://doi.org/10.1093/icc/dtu012

Boschma, R., Coenen, L., Frenken, K., & Truffer, B. (2017). Towards a theory of regional diversification: Combining insights from evolutionary economic geography and transition studies. *Regional Studies*, *51*(1), 31–45. https://doi.org/10.1080/00343404.2016.1258460

Breschi, S., & Lenzi, C. (2015). The role of external linkages and gatekeepers for the renewal and expansion of US cities' knowledge base, 1990–2004. *Regional Studies*, *49*(5), 782–797. https://doi.org/10.1080/00343404.2014.954534

Breschi, S., & Lissoni, F. (2009). Mobility of skilled workers and co-invention networks: An anatomy of localized knowledge flows. *Journal of Economic Geography*, *9*(4), 439–468. https://doi.org/10.1093/jeg/lbp008

Carvalho, M., Dechezleprêtre, A., & Glachant, M. (2017). *Understanding the dynamics of global value chains for solar photovoltaic technologies* (WIPO Economic Research Working Papers No. 40). World Intellectual Property Organization (WIPO) – Economics and Statistics Division.

Castaldi, C., Frenken, K., & Los, B. (2015). Related variety, unrelated variety and technological breakthroughs: An analysis of US state-level patenting. *Regional Studies*, *49*(5), 767–781. https://doi.org/10.1080/00343404.2014.940305

Caviggioli, F. (2016). Technology fusion: Identification and analysis of the drivers of technology convergence using patent data. *Technovation*, *55–56*, 22–32. https://doi.org/10.1016/j.technovation.2016.04.003

Clancy, M. S. (2018). Inventing by combining pre-existing technologies: Patent evidence on learning and fishing out. *Research Policy*, *47*(1), 252–265. https://doi.org/10.1016/j.respol.2017.10.015

Coenen, L., Hansen, T., & Rekers, J. V. (2015). Innovation policy for grand challenges: An economic geography perspective. *Geography Compass*, *9*(9), 483–496. https://doi.org/10.1111/gec3.12231

Cohen, W. M., & Levinthal, D. A. (1990). Absorptive capacity: A new perspective on learning and innovation. *Administrative Science Quarterly*, 35(1), 128–152. https://doi.org/10.2307/2393553

Colombelli, A., Krafft, J., & Quatraro, F. (2014). The emergence of new technology-based sectors in European regions: A proximity-based analysis of nanotechnology. *Research Policy*, 43(10), 1681–1696. https://doi.org/10.1016/j.respol.2014.07.008

Costantini, V., Crespi, F., & Curci, Y. (2015). A keyword selection method for mapping technological knowledge in specific sectors through patent data: The case of biofuels sector. *Economics of Innovation and New Technology*, 24(4), 282–308. https://doi.org/10.1080/10438599.2014.942583

Desrochers, P., & Leppälä, S. (2011). Opening up the 'Jacobs spillovers' black box: Local diversity, creativity and the processes underlying new combinations. *Journal of Economic Geography*, 11(5), 843–863. https://doi.org/10.1093/jeg/lbq028

Dosi, G. (1982). Technological paradigms and technological trajectories: A suggested interpretation of the determinants and directions of technical change. *Research Policy*, 11(3), 147–162. https://doi.org/10.1016/0048-7333(82)90016-6

Eriksson, R. H. (2011). Localized spillovers and knowledge flows: How does proximity influence the performance of plants? *Economic Geography*, 87(2), 127–152. https://doi.org/10.1111/j.1944-8287.2011.01112.x

Feldman, M. P., Kogler, D. F., & Rigby, D. L. (2015). rKnowledge: The spatial diffusion and adoption of rDNA methods. *Regional Studies*, 49(5), 798–817. https://doi.org/10.1080/00343404.2014.980799

Ferguson, J.-P., & Carnabuci, G. (2017). Risky recombinations: Institutional gatekeeping in the innovation process. *Organization Science*, 28(1), 133–151. https://doi.org/10.1287/orsc.2016.1106

Flanagan, K., Uyarra, E., & Laranja, M. (2011). Reconceptualising the 'policy mix' for innovation. *Research Policy*, 40(5), 702–713. https://doi.org/10.1016/j.respol.2011.02.005

Fleming, L. (2001). Recombinant uncertainty in technological search. *Management Science*, 47(1), 117–132. https://doi.org/10.1287/mnsc.47.1.117.10671

Foray, D. (2018a). Smart Specialization strategies as a case of mission-oriented policy – A case study on the emergence of new policy practices. *Industrial and Corporate Change*, 27(5), 817–832. https://doi.org/10.1093/icc/dty030

Foray, D. (2018b). Smart Specialisation strategies and industrial modernisation in European regions – Theory and practice. *Cambridge Journal of Economics*, 42, 1505–1520. https://doi.org/10.1093/cje/bey022

Fraunhofer Institute. (2019). *Photovoltaic report*. Technical Report. Fraunhofer Institute. Retrieved March 10, 2020, from https://www.ise.fraunhofer.de/content/dam/ise/de/documents/publications/studies/Photovoltaics-Report.pdf

Frenken, K. (2017). A complexity-theoretic perspective on innovation policy. *Complexity, Governance & Networks*, 0, 35–47. https://doi.org/10.20377/cgn-41

Furr, N., & Kapoor, R. (2018). Capabilities, technologies, and firm exit during industry shakeout: Evidence from the global solar photovoltaic industry. *Strategic Management Journal*, 39(1), 33–61. https://doi.org/10.1002/smj.2709

Galunic, D. C., & Rodan, S. (1998). Resource recombinations in the firm: Knowledge structures and the potential for Schumpeterian innovation. *Strategic Management Journal*, 19(12), 1193–1201. https://doi.org/10.1002/(SICI)1097-0266(1998120)19:12<1193::AID-SMJ5>3.0.CO;2-F

Geels, F. W. (2018). Disruption and low-carbon system transformation: Progress and new challenges in socio-technical transitions research and the multi-level perspective. *Energy Research & Social Science*, 37, 224–231. https://doi.org/10.1016/j.erss.2017.10.010

Giuliani, E., Martinelli, A., & Rabellotti, R. (2016). Is co-invention expediting technological catch up? A study of collaboration between emerging country firms and EU inventors. *World Development*, 77, 192–205. https://doi.org/10.1016/j.worlddev.2015.08.019

Haščič, I., & Migotto, M. (2015). *Measuring environmental innovation using patent data*. https://doi.org/10.1787/5js009kf48xw-en

Heimeriks, G., & Balland, P.-A. (2016). How smart is specialisation? An analysis of specialisation patterns in knowledge production. *Science and Public Policy*, 43(4), 562–574. https://doi.org/10.1093/scipol/scv061

Heimeriks, G., & Boschma, R. (2014). The path- and place-dependent nature of scientific knowledge production in biotech 1986–2008. *Journal of Economic Geography*, 14(2), 339–364. https://doi.org/10.1093/jeg/lbs052

Henderson, R. M., & Clark, K. B. (1990). Architectural innovation: The reconfiguration of existing product technologies and the failure of established firms. *Administrative Science Quarterly*, 35(1), 9–30. https://doi.org/10.2307/2393549

Henning, M., Stam, E., & Wenting, R. (2013). Path dependence research in regional economic development: Cacophony or knowledge accumulation? *Regional Studies*, 47(8), 1348–1362. https://doi.org/10.1080/00343404.2012.750422

Hidalgo, C. A., Klinger, B., Barabási, A.-L., & Hausmann, R. (2007). The product space conditions the development of nations. *Science*, 317(5837), 482–487. https://doi.org/10.1126/science.1144581

Hoppmann, J., Peters, M., Schneider, M., & Hoffmann, V. H. (2013). The two faces of market support – How deployment policies affect technological exploration and exploitation in the solar photovoltaic industry. *Research Policy*, 42(4), 989–1003. https://doi.org/10.1016/j.respol.2013.01.002

Jaffe, A. B., & de Rassenfosse, G. (2017). Patent citation data in social science research: Overview and best practices. *Journal of the Association for Information Science and Technology*, 68(6), 1360–1374. https://doi.org/10.1002/asi.23731

Janssen, M. J., & Frenken, K. (2019). Cross-specialisation policy: Rationales and options for linking unrelated industries. *Cambridge Journal of Regions, Economy and Society*, 12(2), 195–212. https://doi.org/10.1093/cjres/rsz001

Jean, J., Brown, P. R., Jaffe, R. L., Buonassisi, T., & Bulović, V. (2015). Pathways for solar photovoltaics. *Energy & Environmental Science*, 8(4), 1200–1219. https://doi.org/10.1039/C4EE04073B

Kalthaus, M. (2019). Identifying technological sub-trajectories in patent data: The case of photovoltaics. *Economics of Innovation and New Technology*, 28(4), 407–434. https://doi.org/10.1080/10438599.2018.1523356

Kaplan, S., & Tripsas, M. (2008). Thinking about technology: Applying a cognitive lens to technical change. *Research Policy*, 37(5), 790–805. https://doi.org/10.1016/j.respol.2008.02.002

Klepper, S. (2007). Disagreements, spinoffs, and the evolution of Detroit as the capital of the U.S. automobile industry. *Management Science*, 53(4), 616–631. https://doi.org/10.1287/mnsc.1060.0683

Kogler, D. F., Essletzbichler, J., & Rigby, D. L. (2017). The evolution of specialization in the EU15 knowledge space. *Journal of Economic Geography*, 17, 345–373. https://doi.org/10.1093/jeg/lbw024

Kogut, B., & Zander, U. (1992). Knowledge of the firm, combinative capabilities, and the replication of technology. *Organization Science*, 3(3), 383–397. https://doi.org/10.1287/orsc.3.3.383

Krafft, J., Quatraro, F., & Saviotti, P. P. (2011). The knowledge-base evolution in biotechnology: A social network analysis.

*Economics of Innovation and New Technology*, 20(5), 445–475. https://doi.org/10.1080/10438599.2011.562355

Leydesdorff, L., Alkemade, F., Heimeriks, G., & Hoekstra, R. (2015). Patents as instruments for exploring innovation dynamics: Geographic and technological perspectives on 'photovoltaic cells'. *Scientometrics*, 102(1), 629–651. https://doi.org/10.1007/s11192-014-1447-8

Li, D., Heimeriks, G., & Alkemade, F. (2020). The emergence of renewable energy technologies at country level: Relatedness, international knowledge spillovers and domestic energy markets. *Industry and Innovation*, 0, 1–23. https://doi.org/10.1080/13662716.2020.1713734

Lobo, J., & Strumsky, D. (2008). Metropolitan patenting, inventor agglomeration and social networks: A tale of two effects. *Journal of Urban Economics*, 63(3), 871–884. https://doi.org/10.1016/j.jue.2007.07.005

Magro, E., & Wilson, J. R. (2019). Policy-mix evaluation: Governance challenges from new place-based innovation policies. *Research Policy*, 48, 103612. https://doi.org/10.1016/j.respol.2018.06.010

Mäkitie, T., Normann, H. E., Thune, T. M., & Sraml Gonzalez, J. (2019). The green flings: Norwegian oil and gas industry's engagement in offshore wind power. *Energy Policy*, 127, 269–279. https://doi.org/10.1016/j.enpol.2018.12.015

Malmberg, A., & Maskell, P. (2002). The elusive concept of localization economies: Towards a knowledge-based theory of spatial clustering. *Environment and Planning A: Economy and Space*, 34(3), 429–449. https://doi.org/10.1068/a3457

Martin, R. (2010). Roepke Lecture in Economic Geography: Rethinking regional path dependence: Beyond lock-in to evolution. *Economic Geography*, 86(1), 1–27. https://doi.org/10.1111/j.1944-8287.2009.01056.x

Martin, R., & Sunley, P. (2006). Path dependence and regional economic evolution. *Journal of Economic Geography*, 6(4), 395–437. https://doi.org/10.1093/jeg/lbl012

Martínez, C. (2011). Patent families: When do different definitions really matter? *Scientometrics*, 86(1), 39–63. https://doi.org/10.1007/s11192-010-0251-3

Miguelez, E., & Moreno, R. (2018). Relatedness, external linkages and regional innovation in Europe. *Regional Studies*, 52(5), 688–701. https://doi.org/10.1080/00343404.2017.1360478

Montresor, S., & Quatraro, F. (2020). Green technologies and Smart Specialisation strategies: A European patent-based analysis of the intertwining of technological relatedness and key enabling technologies. *Regional Studies*, 54(10), 1354–1365. https://doi.org/10.1080/00343404.2019.1648784

National Renewable Energy Laboratory. (2019). *Research cell record efficiency chart*. Retrieved March 10, 2020, from https://www.nrel.gov/pv/assets/images/efficiency-chart.png

Nelson, R. R., & Winter, S. G. (1982). *An evolutionary theory of economic change*. Belknap/Harvard University Press.

Nemet, G. F. (2012). Inter-technology knowledge spillovers for energy technologies. *Energy Economics*, 34(5), 1259–1270. https://doi.org/10.1016/j.eneco.2012.06.002

Nooteboom, B. (2000). *Learning and innovation in organizations and economies*. Oxford University Press.

Nooteboom, B., Van Haverbeke, W., Duysters, G., Gilsing, V., & van den Oord, A. (2007). Optimal cognitive distance and absorptive capacity. *Research Policy*, 36(7), 1016–1034. https://doi.org/10.1016/j.respol.2007.04.003

Perez, C., & Soete, L. (1988). Catching up in technology: Entry barriers and windows of opportunity. In Dosi, G., Freeman, C., Nelson, R., Silverberg, G., & Soete, L. (Eds.), *Technical change and economic theory* (pp. 458–479). Pinter.

Perruchas, F., Consoli, D., & Barbieri, N. (2020). Specialisation, diversification and the ladder of green technology development.

*Research Policy*, 49(3), 103922. https://doi.org/10.1016/j.respol.2020.103922

Petralia, S., Balland, P.-A., & Morrison, A. (2017). Climbing the ladder of technological development. *Research Policy*, 46(5), 956–969. https://doi.org/10.1016/j.respol.2017.03.012

Rigby, D. L. (2015). Technological relatedness and knowledge space: Entry and exit of US cities from patent classes. *Regional Studies*, 49(11), 1922–1937. https://doi.org/10.1080/00343404.2013.854878

Safarzyńska, K., & van den Bergh, J. C. J. M. (2013). An evolutionary model of energy transitions with interactive innovation-selection dynamics. *Journal of Evolutionary Economics*, 23(2), 271–293. https://doi.org/10.1007/s00191-012-0298-9

Sbardella, A., Perruchas, F., Napolitano, L., Barbieri, N., & Consoli, D. (2018). Green technology fitness. *Entropy*, 20(10), 776. https://doi.org/10.3390/e20100776

Schmalensee, R. (2015). *The future of solar energy: An interdisciplinary MIT study*. Energy Initiative, Massachusetts Institute of Technology (MIT).

Schmidheiny, K., & Brülhart, M. (2011). On the equivalence of location choice models: Conditional logit, nested logit and Poisson. *Journal of Urban Economics*, 69(2), 214–222. https://doi.org/10.1016/j.jue.2010.09.004

Storper, M., & Venables, A. J. (2004). Buzz: Face-to-face contact and the urban economy. *Journal of Economic Geography*, 4(4), 351–370. https://doi.org/10.1093/jnlecg/lbh027

Strumsky, D., & Lobo, J. (2015). Identifying the sources of technological novelty in the process of invention. *Research Policy*, 44(8), 1445–1461. https://doi.org/10.1016/j.respol.2015.05.008

Tanner, A. N. (2014). Regional branching reconsidered: Emergence of the fuel cell industry in European regions. *Economic Geography*, 90(4), 403–427. https://doi.org/10.1111/ecge.12055

Tanner, A. N. (2016). The emergence of new technology-based industries: The case of fuel cells and its technological relatedness to regional knowledge bases. *Journal of Economic Geography*, 16(3), 611–635. https://doi.org/10.1093/jeg/lbv011

Tavassoli, S., & Carbonara, N. (2014). The role of knowledge variety and intensity for regional innovation. *Small Business Economics*, 43(2), 493–509. https://doi.org/10.1007/s11187-014-9547-7

Torre, A., & Rallet, A. (2005). Proximity and localization. *Regional Studies*, 39(1), 47–59. https://doi.org/10.1080/0034340052000320842

Trancik, J. E., Jean, J., Kavlak, G., Klemun, M. M., Edwards, M. R., McNerney, J., Miotti, M., Brown, P. R., Mueller, J. M., & Needell, Z. A. (2015). *Technology improvement and emissions reductions as mutually reinforcing efforts: Observations from the global development of solar and wind energy* (Technical Report). Massachusetts Institute of Technology (MIT).

Uyarra, E., Flanagan, K., Magro, E., Wilson, J. R., & Sotarauta, M. (2017). Understanding regional innovation policy dynamics: Actors, agency and learning. *Environment and Planning C: Politics and Space*, 35(4), 559–568. https://doi.org/10.1177/2399654417705914

Van den Berge, M., Weterings, A., & Alkemade, F. (2020). Do existing regional specialisations stimulate or hinder diversification into cleantech? *Environmental Innovation and Societal Transitions*, 35, 185–201. https://doi.org/10.1016/j.eist.2019.10.002

Van der Loos, H. Z. A., Negro, S. O., & Hekkert, M. P. (2020). International markets and technological innovation systems: The case of offshore wind. *Environmental Innovation and Societal Transitions*, 34, 121–138. https://doi.org/10.1016/j.eist.2019.12.006

Veefkind, V., Hurtado-Albir, J., Angelucci, S., Karachalios, K., & Thumm, N. (2012). A new EPO classification scheme for climate change mitigation technologies. *World Patent Information*, 34(2), 106–111. https://doi.org/10.1016/j.wpi.2011.12.004

Verhoeven, D., Bakker, J., & Veugelers, R. (2016). Measuring technological novelty with patent-based indicators. *Research Policy*, *45*(3), 707–723. https://doi.org/10.1016/j.respol.2015.11.010

Wanzenböck, I., & Frenken, K. (2020). The subsidiarity principle in innovation policy for societal challenges. *Global Transitions*, *2*, 51–59. https://doi.org/10.1016/j.glt.2020.02.002

Weber, K. M., & Rohracher, H. (2012). Legitimizing research, technology and innovation policies for transformative change: Combining insights from innovation systems and multi-level perspective in a comprehensive 'failures' framework. *Research Policy, Special Section on Sustainability Transitions*, *41*, 1037–1047. https://doi.org/10.1016/j.respol.2011.10.015

Wieczorek, A. J., Negro, S. O., Harmsen, R., Heimeriks, G. J., Luo, L., & Hekkert, M. P. (2013). A review of the European offshore wind innovation system. *Renewable and Sustainable Energy Reviews*, *26*, 294–306. https://doi.org/10.1016/j.rser.2013.05.045

Wilson, C. (2018). Disruptive low-carbon innovations. *Energy Research & Social Science*, *37*, 216–223. https://doi.org/10.1016/j.erss.2017.10.053

Zeppini, P., & van den Bergh, J. C. J. M. (2011). Competing recombinant technologies for environmental innovation: Extending Arthur's model of lock-in. *Industry and Innovation*, *18*(3), 317–334. https://doi.org/10.1080/13662716.2011.561031