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Abstract

Studies show that local capabilities contribute to the green transition, yet little attention has been devoted to the role of scientific capabilities. The paper assesses the importance of local scientific capabilities and the inflow of scientific knowledge from elsewhere for the ability of regions in Europe to diversify into photovoltaic (PV) segments during the period 1998 to 2015, employing a combined dataset on patents and scientific publications. We find that local scientific capabilities matter, but not so much the inflow of relevant scientific knowledge from other regions, as proxied by scientific citations of patents in PV segments. Regions are also likely to diversify into a PV segment when they have technological capabilities related to other PV segments. Finally, we found that European regions are less likely to lose an existing PV segment specialization when they have intra-regional and extra-regional scientific capabilities in this PV segment.

Keywords: relatedness, photovoltaic technologies, green diversification, regional diversification, scientific capabilities, related scientific capabilities, inter-regional linkages, Europe

JEL codes: o25, o38, r11

1. Introduction

Regional capabilities are considered important for regions to innovate and to develop new technologies (Boschma, 2017). A large body of literature has applied the relatedness framework to identify technological capabilities and to map diversification opportunities of regions (Balland, 2016; Balland et al., 2019; Barbieri et al., 2020; Boschma, 2017; Perruchas et al., 2020). What these studies observe is that regions rely heavily on technological capabilities when diversifying into new technologies. There is increasing evidence that this process of related diversification is also happening in regions in the case of green technologies (Corrocher et al., 2024; Corrocher & Ozman, 2020; Montresor & Quatraro, 2020; Moreno & Ocampo-Corrales, 2022; Ning & Guo, 2022; Orsatti et al., 2024; Santoalha & Boschma, 2021; Tanner, 2014, 2016; van den Berge et al., 2020).

Yet, knowledge capabilities of regions are not limited to technological knowledge only. Regions also constitute repositories of scientific research and knowledge. Studies have provided evidence that local scientific capabilities may enhance the ability of countries and regions to develop new scientific fields (Catalán et al., 2020; Guevara et al., 2016; Pugliese et al., 2019). Balland and Boschma (2022) found that scientific capabilities in specific fields also enhance technological diversification in regions. However, no such study has yet applied the relatedness framework to the role of a local supply of scientific knowledge for the development of green technologies in regions.

What is more, regions have to develop linkages to access external knowledge that regions do not possess themselves but which they need in order to develop new technologies (Miguélez & Moreno, 2015). This requires absorptive capacity of regions to understand and exploit external knowledge (Boschma & Iammarino, 2009; Miguelez & Moreno, 2018). Balland and Boschma (2022) have shown that complementary inter-regional linkages are important for the development of new technologies in regions, on top of regional capabilities. What has not yet been investigated is the extent to which scientific knowledge sourced from other regions makes a difference in this diversification process, and for green diversification in particular. The paper aims to fill this gap.

The contribution of this paper is threefold. The first objective is to determine whether local scientific capabilities in specific fields enhance the ability of regions to develop new green technologies. We adopt the relatedness framework to investigate whether the entry of new green technologies in a region is enhanced when related to the scientific capabilities present in the region. The second objective is to assess whether the inflow of external scientific knowledge related to the local scientific knowledge base enhances the entry of green technologies in regions. For this purpose, we construct a novel indicator of relatedness between the scientific fields from which green technologies source their external scientific knowledge. We control for two types of technological relatedness that might affect green diversification in regions, i.e., relatedness to wider technologies independently of their green nature, and the relatedness to green technological segments in the region. The third objective is to investigate the exit or loss of a green technological specialization in a region, and to what extent that depends on the local presence of scientific and technological capabilities.

The paper investigates the regional entry and exit of technologies in solar photovoltaics (PV), a set of green technologies that are considered crucial to tackle climate change (Binz & Anadon, 2018; Binz et al., 2020; Brachert et al., 2013; Gao & Rai, 2020; Gosens et al., 2020; Gul et al., 2016; Yang et al., 2022; Yap et al., 2022). We employ a combined dataset of patents, scientific publications, and citations of patents to scientific publications on twelve PV technologies in Europe. We analyze the entry and exit of PV technologies in 263 NUTS-2 regions in EU-27 countries, plus the United

Kingdom, Norway, Switzerland and Iceland for the period 1998 to 2015. Regional entry models assess the role of technological and scientific capabilities for the development of new PV technological segments in Europe.

The paper is structured as follows. Section 2 presents a review of the literature on (green) technological diversification in regions from which a set of hypotheses is derived. Section 3 introduces the PV technologies, and explains the datasets, the methods and the variables that will be used, including the relatedness indicators. Section 4 presents the econometric analysis and the findings of the regional entry and exit models concerning PV technologies in Europe. Section 5 discusses our findings as well as its implications for policy and future research.

2. What makes regions diversify into green technologies

Technological knowledge and innovation do not emerge out of the blue. Knowledge creation accumulates over time (Nelson & Winter, 1982), in which pieces of knowledge are combined in new ways (Dosi, 1982). For this reason, knowledge is also not distributed equally across space: regions differ in their capabilities to produce new knowledge and therefore follow different technological trajectories (Kogler et al., 2013; Storper, 1995). Knowledge does not travel well over large distances (Jaffe et al., 1993), especially tacit knowledge that is embedded in individuals and ways of doing things (Gertler, 2003). The kind of technological knowledge developed in a region depends on the variety of knowledge in a region, and the extent to which the pieces of the local knowledge base are related (Frenken et al., 2007). Relatedness refers to the proximity between the different knowledge elements in terms of their utilization (i.e. they may be close substitutes) or their cognitive content (i.e. the skills that are required for these knowledge elements to be used) (Breschi et al., 2003).

The notion of relatedness has been applied to explain how regions diversify into new activities (Boschma, 2017; Frenken & Boschma, 2007; Neffke et al., 2011). Relatedness constitutes an important driver for the diversification of regions in new technologies, as regions extend the scope of their activities around the technological competencies they accumulate over time (Balland, 2016). Regions that are specialized in a technology diversify more easily in a technology that requires a related knowledge set because this entails lower costs and risks, as they can build on existing regional capabilities (Boschma et al., 2015b; Rigby, 2015). This concept of related diversification has been influential in placing regional capabilities as a key pillar of Smart Specialization policy (Foray, 2014; McCann & Ortega-Argilés, 2019).

Studies show that the development of green technologies in regions is subject to a similar related diversification process (Corrocher et al., 2024; Montresor & Quatraro, 2020; Moreno & Ocampo-Corrales, 2022; Ning & Guo, 2022; Orsatti et al., 2024; Santoalha & Boschma, 2021; Tanner, 2014, 2016; van den Berge et al., 2020), besides the role of green policies (Robinson & Mazzucato, 2019). Knowledge capabilities are different across regions, and they play an important role in green diversification (Coenen et al., 2021; Fusillo, 2023). Li et al. (2020) found that countries diversify into green technologies related to their existing competences, while the level of technological maturity is also important (Barbieri et al., 2020; Perruchas et al., 2020). At the regional level, studies confirm that technological relatedness enhances green regional diversification. Santoalha and Boschma (2021) found that related capabilities play a more important role in green diversification than what they refer to as political support. Interestingly, in certain cases, regions even relied on local capabilities in fossil fuels when diversifying into green (van den Berge et al., 2020).

Apart from technological knowledge, local scientific knowledge may also be important for green diversification. Scientists are involved in highly localized research activities, that is, they develop new ideas mainly within their own scientific domain or close to that (Guevara et al., 2016). This makes regions accumulate pools of scientific competencies that evolve in a rather similar way as technological competencies. These competencies are reflected in specific scientific profiles of regions that constitute the basis of technological knowledge. These scientific regional specializations may affect the ability of regions to develop new technologies (Catalán et al., 2020; Pugliese et al., 2019). Balland and Boschma (2022) indeed showed that the probability of a region to enter a new technology depends on the local presence of scientific fields related to this technology.

This may also be important in the case of green technologies. In green technologies that rely primarily on codified knowledge such as photovoltaic technologies (Binz & Truffer, 2017), regional scientific capabilities are expected to play an important role. However, there is little research whether local scientific knowledge is actually translated in the development of new green technologies in regions. Tanner (2014) showed that local universities played a role in the emergence of fuel cells in European regions. More in general, Balland and Boschma (2022) showed there may not be a perfect overlap between scientific and technological excellence in the same domain in a region, as the absorptive capacity of local industry may be too low (Bonaccorsi, 2017), or because public universities and private industries operate according to different logics that may hamper university-industry collaborations (Dasgupta & David, 1994; Ponds et al., 2007). To test whether local scientific knowledge matters for green diversification, we therefore developed two hypotheses:

H1a: *Regions are more likely to develop new green specializations when they have a scientific specialization in the same domain.*

H1b: *Regions are more likely to develop new green specializations that are related to their local scientific capabilities.*

Relevant scientific knowledge may be tapped in the region, but also from other regions. As much scientific knowledge is codified in scientific publications, it can more easily pass national and regional borders (Robinson et al., 2013). Therefore, inflow of scientific knowledge may enhance green diversification in regions, but there exists little research on this topic. The important role of extra-regional linkages for innovation has been highlighted in many papers (Bathelt et al., 2004; Fitjar & Rodríguez-Pose, 2011; Grillitsch & Nilsson, 2015). A key insight is that regions have a better capacity to develop new technologies when having access to external knowledge they do not possess themselves (Barzotto et al., 2019; Miguélez & Moreno, 2015).

More recently, studies show that the absorptive capacity of regions is crucial to exploit external knowledge (Boschma & Iammarino, 2009; Miguelez & Moreno, 2018). Balland and Boschma (2022) have shown that complementary inter-regional linkages are important for the development of new technologies in regions, on top of regional capabilities. What has not yet been investigated is the extent to which scientific knowledge sourced from other regions makes a difference in this diversification process, and for green diversification in particular. The paper aims to fill this gap. To test these ideas, we developed two other hypotheses:

H2a: *Regions are more likely to develop new green specializations when they source scientific knowledge external to the region.*

H2b: *Regions are more likely to develop new green specializations when they source related scientific knowledge external to the region.*

3. Data, variables, and methods

The case of photovoltaics

This study focuses on the emergence of solar photovoltaic (PV) technologies as a case of green diversification in regions. PV technology is one of the most established renewable energy technologies that contribute to climate change mitigation. Although it is a technology born overseas, Europe was central in its production, while today it struggles with Chinese competition (Binz et al., 2017; Gosens et al., 2020; Yap et al., 2022). Although European actions such as the Green Deal highlight the use of renewable energy technologies, strong policy for PV has been almost absent[1]. However, the latest policies support the development of PV technologies in the EU, with the aim of decarbonizing EU's energy system[2].

PV systems are composed of a set of technologies that convert sunlight into electricity. The core technology is the PV cell which converts sunlight into electricity. Some of the PV cell types can be complemented by concentrators, a technology that may differentiate the solar cell. Finally, the PV cells need to be connected with each other and with the wider infrastructure by grid and power conversion systems. This last component is generic for all PV systems (Cantner et al., 2016; Graf & Kalthaus, 2018; Kalthaus, 2019). The different PV cell technological solutions, alongside with the complementary concentrators, conversion and connection to the grid technologies, and the generic PV applications, constitute the different PV technological segments summarized in Table 1.

Table 1: The twelve PV technological segments and their classification, according to European Patent Office

CPC patent classification	Title and description
Y02E 10/50	Photovoltaic [PV] energy (generic applications)
Y02E 10/52	PV systems with concentrators
Y02E 10/541	CuInSe2 material PV cells
Y02E 10/542	Dye sensitized solar cells
Y02E 10/543	Solar cells from Group II-VI materials
Y02E 10/544	Solar cells from Group III-V materials
Y02E 10/545	Microcrystalline silicon PV cells
Y02E 10/546	Polycrystalline silicon PV cells
Y02E 10/547	Monocrystalline silicon PV cells
Y02E 10/548	Amorphous silicon PV cells
Y02E 10/549	Organic PV cells
Y02E 10/56	Power conversion systems, e.g. maximum power point trackers

PV technology and its segments is a relevant case for exploring green diversification in European regions. This is due to the technology's high degree of standardization. PV technological segment

[1] Delivering the European Green Deal https://ec.europa.eu/info/strategy/priorities-2019-2024/european-green-deal/delivering-european-green-deal_en

[2] Ecodesign – European Commission to examine need for new rules on environmental impact of photovoltaics https://ec.europa.eu/info/law/better-regulation/have-your-say/initiatives/12819-Ecodesign-European-Commission-to-examine-need-for-new-rules-on-environmental-impact-of-photovoltaics_en

development is based on extensive R&D knowledge, while patenting and other codified knowledge, such as scientific publications, are important for the technological standardization of PV. The high standardization alongside with its early development (patents since 1950s) have led to the development of this technology in multiple technological segments. These multiple PV technological segments have distinct technological and economic characteristics that need different knowledge elements to be developed. Some technological segments compete with each other (such as different types of photovoltaic cells) while others are complementary (like photovoltaic cells and concentrators). What is important for our study is that technological segments may require different regional capabilities to emerge and develop.

Data collection

This paper aims to measure the potential of regions to diversify in new photovoltaic technological segments, depending on their own technological competencies, their scientific competencies, and their external access to relevant scientific competencies. For this purpose, we use three types of data: PV patents, scientific papers on PV, and scientific citations of PV patents.

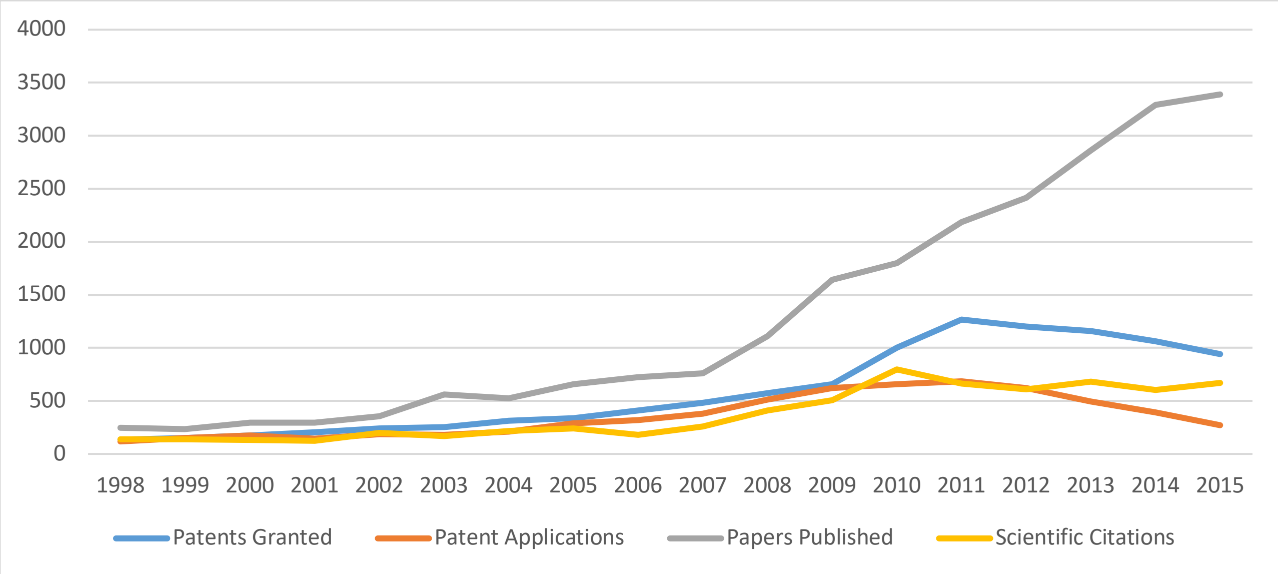
We used the PATSTAT database to identify all granted patents in photovoltaics for the period 1998-2015. We selected all granted patents with a Cooperative Patent Code (CPC) on photovoltaics (Y02E10/5*) in 31 European countries: the EU-28, Iceland, Norway, and Switzerland. We selected patents with at least one inventor located in one of the European countries. As Table 1 indicates, the CPCs of photovoltaics consist of twelve sub-classes that represent different technological segments of PV. We geolocated all inventors in NUTS-2 regions and assigned patents to these regions according to the inventor address. We made sure that the granted patens are unique using their application number. We identified 12,296 unique patents on PV.

With the use of keywords (‘photovoltaics’, ‘pv’, ‘solar energy’), we extracted from Scopus the scientific publications on PV technologies. We focused only to scientific publications with at least one author located in Europe. We identified in total 23,426 scientific publications for the entire period. We used specific keywords (corresponding to each category of Table 1) to identify each PV technological segment, so the categories of patents correspond to the categories of scientific publications. Then we geolocated the scientific publications to the NUTS2 level, according to the author’s affiliation address. Finally, we attributed each scientific publication to the scientific fields it belongs, through the journal they were published in, using Scopus journal classification. In this way, we made it possible to define the scientific knowledge space to which PV technologies belong.

Similarly to scientific domains that are considered related when they cite each other, technological segments can be considered related when they cite similar scientific literature (Marx & Fuegi, 2020; Waltman et al., 2010). For all granted PV patents with at least one inventor based in Europe, we extracted their scientific citations (i.e. the citations of patents to academic journals). These scientific papers can come from authors all around the world. They represent the scientific knowledge external to the region that PV patents source. There are in total 6,457 scientific papers cited by PV patents during the entire period under consideration. We assigned each of these publications to one or more scientific fields. The scientific fields were attributed to the publications through the journal they were published in, using the Scopus journal classification. In this way, we defined the link between technological knowledge from patents and the scientific knowledge on which the former relies.

Figure 1 shows the number of patents, scientific publications and citations in Europe for the period 1998-2015. In the first years, not much happened. Scientific publications on PV started to increase slowly in Europe from 2002 onwards, and this growth accelerated after 2007. Number of PV patents grew slowly but steadily in Europe after 2005. During the years 2009-2010, China entered the PV market creating an external shock in the European market (Binz & Truffer, 2017) which led to a decrease in patent applications and granted patents in Europe after 2011. The number of citations to scientific publications increased in the years 2006-2010, but remained more or less stable after.

Figure 1: Number of PV patents granted, PV patent applications, scientific papers published on PV, and scientific citations by PV patents, with at least one co-inventor or co-author located in Europe



Revealed Technological and Scientific Advantage in PV

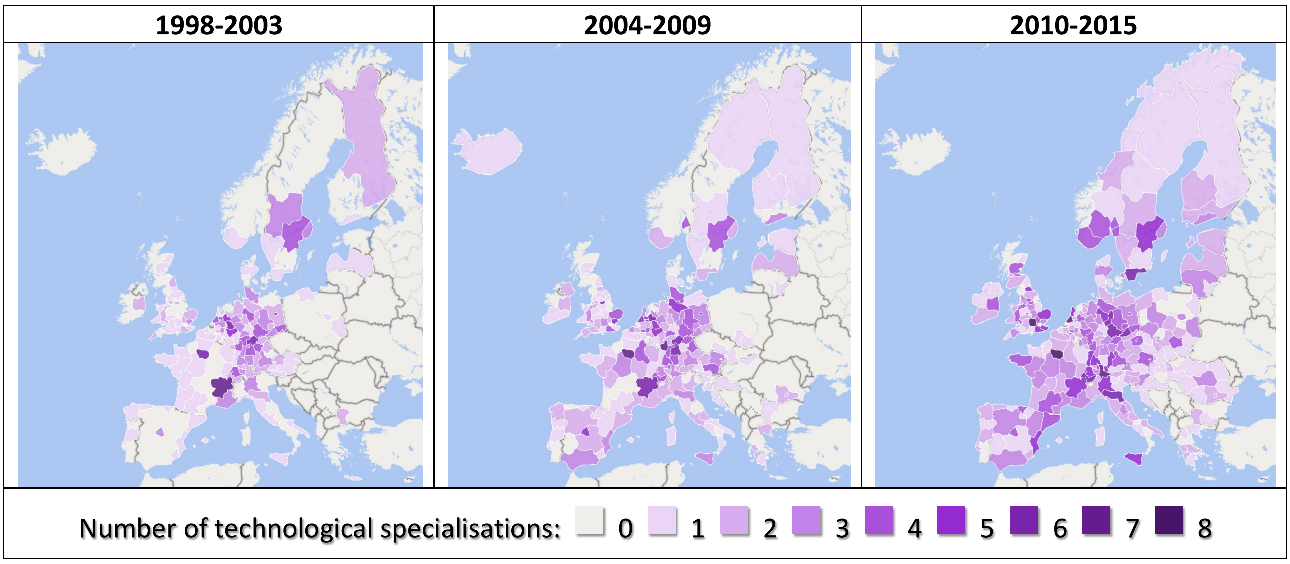
We divided the patents and the scientific publications according to the PV technological segment they belong. We also split the entire period of eighteen years in six-year windows (1998-2003, 2004-2009, 2010-2015). Following studies on regional diversification (Boschma et al., 2015a; Rigby, 2015), we expressed for each six-year time window the relative technological specialization of a region in a PV segment, calculating its revealed technological advantage (RTA) in that specific PV segment. RTA is defined as the share of patents in a PV segment in a region’s overall patenting activity in photovoltaics, divided by the European share of this PV segment in all PV patents.

$$\frac{patents_{r,i}^{t} / \sum_i patents_{r,i}^{t}}{\sum_r patents_{r,i}^{t} / \sum_r \sum_i patents_{r,i}^{t}} > 1$$

RTA is a binary measure that takes the value 1 when a region r has a greater share of patents in a PV segment i for a period t than the EU as whole in the same period t, and 0 otherwise.

A region can be specialized technologically in more than one PV segments. This means that it possesses strong capabilities in different kinds of technologies connected to PV. Figure 2 presents the number of PV segment specializations of European regions during the period 1998-2015. In the first sub-period 1998-2003, PV specializations could be found mainly in German regions. Since then, PV specializations have diffused over the European continent, especially in Western Europe, but also spreading to some extent into Eastern Europe in the last sub-period 2010-2015. The Ile-de-France region has succeeded to maintain its dominant position in PV over the years.

Figure 2: Number of PV segments in which European regions have technological specialization

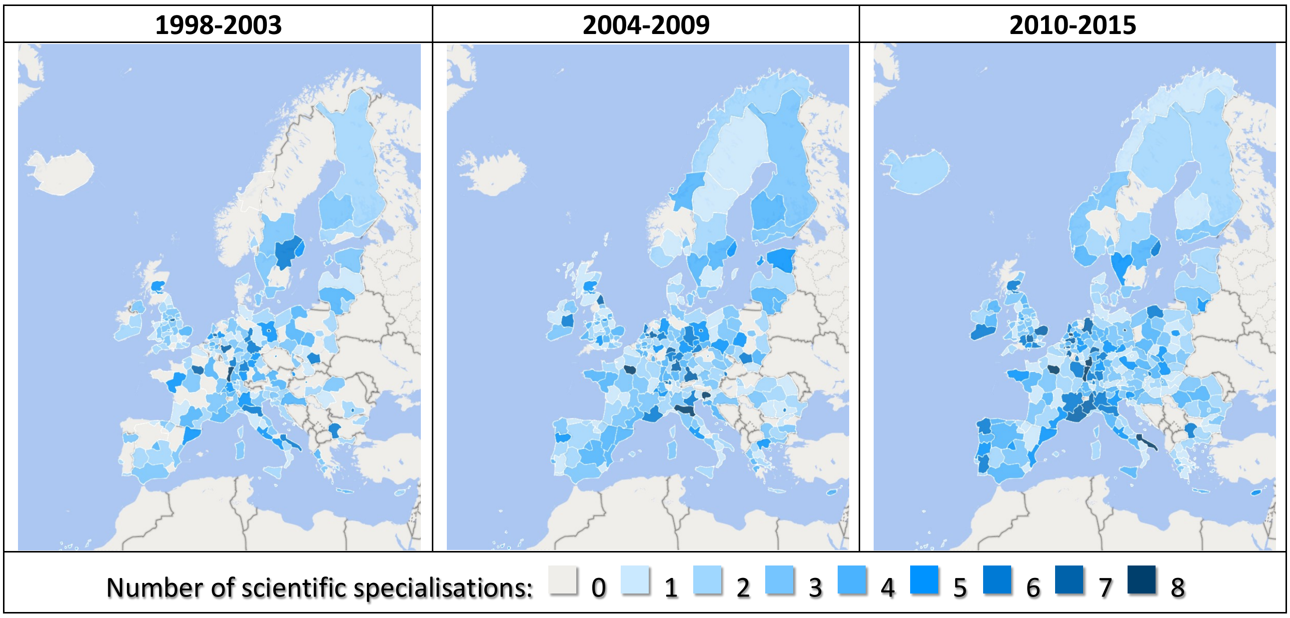


As a key objective of the paper is to assess whether scientific capabilities of a region in a PV segment match the technological capabilities of a region in the same PV segment, we also calculate the revealed scientific advantage (RSA) of European regions in PV segments (Balland & Boschma, 2022). In a similar way to RTA, we calculated for each six-year window the RSA of a region in terms of the share of scientific publications on a PV segment in a region's overall scientific publications in PV, divided by the European share of this PV segment in all scientific publications on PV. RSA is a binary measure that takes the value 1 when a region r has a greater share of scientific publications in a PV segment i for a period t than the EU as whole in the same period t, and 0 otherwise.

$$\frac{publications^{t}_{r,i}/\sum_i publications^{t}_{r,i}}{\sum_r publications^{t}_{r,i}/\sum_r \sum_i publications^{t}_{r,i}} > 1$$

A region can be specialized scientifically in more than one PV segments, mastering scientific capabilities in different kinds of PV technologies. Figure 3 presents the number of scientific specializations in PV segments European regions have. Figure 3 refers to the regions that are scientifically specialized in more than seven PV segments. When we compare the Figures 2 and 3, we observe that the European geography of scientific specializations in PV segments shows a more diffused pattern than the geography of technological specializations in PV segments.

Figure 3: Number of PV segments in which European regions have scientific specialization



Model and variables

Following studies on regional diversification (Boschma, 2017), we employed a linear probability panel data model with time fixed effects to test the probability that a region develops a Revealed Technological Advantage (RTA>1) in a new PV segment during the period 1998-2015. We analysed 263 NUTS-2 regions in Europe that demonstrated activity in patenting in PV, having at least one patent the entire periods under consideration. The dependent variable is the entry (1) or not (0) of a region in a new specialization in each of the twelve PV segments in which the region was not specialized before[3]. We divided the entire period in three non-overlapping periods (1998-2003, 2004-2009, 2010-2015). The maximum number of observations is 263 (regions) x 12 (PV segments) x 3 (periods) = 9,468. The regions that demonstrated no entry in a PV segment because already specialized in that segment in the previous period, were excluded from the analyses. We had a total of 5,556 potential entries.

We have a set of independent variables.

First, to test hypothesis 1a, we assess how the scientific capabilities of a region in a PV segment affect the entry probability of a region to develop a new technological specialization in the same PV segment. Following Balland and Boschma (2022), this is captured by the variable Revealed Scientific Advantage (RSA). As explained earlier, RSA is a binary measure that takes the value 1 when a region has a greater share of scientific publications in a PV segment *i* than the EU as whole, and 0 otherwise. In other words, RSA measures whether a region has a scientific specialization in a PV segment.

Second, to test hypothesis 1b, we developed a new indicator that enables us to assess how other scientific capabilities in PV of a region that are related to the scientific specialization of a region in a PV segment affect the entry probability of a region to develop a new technological specialization in

[3] In order to define the entry to a new specialisation and the exit from an existing specialisation, we considered RTA in two ways: with a margin from 0.99 to 1.01 and from 0.5 to 1.50. We performed the analyses with both margins to avoid the marginal entry or exit biases, without observing any significant differences in the coefficients.

that PV segment. This requires a few steps. As explained before, we first defined the local scientific knowledge through the scientific publications produced in European regions on PV segments. We identified the scientific fields to which these publications belong through their publication journal. We created a $PV\,segment\ \times\ scientific\,field$ matrix that shows the frequency of a specific scientific field occurring in publications for each PV segment i. Then, we created the co-occurrence and standardized related matrices of the PV segments based on local scientific knowledge. The resulting scientific relatedness matrix ($PV\,segment\ \times\ PV\,segment$) shows how much the different PV segments relate to each other in terms of shared scientific fields in PV publications. Finally, we regionalized the data by calculating the relatedness density of scientific knowledge in each PV segment for every region. The scientific relatedness density measure shows for each European region how much the different PV segments are related to the rest of the PV segments in terms of scientific knowledge. Following the conventional logic of a relatedness density measure (Boschma et al., 2015b; Hidalgo et al., 2007), we calculated the density of all related PV scientific segments around a given PV segment i in region r for each period t:

$$Scientific\_relatedness\_density_{i,r,t} = \frac{\sum_{j \in r, j \neq i} \varphi_{ij}}{\sum_{j \neq i} \varphi_{ij}} * 100$$

Third, we constructed an indicator to examine the role of access to relevant scientific knowledge in other regions (as proxied by citations external to the region) for the probability of a region to develop a new technological PV specialization, as formulated in hypothesis 2a. To express this, we used the number of scientific citations of patents in PV whose authors do not have an affiliation in the region to which the patent belongs. The variable Sourced Scientific Knowledge represents the number of citations by patents in each PV segment in a region to scientific publications outside the region.

Fourth, inspired by the idea of complementary inter-regional linkages proposed by Balland and Boschma (2022), we developed a new indicator that measures PV relatedness density in terms of scientific citations to test hypothesis 2b. As explained earlier, we make use of information concerning the scientific knowledge sourced by PV patents through the scientific publications that these patents cite. The indicator assesses how other scientific knowledge in PV that a region cites in other regions that is related to a particular PV segment affects the entry probability of the region in new technologies in that same PV segment. To express the sourcing of scientific knowledge in PV patents external to the region, we first calculated the relatedness between PV segments based on the cited regions external to the region from which the different PV segments source knowledge. We appoint these regions according to the affiliation of the authors of the cited papers by PV patents. We created a $PV\,segment\ \times\ cited\,regions$ matrix which shows the frequency that a specific region can be found cited in patents of each PV segment i. Based on that, we derived the co-occurrence and the standardized related matrices of the PV segments based on sourced scientific knowledge by PV patents. The scientific relatedness matrix ($PV\,segment\ \times\ PV\,segment$) shows how much the different PV segments relate to each other in terms of shared scientific knowledge cited in publications. Finally, we calculated the density of the related scientific knowledge in each PV segment in terms of the sourced scientific knowledge external to the region[4]. This Scientific Citation Relatedness Density indicator shows for each European region how much PV segments are related to each other in terms of externally sourced scientific knowledge. We calculated the density of all related PV scientific segments around a given PV segment i in region r for each period t:

$$Scientific\_citation\_relatedness\_density_{i,r,t} = \frac{\sum_{j\in r, j\neq i} \varphi_{ij}}{\sum_{j\neq i} \varphi_{ij}} * 100$$

Following the literature on technological diversification (Balland et al., 2019; Boschma et al., 2015b; Hidalgo et al., 2007), we controlled for the fact that the entry probability of region in a new PV segment can be enhanced by local supply of technologies related to that PV segment. We measured the technological relatedness between each PV segment and all the rest of the technologies. This indicator measures the relatedness of the different PV segments between them in terms of how these PV segments cooccur in patents with all other (wider) technologies. First, we produced the co-occurrence matrices which show the frequency that two PV segments (i and j) at the 8 or 9 digit level are combined in the same wider technological class (4 digit). We standardized the co-occurrence matrices by the total number of patents with i and j CPC classes. Then, we calculated the technological relatedness density around a given PV segment i in region r for each period t. The relatedness density is derived from the technological relatedness ($\varphi_{i,j,t}$), of the PV segment i to all other PV segments j in which a region has a Revealed Technological Advantage (RTA), divided by the sum of technological relatedness of PV segment i to all other PV segments j in Europe during the period t.

$$Technological\_relatedness\_density_{i,r,t} = \frac{\sum_{j\in r, j\neq i} \varphi_{ij}}{\sum_{j\neq i} \varphi_{ij}} * 100$$

Another control variable is the PV segment relatedness density. It is very similar to the previous indicator, but instead of measuring the degree of technological relatedness between PV segments based on the wider technologies they belong to, here we measure the technological relatedness between PV segments based on their co-occurrence in patents. It shows how much the PV segments are related to each other, which may be either complementary or competing to each other and aim to address the same global challenge. We calculate the relatedness density of all PV technologies j around a PV segment i in region r for each period t as follows:

[4] Alternatively, we have calculated the scientific citation relatedness density using the scientific fields from which the patents cite knowledge, according to the scientific fields that each scientific publication belongs (Scopus journal classification). We have repeated the analysis and the results appear robust as they do not deviate in terms of significance and direction.

$$PV\_segment\_relatedness\_density_{i,r,t} = \frac{\sum_{j \in r, j \neq i} \varphi_{ij}}{\sum_{j \neq i} \varphi_{ij}} * 100$$

In sum, we estimated the following model in which all independent variables are lagged, meaning they are measured in the period prior to the period in which a regional entry takes place or not. We run a pairwise correlation test to detect possible multi-collinearity problems but could not find one (see correlation matrix in Appendix 1).

$$\begin{aligned} Entry_{r,i,t} = {} & \beta_1 RSA_{r,i,t-1} + \beta_2 Scientific\_relatedness\_density_{r,i,t-1} \\ & + \beta_3 Scientific\_citations_{r,i,t-1} \\ & + \beta_4 Scientific\_citation\_relatedness\_density_{r,i,t-1} \\ & + \beta_5 Technological\_relatedness\_density_{r,i,t-1} \\ & + \beta_6 PV\_segment\_relatedness\_density_{r,i,t-1} + +\varepsilon_{r,i,t} \end{aligned}$$

We also assessed the probability of the same 263 NUTS-2 European regions to exit a technological specialization in a PV segment they already have during this period. We employed the same linear probability panel model to test the probability that a region loses its Revealed Technological Advantage in a PV technological segment during the period 1998-2015. The dependent variable is the exit (0 or 1) from a technological specialization in a PV segment in a region. Like the entry model, we divided the entire period in three non-overlapping periods. The regions that demonstrated no exit because having no technological specialization in a PV segment in the previous period, were excluded from the analysis. Overall, we have a total of 708 potential exits. A pairwise correlation test could not detect any multi-collinearity problems (see correlation matrix in Appendix 2).

$$\begin{aligned} Exit_{r,i,t} = {} & \beta_1 RSA_{r,i,t-1} + \beta_2 Scientific\_relatedness\_density_{r,i,t-1} \\ & + \beta_3 Sourced\_scientific\_knowledge_{r,i,t-1} \\ & + \beta_4 Scientific\_citation\_relatedness\_density_{r,i,t-1} \\ & + \beta_5 Technological\_relatedness\_density_{r,i,t-1} \\ & + \beta_6 PV\_segment\_relatedness\_density_{r,i,t-1} + +\varepsilon_{r,i,t} \end{aligned}$$

Table 2 shows the descriptive statistics of the variables. Entry and RSA are binary variables (0/1), while the four relatedness density indicators are expressed in percentages. The sourced scientific knowledge is a continuous variable.

Table 2: Descriptive statistics of the variables

Variable	Obs.	Mean	Std. dev.	Min	Max	Variables	Obs.	Mean	Std. dev.	Min	Max
Entry in a PV specialization	5,556	0.121	0.327	0	1	Exit a PV specialization	708	0.418	0.494	0	1
Technological relatedness density	5,556	10.179	16.389	0	100	Technological relatedness density	708	22.244	20.275	0	100

PV segment relatedness density	5,556	8.910	20.371	0	100	PV segment relatedness density	708	21.902	28.932	0	100
Scientific relatedness density	5,556	18.482	21.402	0	100	Scientific relatedness density	708	29.102	24.424	0	100
Revealed Scientific Advantage	5,556	0.174	0.380	0	1	Revealed Scientific Advantage	708	0.415	0.493	0	1
Sourced scientific knowledge	5,556	0.069	0.767	0	27.4	Sourced scientific knowledge	708	2.450	7.338	0	100.9
Scientific citation relatedness density	5,556	10.076	16.495	0	100	Scientific citation relatedness density	708	20.398	20.855	0	100

4. Results on entry and exit

Table 3 presents the findings of the entry model. Time fixed effects are present in all models as three periods are treated. Technology fixed effects are added in models 4 and 6 to control for differences in the several PV segments. We add country fixed effects in models 5 and 6, capturing characteristics of European countries that are deemed important in PV (Graf & Kalthaus, 2018). The country level was selected as environmental policies tend to be designed and applied at the national, instead of the regional level (Costantini et al., 2015; Costantini et al., 2017; Hansen & Coenen, 2015; Lanjouw & Mody, 1996).

The coefficient of the variable RSA is positive and significant in all specifications, showing that a strong scientific knowledge base in a PV segment enhances the likelihood of a region to develop a new technological specialization in the same PV segment. This confirms hypothesis 1a. The same is true for the variable Scientific Relatedness Density: a local presence in scientific fields related to a PV segment enhances the probability of a region to enter that same PV segment as a new technological specialization. This confirms hypothesis 1b. Overall, this means that the scientific capabilities of a region in a PV segment or around that PV segment play an important role in the technological entry of a region in such PV segment.

Table 3. Linear probability model explaining the probability of a European region to enter a new PV segment specialization

Dependent variable: Entry to a regional specialization in PV (0/1)						
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
RSA	0.093*** (0.012)		0.093*** (0.012)	0.071*** (0.012)	0.093*** (0.012)	0.070*** (0.012)
Scientific relatedness density	0.001*** (0.000)		0.001*** (0.000)	0.001** (0.000)	0.001*** (0.000)	0.000** (0.000)
Sourced scientific knowledge		0.001 (0.006)	-0.006 (0.006)	-0.008 (0.006)	-0.006 (0.006)	-0.009 (0.006)
Scientific citation relatedness density		0.001*** (0.000)	-0.000 (0.000)	0.000 (0.000)	-0.000 (0.000)	0.000 (0.000)

Technological relatedness density	0.002*** (0.000)		0.002*** (0.000)	0.001** (0.000)	0.001*** (0.000)	0.000 (0.000)
PV segment relatedness density	0.001** (0.000)		0.001** (0.000)	0.001*** (0.000)	0.001** (0.000)	0.001** (0.000)
Period FE	Yes	Yes	Yes	Yes	Yes	Yes
Technology FE	No	No	No	Yes	No	Yes
Country FE	No	No	No	No	Yes	Yes
Observations	5,556	5,556	5,556	5,556	5,556	5,556
R-squared	0.0390	0.0140	0.0400	0.093	0.0450	0.100
Standard errors in parentheses						
*** < 0.01, ** < 0.05, * < 0.1						

When looking at the two variables that account for external scientific linkages, we found no effect on regional entry probability. In almost all specifications, the coefficient of Sourced Scientific Knowledge is negative but never significant, meaning that external exposure to scientific knowledge through inter-regional citations does not affect the entry of the region to a new technological PV segment. This implies we have to reject Hypothesis 2a. However, the coefficient of Scientific Citations Relatedness Density is positive in all entry models, but significant only in model 2. Consequently, a region with external access to scientific knowledge that is related to a PV segment does not increase the probability of the region to enter that PV segment as a new technological specialization. This implies we have to reject Hypothesis 2b as well.

Overall speaking, the findings tend to indicate that regions rely mostly on their local scientific capabilities, and not so much on external scientific linkages, when diversifying into new specializations in PV technologies.

Concerning our two control variables of technological capabilities, Table 3 shows that the coefficients of both are positive and significant, meaning they tend to enhance the development of a new regional specialization in a PV segment. When one considers the individual characteristics of PV technological segments (technology FE in models 4 and 6), the PV Segment Relatedness Density turns out to be more important than Technological Relatedness Density. In other words, when considering the differences between PV segments, we observe that a region is more probable to diversify into a new PV segment when it has already technological competencies to other related PV segments. This means that diversification is more probable when it has competencies more proximate to the technological segment it enters, rather than to the wider set of technologies on which all the PV technological segments rely. This is also apparent from the increase of the explanatory power of the model when technological fixed effects are added. When only the country individual characteristics are considered (country FE), the relatedness to the wider set of technological fields is more important than the more narrowly defined relatedness to the PV technological segments.

Table 4 presents the findings concerning the probability of a region to exit an existing PV segment specialization. The results indicate that a local scientific knowledge base also matters for exit. Both the variables RSA and Scientific Relatedness Density show a negative and significant coefficient, meaning that scientific capabilities of a region in a PV segment or around that PV segment reduce the likelihood that this PV segment will disappear from the region as a technological specialization.

Table 4. Linear probability model explaining the probability of a European region (NUTS-2) to exit from an existing PV segment specialization

Dependent variable: Exit from a regional specialization in PV (0/1)						
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
RSA	-0.087** (0.038)		-0.087** (0.038)	-0.090** (0.038)	-0.093** (0.039)	-0.100** (0.039)
Scientific relatedness density	-0.003*** (0.001)		-0.002*** (0.001)	-0.002*** (0.001)	-0.002*** (0.001)	-0.003*** (0.001)
Sourced scientific knowledge		-0.008*** (0.002)	-0.007*** (0.003)	-0.008*** (0.003)	-0.007*** (0.003)	-0.008*** (0.003)
Scientific citation relatedness density		0.000 (0.001)	0.001 (0.001)	0.001 (0.001)	0.001 (0.001)	0.000 (0.001)
Technological relatedness density	0.000 (0.001)		-0.000 (0.001)	-0.000 (0.001)	0.001 (0.001)	0.000 (0.001)
PV segment relatedness density	-0.000 (0.001)		-0.000 (0.001)	-0.001 (0.001)	-0.000 (0.001)	-0.000 (0.001)
Period FE	Yes	Yes	Yes	Yes	Yes	Yes
Technology FE	No	No	No	Yes	No	Yes
Country FE	No	No	No	No	Yes	Yes
Observations	708	708	708	708	708	708
R-squared	0.029	0.016	0.040	0.079	0.093	0.136
Standard errors in parentheses						
*** < 0.01, ** < 0.05, * < 0.1						

What is interesting to observe is that the amount of external scientific linkages, as proxied by Sourced Scientific Knowledge, also prevents the region to exit its existing specialization in a PV segment. The more scientific knowledge is sourced from outside the region, the less probable it is that this region will exit a PV segment specialization. However, this is not the case for Scientific Citation Relatedness Density, showing no such significant effect on the exit probability of a region.

Our control variables Technological Relatedness Density and Related Density on PV segments show no significant effect on the probability that the region exists and existing PV specialization. This might have something to do with the specific nature of green technologies, and especially PV segments, whose development can be policy-driven. They might have also different degrees of technological complexity and may find themselves in different phases of their technological life cycle. Indeed, certain PV segments are phasing out (Barbieri et al., 2020).

5. Conclusions

There is increasing understanding that local capabilities contribute to the green transition in regions to a considerable degree, yet little evidence exists whether local scientific capabilities matter, and what is the role of inter-regional scientific linkages. To fill these gaps, the paper has assessed the importance of local scientific capabilities and the inflow of external scientific knowledge for the ability of regions in Europe to develop new technological photovoltaic segments. Our findings contribute to the literature on regional diversification and the role of scientific knowledge in it.

We find that relevant local scientific knowledge matters in Europe. Strong scientific capabilities of a region in a PV segment or related to that PV segment enhanced the probability of a region to build a new technological specialization in the same PV segment. These findings support the notion that a strong local scientific knowledge base in a specific PV segment enhances the likelihood of a region developing a new technological specialization in that very segment, aligning with previous research that highlights the importance of local scientific capabilities in fostering regional specialization (Balland & Boschma, 2022). It suggests that regions with a solid scientific foundation in a particular PV segment are more likely to enter and thrive in that specific segment, possibly due to the availability of human capital, research infrastructure, and knowledge spillovers.

However, we could not find significant evidence for the importance of inflow of relevant scientific knowledge from other regions which we proxied by scientific citations by PV patents, which deviates from our expectations. In sum, the findings indicate that regions rely primarily on their own local scientific capabilities, and not so much on external scientific linkages, when diversifying into new specializations in PV technologies. We did a similar analysis on the probability of European regions to keep or maintain existing PV specializations. This probability was significantly higher when the region had a strong relevant scientific base around them, and when they had access to scientific capabilities in other regions in the same PV specializations. The lack of significance of the technological base on the maintenance of existing PV specializations, suggests that the specific characteristics and dynamics of different PV segments may outweigh the scientific relatedness in influencing exit probabilities. This finding resonates with the idea that green technologies, including PV, may depend on policy-driven changes, different levels of technological complexity, and various stages of the technological life cycle.

Overall, our findings contribute to our understanding of the factors shaping regional specialization in PV technologies. They highlight the significance of the local scientific capabilities and technological competencies in determining the regional entry and exit probabilities in PV segments. The limited impact of external scientific linkages and the nuanced role of technological relatedness to PV segments emphasize the specific nature of green technologies and the need for region-specific analyses.

So, both scientific and technological capabilities play a role in green diversification, providing opportunities to regions to developing new green technologies (Montresor & Quatraro, 2020). The findings of this study have, therefore, relevant implications to green policies and Smart Specialization policies in Europe alike. Although environmental policies are often designed and implemented at the national level, this study confirms other studies (van den Berge et al., 2020) showing that regional capabilities, both of a technological and scientific nature, could be important for green diversification. Another lesson that could be drawn is that policy should target those green segments in which they have built capabilities that they could exploit for the development of green technologies.

Policy makers can focus on fostering and strengthening local scientific capabilities through investments in research infrastructure, promoting collaboration between universities and industry and providing financial support for research and development activities. By nurturing a robust local scientific ecosystem, regions can enhance their chances of entering new PV specializations. Despite the limited significance of external scientific linkages in PV, policy makers can still support knowledge spillovers and collaboration across regions (Cantner et al., 2016). Collaboration programs, joint research initiatives, and technology transfer mechanisms can help promote cross-pollination of ideas, ultimately strengthening the overall PV innovation ecosystem. Moreover, policies should be tailored to the unique needs and challenges of each PV segment, taking into account factors such as technological complexity, policy support mechanisms, market conditions, and stage in the technological life cycle. A nuanced approach that recognizes the heterogeneity within the PV sector can help foster specialization in different segments and support a diverse and sustainable PV industry in European regions. Additionally, given the nature of PV technologies and their dependence on long-term investment horizons, policy makers should provide stable and consistent policy frameworks. Clear and predictable policies, including renewable energy targets, research grants, and supportive regulatory frameworks, can provide a conducive environment for the growth of regional PV specializations. Long-term policy stability reduces uncertainty and facilitates the emergence of sustainable PV ecosystems in different regions. Finally, as environmental policies are typically designed and implemented at the national and supra-national levels, policy makers should ensure effective coordination and collaboration between national and regional levels. National policies should consider the unique regional characteristics and strengths in the PV sector, allowing for flexible implementation and tailored approaches at the regional level. Encouraging regional initiatives, fostering interregional cooperation, and empowering regional institutions can facilitate the development of regional PV specialization within the broader national policy framework.

Yet, our study entails certain limitations that require for further research. The findings call for further research on the characteristics of each technological segment (e.g. complexity or maturity) and of the national and regional institutions that are fostering or not regional green diversification. This study focuses to PV technology and its segments, which is the most representative of green technologies due to its standardization and number of technological segments. However, comparative research with other green technologies is needed, in order to generalize our findings. Finally, although we account for sourced scientific knowledge incoming to the region through citations, we do not account for other ways that regions source external scientific knowledge, i.e. through interregional collaboration, co-authorship. Co-authorship would import scientific knowledge in the region, in addition to the one obtained through citations of scientific publications, embedded to the co-authoring individuals.

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Appendix 1. Correlation between the variables of the entry model

	Entry in a PV specialization	Technological relatedness density	PV segment relatedness density	Scientific relatedness density	RSA	Sourced scientific knowledge	Scientific citation relatedness density
Entry in a PV specialization	1.000						
Technological relatedness density	0.138 (0.000)	1.000					
PV segment relatedness density	0.098 (0.000)	0.461 (0.000)	1.000				
Scientific relatedness density	0.111 (0.000)	0.252 (0.000)	0.147 (0.000)	1.000			
RSA	0.137 (0.000)	0.117 (0.000)	0.039 (0.000)	0.268 (0.000)	1.000		
Sourced scientific knowledge	0.026 (0.051)	0.165 (0.000)	0.109 (0.000)	0.089 (0.000)	0.032 (0.019)	1.000	
Scientific citation relatedness density	0.123 (0.000)	0.696 (0.000)	0.459 (0.000)	0.260 (0.000)	0.106 (0.000)	0.160 (0.000)	1.000

Appendix 2. Correlation between the variables of the exit model

	Exit a PV specialization	Technological relatedness density	PV segment relatedness density	Scientific relatedness density	RSA	Sourced scientific knowledge	Scientific citation relatedness density
Exit a PV specialization	1.000						
Technological relatedness density	0.044 (0.248)	1.000					
PV segment relatedness density	0.004 (0.907)	0.501 (0.000)	1.000				
Scientific relatedness density	-0.136 (0.000)	0.213 (0.000)	0.160 (0.000)	1.000			
RSA	-0.110 (0.003)	0.059 (0.117)	0.123 (0.001)	0.226 (0.000)	1.000		
Sourced scientific knowledge	-0.121 (0.001)	0.039 (0.306)	0.134 (0.000)	0.142 (0.000)	0.069 (0.065)	1.000	
Scientific citation relatedness density	0.004 (0.926)	0.647 (0.000)	0.498 (0.000)	0.192 (0.000)	0.061 (0.104)	0.049 (0.196)	1.000