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Do scientific capabilities in specific domains matter for technological diversification in European regions?

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ABSTRACT

Do scientific capabilities in regions translate into technological leadership? This is one of the most pressing questions in academic and policy circles. This paper analyzes the matching of scientific and technological capabilities of 285 European regions. We build on patent and publication records to identify regions that lie both at the scientific and technological frontiers (strongholds), that are pure scientific leaders, pure technological leaders, or just followers in 18 domains. Our regional diversification model shows that local scientific capabilities in a domain are a strong predictor of the development of new technologies in that domain in regions. This finding is particularly relevant for the Smart Specialization policy because it implies that the analysis of *domain-specific* scientific knowledge can be a powerful tool to identify new diversification opportunities in regions.

1. Introduction

Regional capabilities are considered a key pillar of Smart Specialization policy (Foray et al., 2009; McCann and Ortega-Argilés, 2015; Balland et al., 2019). According to his policy, regions should build on existing capabilities to develop new activities. This is in line with a general observation that regions tend to develop primarily new activities that draw on relevant (related) capabilities present in the region (Boschma, 2017; Hidalgo et al., 2018).

This so-called relatedness framework has been applied to map diversification opportunities of regions using different data sets, such as industry data (Neffke et al., 2011), occupational data (Muneepeerakul et al., 2013), product data (Boschma et al., 2013), and patent data (Kogler et al., 2013; Rigby, 2015; Petralia et al., 2017). Boschma et al. (2014) and Guevara et al. (2016) were the first to apply this framework to explain the evolution of science at the city level in biotech and physics respectively. Guevara et al. (2016) showed that the probability of developing a new scientific field in a country increases when related to scientific fields in which a country has strong expertise. Studies have also investigated whether scientific capabilities impact the probability of countries developing technologies that are related to scientific fields (Pugliese et al., 2019; Catalána and Figueroae, 2020). However, the relatedness framework has not yet been used to explore how scientific capabilities in specific fields affect the development of new technologies at the regional level. Increasing understanding of the importance of scientific knowledge for opportunities of regions to develop new activities would add another dimension to the Smart Specialization policy that is still relatively unexplored (Goddard et al., 2013).

It would also provide new insights into the role of scientific knowledge and universities for regional development. The science-technology nexus has been extensively examined (Narin et al., 1997; Patelli et al., 2017). There is a large body of literature showing that science acts as a source of knowledge for regional innovation (e.g. Jaffe et al., 1993; Audretsch and Feldman, 1996; Autant-Bernard, 2001; Acs et al., 2002). But studies also show that this relationship is far from straightforward. Local firms may lack the absorptive capacity to benefit from scientific excellence in a region (Roper and Love, 2006; Bonaccorsi, 2017). Academic and private organizations also have different incentive structures concerning knowledge production which may hamper university-industry collaborations in regions (Dasgupta and David, 1994; Gittelman and Kogut, 2003; Ponds et al., 2007). However, no study has applied the relatedness framework to assess how well scientific

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knowledge is transformed into technologies in regions.

The objective of this paper is to map the scientific and technological capabilities of regions in Europe for 18 domains, based on scientific publication and patent data. We examine whether there is an overlap between the scientific and technological base of regions in Europe in each of the domains. Our study identifies 4 types of regions in Europe, depending on the degree of overlap between the scientific and technological bases of regions in the 18 domains. We also find that regions in Europe change their position now and then, like scientific leaders that manage to transform into strongholds in a specific domain. Finally, we estimate a regional entry model to assess the role of local scientific capabilities for the development of technologies in 18 domains in 285 NUTS-2 regions in Europe. We find a positive relationship between a strong local scientific base in a domain and the ability of a region to develop technologies in the same domain during the period 2004–2018.

The paper is structured as follows. Section 2 provides a literature review. Section 3 explains how scientific domains are linked to technology fields, how relatedness between domains is calculated, and how a complexity measure for a domain is derived. Section 4 introduces a new typology of regions, depending on the overlap between the scientific and technological bases of a region in a domain. Section 5 presents the findings of the regional diversification model. Section 6 concludes and discusses implications for policy and future research.

2. Science and technology in regions

There is general agreement that new scientific and technological knowledge often builds on existing pieces of knowledge that are combined in new ways (Dosi, 1982). Researchers are often trained in narrowly defined domains, they work in relatively homogenous organizations, and they interact in professional communities they know well (Guevara et al., 2016). This makes that researchers and organizations are involved in search processes that tend to be highly localized (Nelson and Winter, 1982). This limits the opportunities to acquire new knowledge they are not familiar with and prevents them to enter distant fields (Atkinson and Stiglitz, 1969), like it will be extremely hard for an anthropologist to excel in physics. This makes that researchers develop new ideas mainly within their own scientific and technological domain.

However, researchers also cross scientific and technological boundaries. When they do so, they tend to interact and collaborate with fields that are close (related) to their own domain, as reflected in the composition of research consortia and citation behavior across different domains (Guevara et al., 2016). Studies consider domains to be related when they cite each other, or when they cite similar literature (Boyack et al., 2005; Leydesdorff and Rafols, 2009; Waltman et al., 2010). These patterns of knowledge flows across related domains have been used to assess the potential of regions to enter new domains (Guevara et al., 2016; Alshamsi et al., 2018). The probability that a region will enter a new domain is then expected to depend on the local presence of related domains. This principle of relatedness (Boschma, 2017; Hidalgo et al., 2018) has been applied to explain the emergence of industries (Neffke et al., 2011), occupations (Muneepeerakul et al., 2013) and technologies (Rigby, 2015) in regions. Boschma et al. (2014) and Guevara et al. (2016) applied this relatedness framework to explain the emergence of new scientific specializations in cities. In a study on the dynamics of scientific knowledge in biotech in 276 global cities, Boschma et al. (2014) showed that new scientific topics in biotech develop in cities where related scientific topics are already present. Guevara et al. (2016) showed that the probability of developing a new scientific field in physics in a country increases when related to scientific fields in which a country has already strong expertise.

Besides moving into related domains, regions are also perceived to have an incentive to develop more complex domains (Balland et al., 2019; Balland et al., 2022). Knowledge that is complex is hard to codify and difficult to imitate (Kogut and Zander, 1993). The more complex a knowledge domain is, the more it acts as a source of regional competitive advantage. Hidalgo and Hausmann (2009) defined products as complex when they combine many capabilities which makes them hard to copy. In contrast, simple knowledge domains are easy to copy and therefore have little economic value (Davies and Mare, 2019). Increasing the complexity of an economy has indeed shown to be beneficial for regional development (Davies and Mare, 2019; Mewes and Broekel, 2020; Pintar and Scherngell, 2020). But despite this incentive to develop complex activities, regions often fail to do so, unless they build on local related capabilities (Balland et al., 2019). Studies have measured the complexity of products and technologies (Balland and Rigby, 2017), but few studies have attempted to assess the complexity of scientific knowledge and domains (Wuchty et al., 2007; Heimeriks et al., 2019; Balland et al., 2020).

A critical question is whether the production of scientific knowledge actually leads to new technologies in regions. This relationship between science and technology has been extensively examined (Narin et al., 1997; Callaert et al., 2014; Patelli et al., 2017). Studies tend to report a positive impact of science on patenting in regions (e.g. Jaffe, 1989; Feldman, 1994; Audretsch and Feldman, 1996; Jaffe and Trajtenberg, 1996; Anselin et al., 1997; Varga, 2000; Autant-Bernard, 2001; Acs et al., 2002; Fleming and Sorenson, 2004; Moreno et al., 2005; Fritsch and Slavtchev, 2007; Leten et al., 2014). Jaffe et al. (1993) were one of the first to show that university research in a region is beneficial for innovation in that region, as knowledge spillovers from universities and academic research institutes are often geographically bounded.

However, studies also show this relationship is far from straightforward. There are different logics of knowledge production between science and industry that may hamper university-industry collaboration in regions. Broadly speaking, the objective of science is to create new knowledge and diffuse it as much as possible (e.g. through academic publishing), while the objective of industry research is to appropriate rents from private knowledge and thus to prevent its diffusion (Dasgupta and David, 1994; Etzkowitz and Leydesdorff, 2000; Gittelman and Kogut, 2003; Ponds et al., 2007; Bikard and Marx, 2020). Universities (especially the excellent ones) often tend to show a global orientation in their research, in which their home regions are not necessarily their primary focus (Power and Malmberg, 2008; Goddard et al., 2013; Bonaccorsi, 2017). Scientific research is also not useful for every industry to the same degree (Pavitt, 1984; Audretsch and Feldman, 1996; Klevorick et al., 1995; Cohen et al., 2002; Laursen and Salter, 2004; Leten et al., 2014). Moreover, there may be a disconnect between the local scientific knowledge base (especially stemming from basic research) and the absorptive capacity of local firms, especially in peripheral regions (Azagra-Caro et al., 2006; Roper and Love, 2006; Muscio, 2013; Scherngell and Barber, 2011; Bonaccorsi, 2017). Regions characterized by low-tech activities and small firms tend to show little appetite or demand for local scientific knowledge (Rodríguez-Pose, 2001; Lehmann and Menter, 2015).

So, knowledge produced in local universities is not necessarily relevant to regional industries. What is underexplored in this body of literature is that relatedness might be an important factor that enables the deployment of scientific knowledge and the development of new technologies in regions. Tran (2020) found that relatedness between science and technology facilitates knowledge diffusion from science to inventions in a region and increases the value of inventions. Other studies such as Pugliese et al. (2019) examined whether scientific capabilities impact the probability of countries to diversify into technologies that are related to scientific fields. Catalána and Figueroae (2020) found that the more a technology is related to the scientific portfolio of a country, the higher its entry probability. However, there is still little understanding of how scientific capabilities in specific domains provide opportunities to regions to develop new technologies in these domains. This is done in this paper for 285 European regions.

3. Characterizing scientific domains

The first step to take is to map the scientific and technological capabilities of regions in Europe, based on scientific publication and patent data. In particular, we assess whether there is an overlap between the scientific and technological base of regions in Europe in 18 domains. This section explains how we link scientific domains to technologies. Then, we characterize each scientific domain in terms of its level of relatedness with other domains and their level of complexity.

3.1. Linking scientific domains to technologies

There are several ways of determining a link between scientific fields and technologies. Scientific fields are often identified by linking scientific journals to specific scientific domains. Technological fields are identified by technology classes that are mentioned on patents. To connect scientific to technological domains, some studies use publication-patent citations (Callaert et al., 2014; Narin et al., 1997), that is, data on citations on a patent by a local inventor in the region to scientific publications of researchers in the region. A relatedness measure for each pair of technology domain (patent class) and scientific field (linked to scientific journals) can then be derived from co-occurrences between a technology and scientific field (Tran, 2020).

We use patent documents to link scientific domains to technologies, based on the description of technology (CPC) classes at the sub-domain level. Patent data are derived from the OECD REGPAT dataset (2020 version). Scientific publication data are based on Scopus bibliometric data provided by Elsevier and prepared by Science Metrix[1]. Science Metrix defines 20 scientific domains. Each scientific domain consists of sub-domains. For instance, the domain Agriculture, Fisheries & Forestry includes the sub-domains Agronomy & Agriculture, Dairy & Animal Science, Fisheries, Food Science, Forestry, Horticulture, and Veterinary Sciences. For some scientific sub-domains, it is straightforward to link them to technological classes, based on the description of the CPC classes in patent documents. For other scientific domains, this is less straightforward. For example, the domain of Enabling & Strategic Technologies consists of 7 sub-domains that do not always have a perfect match with CPC classes. In those cases, we employ text-mining techniques to link each sub-domain to CPC classes[2]. We managed to link 18 scientific domains to specific technology classes. The domain of Philosophy & Theology was removed because it could not be linked to any of the CPC classes, while the domain of Engineering was removed because it was connected to almost every CPC class.

3.2. Measuring relatedness between scientific domains

As mentioned before, some scientific fields are relevant to each other for knowledge production because they share similar capabilities, while other scientific fields have nothing in common. But how to determine which scientific domains are related to each other? This can be done in various ways. One can identify knowledge flows between scientific fields through co-citation networks that are based on references to different papers associated with disciplines in the same reference list of a paper (Boyack et al., 2005). Direct citation networks link academic fields when a paper from one discipline cites a paper from another. Another way concerns bibliographic coupling in which pairs of disciplines are connected when papers from different fields cite the same papers. An alternative is making use of the product space methodology (Hidalgo et al., 2007), in which two scientific fields are considered related if they are simultaneously over-represented in the same regions.

We developed a new approach to assess relatedness between scientific domains. We use the information on the links between scientific domains and CPC classes to derive a measure of relatedness between scientific fields. Relatedness is based on normalized co-occurrences of the 18 scientific domains on patent documents. If CPC classes linked to scientific field *1* often show up in combination on the same patent document with CPC classes linked to scientific field *2*, we consider the two scientific fields related. We normalize the co-occurrences using the cosine method (Balland and Boschma, 2021). The relatedness between scientific fields can be formalized as a network, the *Science Space*, a $n*n$ network where the individual nodes i ($i = 1, \ldots, n$) represent 18 scientific fields, and the links between them indicate their degree of relatedness.

Fig. 1 shows the Science Space for the period 2014–2018. Colours indicate groups of sciences by Science Metrix: the red coloured represent Applied Sciences, the yellow coloured Arts and Humanities, the orange coloured Economic and Social Sciences, the blue coloured Health Sciences, and the green coloured Natural Sciences. The highest relatedness scores are between the scientific fields of Information & Communication Technologies, Mathematics & Statistics, and Physics & Astronomy. Some scientific fields like Physics & Astronomy and Information & Communication Technologies are positioned more central in this scientific network: they share similar capabilities with many other sciences. This stands in contrast to other sciences like Historical Studies, Earth & Environmental Sciences, Psychology & Cognitive Sciences, and Built Environment & Design that are related to one other scientific domain only.

3.3. Measuring the complexity of scientific fields

Some scientific knowledge might be complex while other scientific knowledge is less so. Hidalgo and Hausmann (2009) argued that economic complexity is about the division of labor in which individuals narrow down their expertise and specialize (Jones, 2009). This idea can be applied to science where a division of labor between scientists can be observed at the level of a scientific paper (Wuchty et al., 2007). The complexity of a scientific field can then be proxied by the average size of a team involved in a publication in a scientific field (Balland et al., 2020) or by the share of publications in a field that involves international co-authorship.

We follow Hidalgo and Hausmann (2009) in which complexity reflects the difficulty of mastering capabilities that are required to excel in a domain which is shown by its rarity on the one hand, and the diversity of capabilities that need to be combined on the other hand. These features serve our purpose because it allows us to identify the capacity of regions to become technological leaders in a domain. This is because the domains that will appear on top will be the fields that most regions want to be leaders in but very few actually can.

Complexity is measured by using the eigenvector reformulation of the method of reflection (Caldarelli et al., 2012; Balland and Rigby, 2017). The starting point is a two-mode network that connects regions to scientific domains in which they have a Relative Scientific Advantage (RSA). RSA stands for the degree of specialization of a region in a scientific domain. The RSA in a scientific domain i equals the share of publications in domain i in the scientific portfolio of region r, divided by the share of scientific domain i in the scientific portfolio of Europe as a whole:

$$RSA_{r,i} = \frac{publications_{r,i} / \sum_i publications_{r,i}}{\sum_r publications_{r,i} / \sum_r \sum_i publications_{r,i}}$$

This two-mode network can be represented as a matrix M with dimension $n = 285$ regions (NUTS-2) by $k = 18$ scientific domains. This

[1] Science-Metrix is an independent research evaluation firm specializing in the assessment of science and technology (S&T) activities (science-metrix.com).

[2] We used text-mining techniques to identify CPC classes at whatever digit level (>250,000 CPC classes) so as to link them to a sub-domain. For instance, the sub-domain Nanotechnology in the domain Enabling and Strategic Technologies was linked to 15 CPC classes: B82Y, Y10S977, B82B, C01P2004, A61K9/51, B05D1/20, C01B32/05, G01Q, G02F1/017, H01F10/32, H01F41/30, H01L29/775, B81C1/00031, B81C2201/0149 and B81C2201/0187.

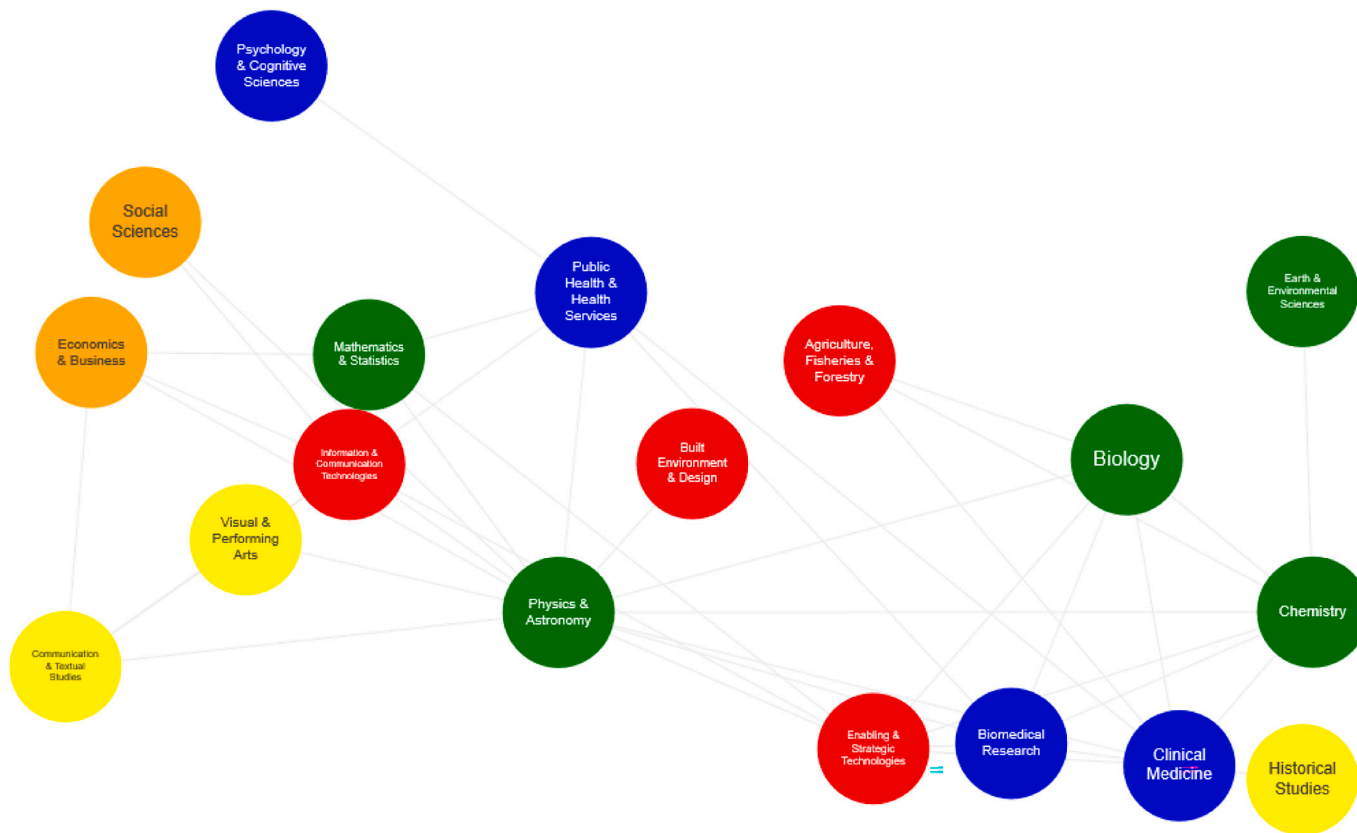


Fig. 1. Science space in Europe.

matrix M is row standardized along with its transpose. The resulting product matrix is a square matrix with dimensions equal to the number of scientific domains. The complexity of each domain is given by the elements of the second eigenvector of the matrix.

Table 1 ranks the 18 scientific domains in terms of their complexity for the period 2014–2018. The most complex domain is Physics & Astronomy, followed by Chemistry, Mathematics & Statistics, Enabling & Strategic Technologies, and Information & Communication Technologies. The least complex scientific domains are in Public Health & Health Services, Social Sciences, and Psychology & Cognitive Sciences.

Table 1
Complexity of scientific fields.

Rank	Scientific field	Complexity
1	Physics & Astronomy	1,28
2	Chemistry	1,19
3	Mathematics & Statistics	1,03
4	Enabling & Strategic Technologies	1,03
5	Information & Communication Technologies	0,78
6	Earth & Environmental Sciences	0,15
7	Agriculture, Fisheries & Forestry	0,06
8	Biology	−0,06
9	Clinical Medicine	−0.26
10	Built Environment & Design	−0,3
11	Historical Studies	−0,32
12	Economics & Business	−0,41
13	Biomedical Research	−0,48
14	Communication & Textual Studies	−0,7
15	Visual & Performing Arts	−0,73
16	Psychology & Cognitive Sciences	−0,92
17	Social Sciences	−1,02
18	Public Health & Health Services	−1,49

4. Overlap between scientific and technology domains in regions

An objective of the study is to determine whether a region with a strong scientific base in a particular field also shows a strong technological base in the same field. This would signal the region has a strong capacity to turn scientific knowledge into new technologies and that the two have co-evolved in the region. The previous section explained how scientific domains have been linked to technology fields. We use this information to determine whether there is a (mis)match between the scientific and the technological base in a region.

We measure the scientific knowledge base of a region by the number of scientific publications by local researchers in scientific journals that are linked to a scientific domain. We use the information provided by Science Metrix that links scientific journals to the 18 scientific domains. We measure the technological base of a region by the number of patents[3] by local inventors in a particular domain (which is associated with specific technology classes). In Table 2, we outline the number of scientific publications and patents for each domain in 32 European countries (EU-27, the UK and the four EFTA countries) for the period 2014–2018.

4.1. Four types of regions

For each domain, we compare the spatial distributions of

[3] The results we present use raw counts. If a patent/publication has 2 inventors located in 2 different regions, each region receives a '1'. If a patent/publication has 3 inventors located in 2 different regions (so two of the three inventors are in the same region), each region receives a '1' (so no double counting within the region). Using fractional counting leads to the same results: it does not impact the variation of field-region pairs.

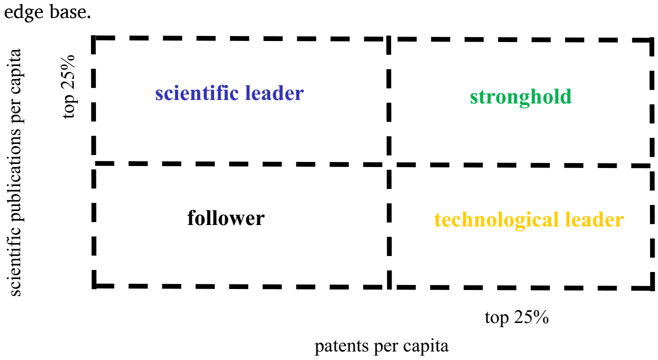
Table 2
Number of scientific publications and patents in 18 domains in Europe 2014–2018.

Domain	Scientific publications	Patents
Agriculture, Fisheries & Forestry	174,869	17,929
Biology	261,907	13,455
Biomedical Research	489,247	18,207
Built Environment & Design	56,962	16,668
Chemistry	325,519	59,559
Clinical Medicine	1,721,224	44,301
Communication and Textual Studies	52,583	1,609
Earth & Environmental Sciences	285,800	9,106
Economics & Business	185,927	4,254
Enabling & Strategic Technologies	485,100	42,118
Historical Studies	59,627	137
Information & Communication Technologies	478,046	57,334
Mathematics & Statistics	134,949	26,875
Physics & Astronomy	777,400	80,794
Psychology and Cognitive Sciences	152,768	389
Public Health & Health Services	167,250	2655
Social Sciences	200,467	2076
Visual & Performing Arts	6747	2335

publications per capita and patents per capita in Europe. As shown in Table 3, we distinguish four types of regions: (1) **strongholds** refer to regions that are successful in technologies in the same domain in which they have a strong scientific presence. Strongholds belong to the top 25 % (in terms of ranking) for both the number of patents per capita and the number of publications per capita in a domain; (2) **scientific leaders** refer to regions that show a strong scientific base but a weak performance in patenting in a domain. This signals that local scientific knowledge has not resulted in a strong performance in patenting in the same domain. Scientific leaders belong to the top 25 % (in terms of ranking) for the number of publications but not for the number of patents per capita; (3) **technology leaders** stand for regions that combine a relatively weak scientific base with a strong performance in patenting in a domain. Technology leaders belong to the top 25 % (in terms of ranking) regarding the number of patents but not the number of publications per capita. Technology leaders show that a strong technological base in a region in a domain does not necessarily go together with a strong underlying local scientific knowledge base; (4) **followers** concern regions that do not belong to the previous 3 categories: they score relatively low on both science and technology indicators in a domain.

For illustrative purposes, we show in Fig. 2 the map of the four types of regions for the domain of Information and Communication Technologies (ICT) for the period 2014–2018. Thirty-four regions in Europe were identified as strongholds: they match a strong scientific base with a strong technology base in this domain. The top 5 include Inner London-West, Helsinki-Uusimaa, Zurich, Stockholm, and the Lake Geneva region. Thirty-seven regions in Europe were defined as scientific leaders. They score high on scientific performance per capita but do not match that level as far as patenting per capita is concerned. The top 5 of scientific leaders is Trento, Luxembourg, Ticino, Prague and Saarland. We found 35 technology leaders showing a mismatch between their scientific capabilities (relatively weak) and their technology capabilities (relatively strong) in this domain. The top 5 of technology leaders in ICT consists of South Sweden, Inner London-East, Stuttgart, Hamburg and Oberpfalz.

Table 3
A typology of regions: matching of local scientific and technological knowledge base.



When looking at the geographies of all 18 domains in Europe, we find that strongholds tend to concentrate in regions in Northern and Western Europe. Zurich, Inner London-West and the Capital Region of Denmark are strongholds in many domains, but also regions like Lake Geneva region and Helsinki-Uusimaa. Scientific leaders are often more spread across Europe, combining a strong scientific knowledge base with relatively weak technological capabilities in a certain domain. The Prague region, followed by Upper Norland and Bratislava, are often mentioned in the top 5 scientific leaders. Germany is a country that stands out in particular, because it has no scientific leaders in any of the domains. Technology leaders are often found in Germany instead. Regions like Darmstadt, Central Switzerland, Mittelfranken and Rheinhessen-Pfalz show up most frequently as top 5 technology leaders in Europe that combine high levels of patenting with a relatively weak scientific knowledge base. Followers are located in many parts of Eastern and Southern Europe in almost all domains. Another observation is that regions in Southern Europe pop up as scientific leaders now and then, but rarely as strongholds and technology leaders: they tend to patent at relatively low levels, even when they have strong local scientific capabilities in a domain. In Eastern Europe, some regions sometimes score high as scientific leaders, especially in the domain of Chemistry, but regions in Eastern Europe seldomly belong to the categories of strongholds and technology leaders.

4.2. *Dynamics of regions in Europe, 2009–2018*

We also investigated whether regions shifted from one category to another in all 18 domains from the period 2009–2013 to 2014–2018. What we are especially interested in is whether scientific leaders can transform themselves into strongholds in a domain, and thus show an ability to improve their patenting activity to match their scientific capabilities. And to what extent are followers able to upgrade their technological and scientific capabilities over time?

As shown in Table 4, most regions stayed within the same category, especially followers. Fifty-four scientific leaders were able to transform themselves into strongholds in a domain, which amounts to a transition probability of almost 8 %. This shows that a strong scientific knowledge base of a region can lead to the development of strong technological capabilities in the same domain. This happened in many European countries, like in Trento (3 domains), Brussels (3 domains), Hannover (2 domains), South Finland (2 domains) and Luxembourg (2 domains). However, scientific leaders can also be downgraded to the status of followers, with a transition probability of 12 %. Examples of regions where that happened in 3 domains are Lancashire, Epirus, Estonia and North Holland. What were very rare events is that followers turn into strongholds, or the other way around, and that scientific leaders moved into technology leaders, or vice versa. For example, North Jutland and West Sweden managed to transform from a follower to a stronghold in two domains.

What is remarkable in Table 4 is that technology leaders are quite often downgraded to the category of followers (with a transition probability of 20 %), but seldomly to the ranks of strongholds in a domain. The list of 34 technology leaders that made it to stronghold is dominated by German and Swiss regions, like Oberbayern (3 domains), Hamburg (3 domains), Northwestern Switzerland (3 domains), Köln (2 domains), Mittelfranken (2 domains) and Espace Mittelland (2 domains). Furthermore, strongholds often look resilient over time, but if they

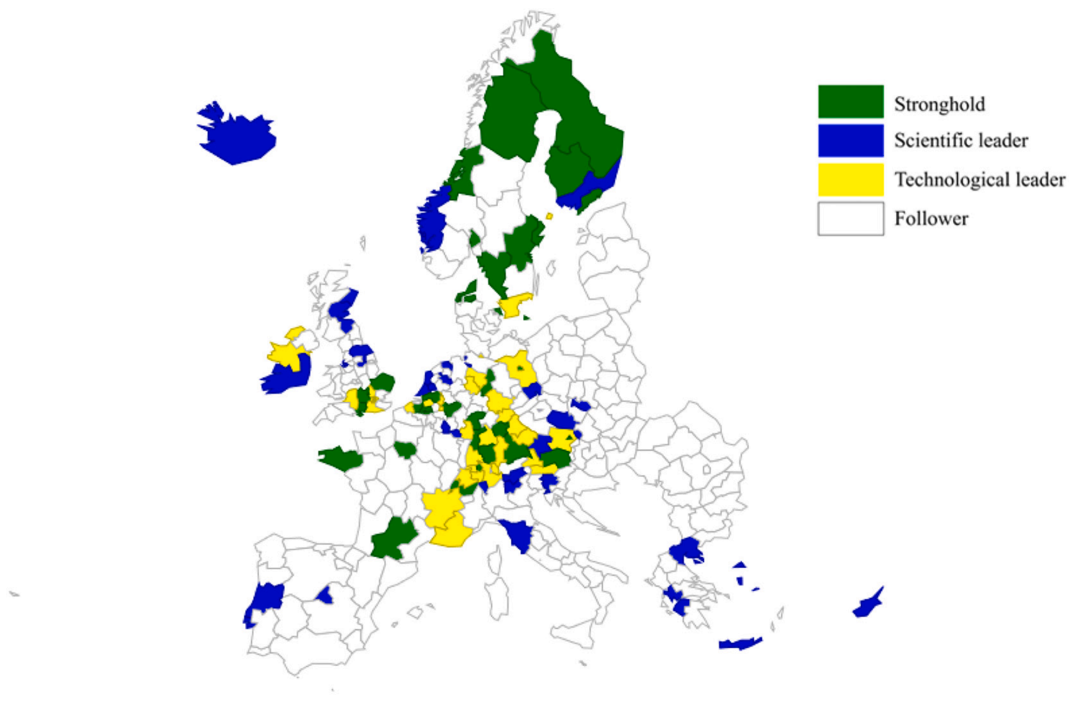


Fig. 2. A map of strongholds, scientific leaders, technology leaders and followers in the domain of Information and Communication Technologies in Europe (per capita).

Table 4
Evolution of types of regions 2009–2018.

		2014–2018				
		Stronghold	Scientific leader	Technology leader	Follower	Total
2009–2013	Stronghold	424	79	33	5	541
	Scientific leader	54	555	10	87	706
	Technology leader	34	5	438	120	597
	Follower	8	102	139	2965	3214
	Total	520	741	620	3177	5,058

change, they are more likely to become scientific leaders than technology leaders. Examples of the former transition are regions like Oslo and Akershus (6 domains), Upper Norrland (4 domains), Groningen (4 domains), Utrecht (3 domains), Brussels (3 domains), Eastern Scotland (3 domains), East Anglia (3 domains), Hampshire and Isle Of Wight (3 domains) and Central Denmark (3 domains). Examples of strongholds that downgraded to technology leaders are Freiburg (3 domains), Espace Mittelland (3 domains), Oberfranken (2 domains), Tubingen (2 domains), Ile de France (2 domains) and Rhone-Alpes (2 domains). Finally, it seems slightly easier for followers to become a technology leader than a scientific leader in a domain, but the transition probabilities are low (3.2 % and 4.3 % respectively).

5. Relationship between scientific base and new technology domains in regions

So far, we showed for each domain whether there is a match or not between the scientific and the technological base of regions. The next step is to determine to what extent a region has the potential to develop technologies in a domain, given its specific scientific base. We make use of the relatedness framework proposed by Balland et al. (2019) to make that assessment.

Balland et al. (2019) argue that regions should develop new technologies that are not only related to existing capabilities in a region but also make the regional economy more complex. Relatedness provides an indicator of the cost of diversifying from existing activities to a new activity in a region. Activities are considered related when they share similar capabilities and rely on similar knowledge and skills. The more related a potential new activity is to existing activities in a region, the lower the costs to develop this new activity. Complexity provides a way of assessing the potential economic benefits of diversifying into a new activity. As discussed, complexity refers to complex activities that are almost impossible to copy and are therefore of high economic value (Hidalgo and Hausmann, 2009): the higher the economic complexity of this activity, the higher the potential economic benefits.

To assess the potential of a region to develop technologies in each domain, we use a relatedness indicator that captures the idea that a region is more likely to develop technological domains that are related to existing technologies in the region. This requires two steps. First, we calculate a Technological Space to determine relatedness between all pairs of technologies. We use the same normalized co-occurrence approach as for the Science Space (using the Cosine). Second, we use the Technological Space to calculate for a region r the density of technologies in the vicinity of a technological domain i. To increase the level of precision, we triangulate the computation of Relatedness Density with all CPC classes rather than with only the 18 domains. Assume that ‘Clinical Medicine’ is related to 100 technologies (we use a binary example here for the sake of simplicity, but the relatedness variable is continuous in reality). If a region has a Relative Technological Advantage (RTA) in 10 of these technologies, Relatedness Density around

Clinical Medicine is 10/100 = 10 %. The density of technologies around technological domain *i* in region *r* is derived from the sum of relatedness $\phi_{i,j}$ of technological domain *i* to all other technologies *j* in which the region has a RTA, divided by the sum of relatedness of technological domain *i* to all other technologies *j* in the reference region (Europe):

$$\text{RELATEDNESS\_DENSITY}_{i,r} = \frac{\sum_{j\in r, j\neq i}\phi_{ij}}{\sum_{j\neq i}\phi_{ij}}*100$$

Besides relatedness, we account for the complexity of domains and the scientific knowledge base of a region to assess the potential of a region to develop technology domains. How we measured the complexity of domains has been explained before. To capture the effect of the local scientific knowledge base, we calculated the degree of specialization or the Relative Scientific Advantage (RSA) of a region in a scientific domain, as explained before.

5.1. Some descriptives

The previous measures allow us to assess the potential of a region to develop new technologies in the 18 domains. We illustrate this by comparing three types of regions: the Île-de-France region in France, as an example of a core urban region, Silesia, an old industrial region in Poland, and Extremadura, a peripheral region in the South of Spain.

In Figs. 3–5, each of the 18 domains is represented by a bullet. The size of the bullet indicates how specialized the region is in a scientific domain (RSA): the larger the size of the bullet, the more the region is specialized in that domain. It captures the idea that a region is more likely to develop a technological domain the more the region is specialized in the same scientific domain. The X-axis shows the Relatedness Density scores of each domain. This indicator captures the idea that a region has a higher potential to develop a technology domain the more technologies are present in the region that are related to this domain. The Y-axis shows the level of complexity of each domain. This captures the idea that a region will accrue higher economic benefits the higher the complexity of a domain.

Fig. 3 shows that Île-de-France has the highest potential to develop new technologies in Mathematics & Statistics, Information & Communication Technologies and Psychics & Astronomy, because the region scores high on all three indicators (scientific excellence, technological relatedness and complexity). Île-de-France also shows some potential in domains like Public Health & Health Services because of its high score on relatedness. However, this domain is not that complex, and the region also lacks very strong scientific capabilities in this domain. In contrast, Île-de-France shows a relatively low potential to develop technologies in the two domains coloured red on the left, which represent Agriculture, Fisheries & Forestry and Built Environment & Design. There is no scientific excellence in the two domains, local technologies that might have supported their development are missing in the region, and the two domains are not complex either.

Fig. 4 represents the case of Silesia which tells a very different story. Silesia has the highest potential to develop new technologies in Chemistry and Earth & Environmental Sciences because the region scores relatively high on all three indicators: it shows scientific excellence, the local presence of related technologies is relatively high, and the two domains are complex. Silesia tends to show some potential also in complex domains like Enabling & Strategic Technologies, Information & Communication Technologies and Agriculture, Fisheries & Forestry due to a strong scientific knowledge base, but the local presence of related technologies is relatively weak. However, Silesia shows low potential to develop new technologies in domains like Visual & Performing Arts, Public Health & Health Services, Economics & Business and Biology, showing low scores in these domains on all three indicators.

Fig. 5 presents the Spanish region of Extremadura, again a very different case. This peripheral region shows potential to develop new technologies in domains like Biology, Clinical Medicine and Agriculture, Fisheries & Forestry, because these domains show some complexity, and the region shows a strong scientific knowledge base in these domains and some presence of related technologies. Other domains like Built Environment & Design and Economic & Business tend to show some potential because the region has some scientific capabilities in these domains, but the region basically lacks related technologies on which these technological domains could build, and the complexity of these domains is not that high.

5.2. Regional diversification model

To test how prior scientific knowledge contributes to technological diversification, we assess quantitatively the extent to which a local scientific knowledge base in a domain contributes to the ability of a region to develop technologies in that same domain in a region. Following

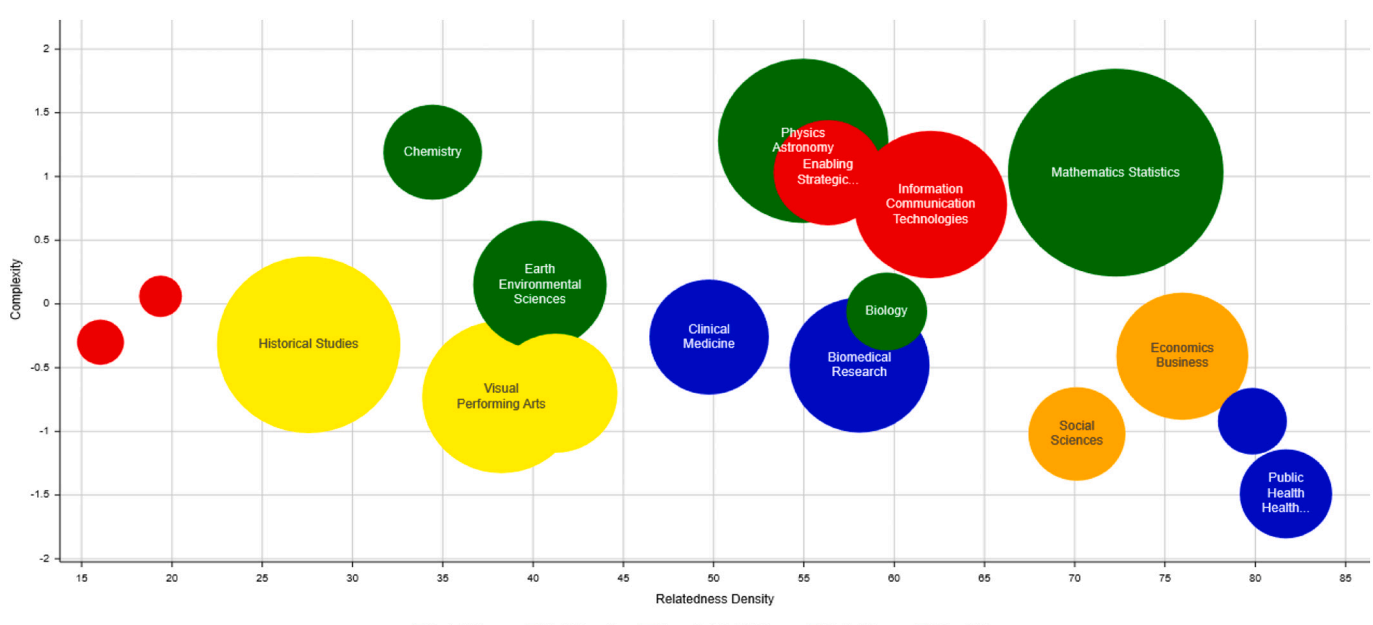


Fig. 3. The potential of Île-de-France (FR10) to develop 18 technological domains.

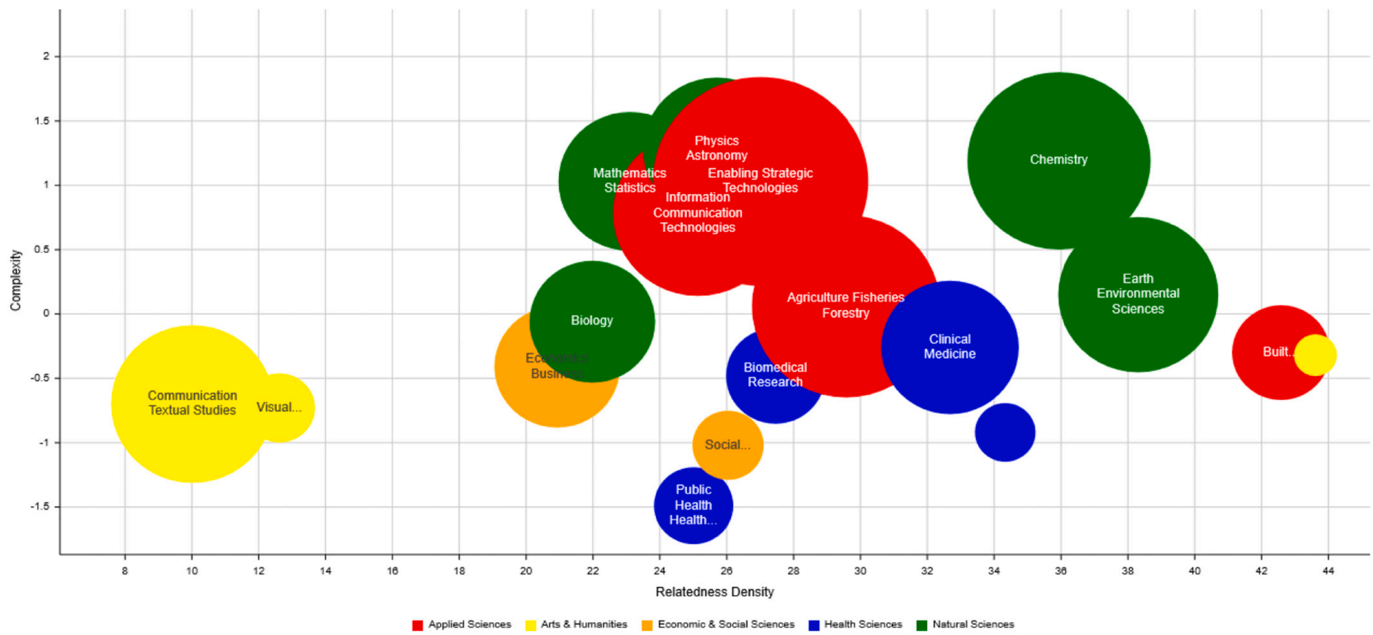


Fig. 4. The potential of Silesia (PL22) to develop 18 technological domains.

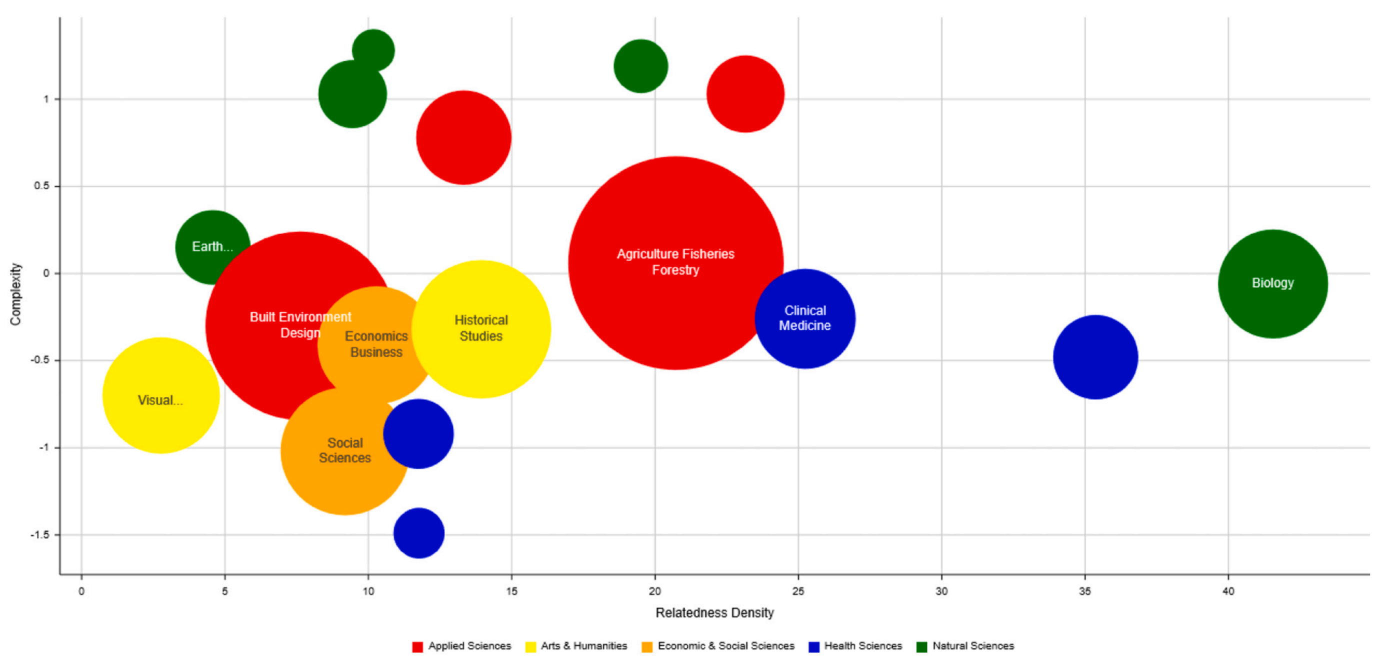


Fig. 5. The potential of Extremadura (ES43) to develop 18 technological domains.

Boschma et al. (2015), we assess the probability of 285 NUTS-2 regions in Europe (EU-27, UK, the four EFTA countries) to enter a new technological domain in the period 2004–2018. Patent data are used and derived from the OECD REGPAT dataset (2020 version) that makes a distinction between 654 patent classes (CPC) at the 4-digit level.

The dependent variable is the entry (1), or not (0), of a new specialization in 1 of the 18 technological domains in a region. A linear probability model is used to assess the probability that a region develops a Relative Technological Advantage (i.e. RTA > 1) in a new technological domain in the period 2004–2018. Following other studies, we assess the entry probability of a new technological domain in a time window of 5 years, for 3 subsequent periods (2004–2008, 2009–2013 and 2014–2018). The maximum number of observations is 285 (regions) *18 (domains)*3 (periods) = 15,390. By construction, we exclude the regions in each next period that are already specialized in a domain. We have a total of 9995 potential entries.

All independent variables are measured in the period before the time window of 5 years. So, for the first entry period 2004–2008, we construct the independent variables for the period 2000–2003. The main variable of interest is Scientific Specialization, captured by the Relative Scientific Advantage (RSA) measure[4]. It assesses the possible effect of the degree of specialization in a scientific domain in a region on the

[4] RSA is a continuous variable in the model. This allows us to use more information about the degree of scientific specialization rather than the existence of scientific specialization.

entry probability of new technologies in that same domain in a region. We included in our analysis all 18 domains, although there is not much patenting going on in some domains, such as 'Historical studies' and 'Psychology and Cognitive Sciences'. By doing so, we follow a conservative approach, because if RSA would still show a positive and significant result, we would have a strong indication it matters for technological diversification, despite including some domains that have a lower propensity to patent. The other variable of interest is Relatedness, which is measured by the Relatedness Density measure. It assesses the possible effect of related technologies on the entry probability of a new technological domain in a region. Finally, we included a control variable Scientific Publications that accounts for the total number of scientific publications in a region in a given period (in a log form). This is to test whether the amount of local scientific knowledge rather than local scientific knowledge in specific domains matters for regional diversification.

We ran a linear probability model with time-fixed effects to estimate the possible impacts of Scientific Specialization and Relatedness Density on technological diversification in regions in Europe. The first model in Fig. 6 shows a positive and significant coefficient of Scientific Specialization: the higher the Scientific Specialization of a region in a specific domain, the higher the likelihood that this region will develop new technologies in that same domain. For instance, this is in line with our earlier observation that followers have a very low probability to become technology leader in a specific domain. The second model shows that Relatedness Density is also positive and significant. This confirms earlier studies that a new technological domain is more likely to enter a region when related to existing technologies in a region. Model 3 shows that the positive effect of Scientific Specialization remains when Relatedness Density is included. So, in general, science does seem to translate well into new technological domains at the regional scale in Europe. In Models 4–6, we included region and industry fixed effects. Results remain qualitatively similar for the two main variables of interest, while the overall fit of the models increases[5]. In Model 7, we include a control variable measuring the total number of scientific publications in a region. This variable is not significant while the other results remain, showing that local scientific knowledge in specific domains, rather than local scientific knowledge per se, matters for technological diversification in regions.

6. Conclusions and implications

This paper compared the scientific and technological capabilities of 285 European regions in 18 domains. When exploring the degree of overlap between the scientific and technological base of regions in Europe in each domain, we identified 4 types of regions. The first type consists of regions that combine a strong scientific and technological base in the same domain. Strongholds tend to concentrate in regions in Northern and Western Europe. The second type concerns a group of regions with a strong scientific base but failing to build a strong local presence in technologies in the same domain. These so-called scientific leaders are often more spread across Europe. The third group of regions consists of technology leaders that have a strong technological base in a domain without having a strong scientific base in that domain. These regions demonstrate that technological capabilities in a domain do not necessarily require a strong underlying local scientific base. The fourth type of region concerns so-called followers and includes the highest number of regions. They score relatively poorly both in science and technology in almost all 18 domains. Followers are found in most East European regions, as well as in many peripheral regions in Southern Europe.

[5] We also ran robustness checks using logit and probit models. As is quite common in the regional diversification literature, we found no meaningful differences.

We also investigated whether regions shifted from one category to another in a domain in the period 2009–2018. We found that most regions did not change position. This is especially true for followers that often seem to be trapped, although some followers managed to upgrade their technological capabilities. Perhaps most interesting was the finding that scientific leaders turn into strongholds in a domain now and then, suggesting that a strong scientific knowledge base in a region may provide a base for the development of technological capabilities in the same domain. Another finding was that technology leaders were quite often downgraded to the category of followers but seldomly managed to move up to the ranks of strongholds in a domain.

Finally, we examined whether a scientific knowledge base of a region enhanced the probability of a region developing technologies in the 18 domains. We estimated a technological diversification model including 285 NUTS regions covering the period 2004–2018. We found a positive relationship between a strong local scientific base in a domain and the ability of a region to develop new technologies in that specific domain.

Now, what are possible policy implications? First, the study shows that local scientific capabilities can provide opportunities to regions to develop new technologies in specific domains. This finding is relevant for the Smart Specialization policy that argues that regions should build on local capabilities to develop new and revive existing activities (Foray et al., 2009; McCann and Ortega-Argilés, 2015; Balland et al., 2019). The study makes clear that local scientific knowledge in specific domains, rather than local scientific knowledge per se, matters in this respect. This aligns with the idea that a Smart Specialization policy should target very specific capabilities and develop a tailor-made policy that accounts for the specific assets and needs in regions (Foray, 2015). Exploiting local scientific capabilities in specific domains would add a dimension to the Smart Specialization policy that is still relatively unexplored (Goddard et al., 2013). Second, the study also makes clear that a strong scientific knowledge base (including the presence of universities) does not necessarily result in new technologies and regional development. This has high policy relevance, as policy could aim to tackle barriers and bottlenecks that prevent regions to exploit fully their scientific potential. We identified 4 types of regions when looking at the overlap between their scientific and technological base. For each of these types, one could formulate region-specific policy recommendations. In strongholds, it seems a matter of maintaining scientific excellence and staying at the scientific frontier, and ensuring there are strong spillovers between science and industry. Scientific leaders are a very interesting case because in these regions policy should take away barriers that prevent the exploitation of local scientific capabilities and their diffusion into the regional economy. In the case of technological leaders, our findings suggest they often have a hard time becoming a stronghold. On top of that, there might be a risk of lock-in when these regions do not build a solid science base that connects to their technological base (Sánchez-Barrioluengo, 2014). As Pezzoni et al. (2019) have shown, combining technological components with a science-based nature can result in new technologies that are more disruptive and have more of an impact. While for followers, it is important that new scientific knowledge (or a new center of excellence) is created not in isolation from but closely related to existing activities in the region. This would prevent the classic policy mistake to build scientific cathedrals in the desert in less developed regions (Vallance et al., 2018; Marques et al., 2019).

These findings also call for further research. First, it would be very interesting to study how EU regions compare to regions in the US and China when it comes to the matching of scientific and technological output. Second, there is a need to replicate this study using other relatedness measures that capture relatedness between scientific fields and technologies (Catalána and Figueroae, 2020), to test whether regions in Europe are more likely to develop technologies that are related to scientific fields. Third, we identified a match or mismatch between scientific and technological output in specific domains in regions, but we did not investigate why this is the case in particular regions. A follow-up study should examine systematically whether this is due to a weak

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Scientific specialization	0.014***		0.013***	0.014***	0.013***	0.014***	0.014***
	(0.004)		(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Relatedness density		0.002***	0.002***	0.002***	0.004***	0.004***	0.004***
		(0.0003)	(0.0003)	(0.0003)	(0.0005)	(0.001)	(0.001)
Scientific publication (log)							0.014
							(0.022)
Period FE	YES	YES	YES	YES	YES	YES	YES
Region FE	NO	NO	NO	YES	NO	YES	YES
Industry FE	NO	NO	NO	NO	YES	YES	YES
Constant	0.162***	0.151***	0.139***	0.076	0.092***	0.023	-0.031
	(0.007)	(0.007)	(0.008)	(0.060)	(0.020)	(0.062)	(0.103)
Observations	9,995	9,995	9,995	9,995	9,995	9,995	9,995
R^2	0.001	0.005	0.006	0.074	0.021	0.091	0.091
Adjusted R^2	0.001	0.004	0.006	0.047	0.019	0.062	0.062
Residual Std. Error	0.383 (df = 9991)	0.382 (df = 9991)	0.382 (df = 9990)	0.374 (df = 9706)	0.379 (df = 9973)	0.371 (df = 9689)	0.371 (df = 9688)
F Statistic	4.964*** (df = 3; 9991)	15.697*** (df = 3; 9991)	15.096*** (df = 4; 9990)	2.701*** (df = 288; 9706)	10.390*** (df = 21; 9973)	3.163*** (df = 305; 9689)	3.154*** (df = 306; 9688)
Note:			*p**p***p<0.01				

Fig. 6. Technological diversification model.

absorptive capacity of local firms, poor science-industry linkages, national institutions, among other factors. Fourth, we did not account for the fact that scientific knowledge available in other regions may be relevant for a region, the more so when the region is short of that knowledge. Regions have access to scientific knowledge in other regions through research collaborations, among other channels (McKelvey et al., 2003; Moodysson, 2008; Ponds et al., 2010; Hoekman, 2012). Future work could assess the effect of inter-regional scientific ties on the ability of regions to develop technologies, including the effect of complementary inter-regional linkages (Balland and Boschma, 2021). Fifth, when identifying technological capabilities and leadership of regions, we made use of the inventor address on the patent document, because it provides information on where the knowledge production took place. This is not necessarily the same region where the applicant is located, especially when this concerns a big company with headquarters elsewhere. Future research should therefore focus on whether technological leadership is actually followed by commercial exploitation in the same region. Sixth, we used patent data to assess whether local scientific knowledge results in new technologies in regions. This is just one way of measuring the local impact of science. There might be other effects, like the education of high-skilled people, knowledge spillovers to local firms, academic spinoffs, and innovations by firms (D'Este et al., 2013; Goddard and Vallance, 2013; Vallance, 2016). Finally, it would be interesting to explore in detail the dynamic interplay between science and technology in regions over time, using a qualitative case study approach. Our study found intriguing cases of scientific leaders transforming into strongholds in a specific domain, but the question is why and how. Studies that have investigated in detail the co-evolution of academic and industrial domains in regions should act as a source of inspiration (Kenney and Mowery, 2014; Lehmann and Menter, 2015).

CRediT authorship contribution statement

Pierre-Alexandre Balland: Conceptualization, Data curation, Formal analysis, Funding acquisition, Investigation, Methodology, Software, Validation, Visualization, Writing – original draft, Writing – review & editing. **Ron Boschma:** Conceptualization, Formal analysis, Funding acquisition, Investigation, Project administration, Resources, Supervision, Writing – original draft, Writing – review & editing.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Pierre-Alex Balland reports financial support was provided by European Commission, DG Urban and Regional Policy. Ron Boschma reports financial support was provided by European Commission, DG Urban and Regional Policy.

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