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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.

Key words: science-technology link, regional diversification, relatedness, strongholds, scientific capabilities, technological capabilities, Smart Specialization policy

JEL codes: B52, O33, R11

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 framework, 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. Guevarra 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 et al. 2020). However, no study yet exists using the relatedness framework that explores 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 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 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 how 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 (Guevarra 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 (Guevarra 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 (Guevarra 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. Guevarra 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). 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) was 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; 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; 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; Lehman 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 et al. (2020) found that the more a technology is related to the scientific portfolio of a country, the higher its entry probability. However, there exists no study that explores 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

A first step to take is to map 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 their level of relatedness with other domains and their level of complexity.

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, 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 a 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 Metrix¹. 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. 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.

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

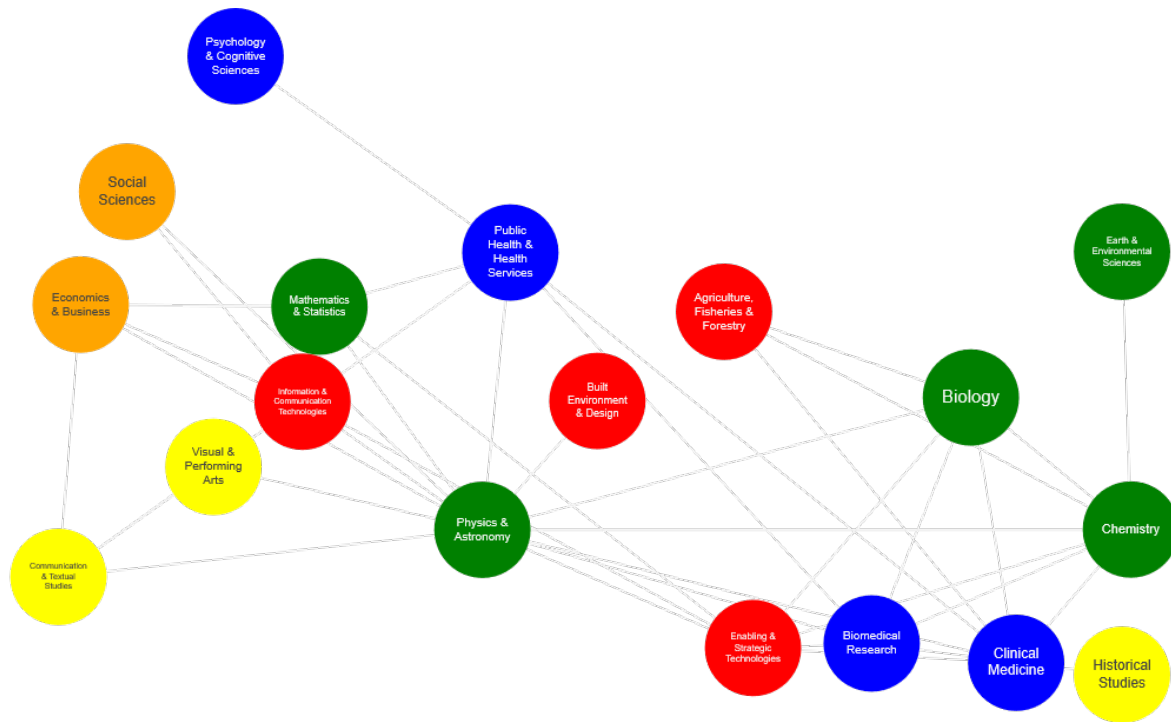
¹ Science-Metrix is an independent research evaluation firm specializing in the assessment of science and technology (S&T) activities ([science-metrix.com](https://www.science-metrix.com)).

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. The relatedness between scientific fields can be formalized as a network, the *Science Space*, a $n*n$ network where the individual nodes i ($i = 1, \dots, n$) represent 18 scientific fields, and the links between them indicate their degree of relatedness.

Figure 1 shows the Science Space for the period 2014-2018. Colors 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.

Figure 1. Science Space in Europe



Measuring the complexity of scientific fields

Some scientific knowledge might be complex while other scientific knowledge is less so. To our knowledge, there exists no complexity measure for scientific fields. 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. Complexity is measured by using the eigenvector reformulation of the method of reflection (Balland and Rigby 2017). The starting point is a binary-valued network that connects regions to scientific domains in which they have a Relative Scientific Advantage. This matrix M has dimension $n = 285$ regions (NUTS-2) by $k = 18$ scientific domains. This matrix M is row standardized along with its transpose. The resulting product matrix is a square matrix with dimension 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 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.

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 |

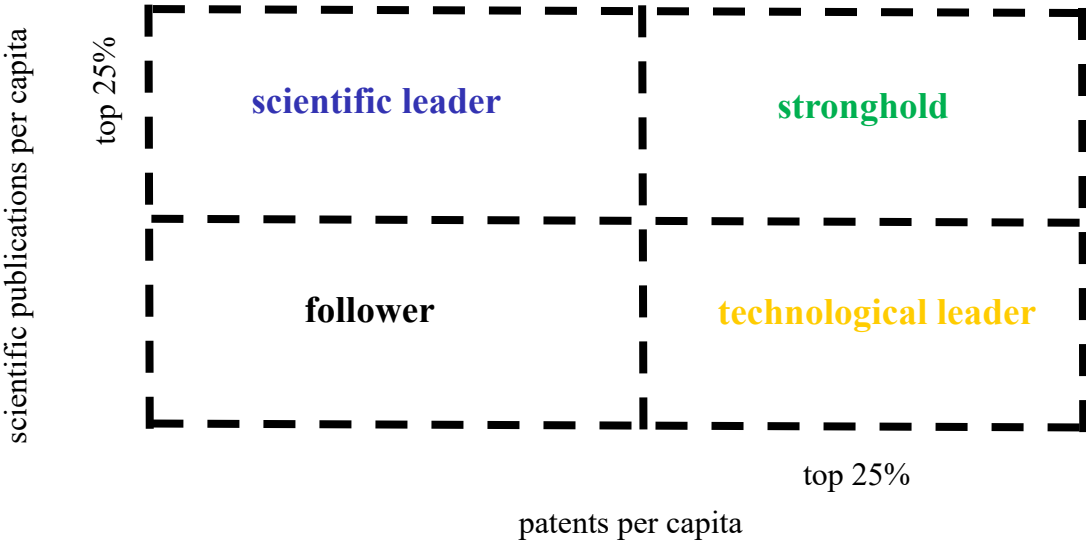
| | | |
|--|-----------|--------|
| Biology | 261,907 | 13,455 |
| Biomedical Research | 489,247 | 18,207 |
| Built Environment & Design | 56,962 | 16,668 |
| Chemistry | 325,519 | 59,559 |
| Clinical Medicine | 1,721,224 | 44,301 |
| Communication and Textual Studies | 52,583 | 1,609 |
| Earth & Environmental 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 | 2,655 |
| Social Sciences | 200,467 | 2,076 |
| Visual & Performing Arts | 6,747 | 2,335 |

Four types of regions

For each domain, we compare the spatial distributions of 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**

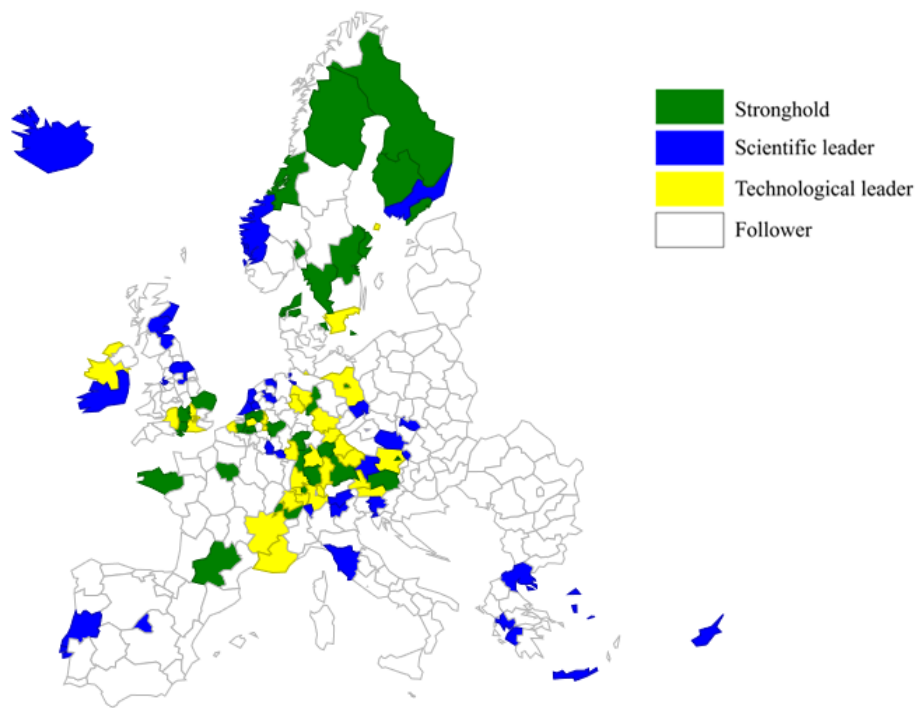
concern regions that do not belong to the previous 3 categories: they score relatively low on both science and technology indicators in a domain.

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



For illustrative purposes, we show in Figure 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 stronghold: they match a strong scientific base with a strong technology base in this domain. The top 5 includes 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.

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



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 of 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.

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 showing 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.

Table 4. Evolution of types of regions 2009-2018

| | | 2014-2018 | | | |
|-----------|-------------------|------------|-------------------|-------------------|----------|
| | | Stronghold | Scientific leader | Technology leader | Follower |
| 2009-2013 | Stronghold | 424 | 79 | 33 | 5 |
| | Scientific leader | 54 | 555 | 10 | 87 |
| | Technology leader | 34 | 5 | 438 | 120 |
| | Follower | 8 | 102 | 139 | 2,965 |
| | | | | | |

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 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 their 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 $\phi_{i,j,t}$ 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 calculate the degree of specialization in a scientific domain in a region, measured as the Relative Scientific Advantage (RSA) in a scientific domain. The RSA in a scientific domain i in time t is given as the share of publications in domain i in the region’s scientific portfolio, divided by the share of scientific domain i in the scientific portfolio of Europe as a whole:

$$RSA_{r,i} = \frac{publications_{r,i} / \sum_i publications_{r,i}}{\sum_r publications_{r,i} / \sum_r \sum_i publications_{r,i}} > 1$$

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 Figures 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.

Figure 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 colored 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.

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

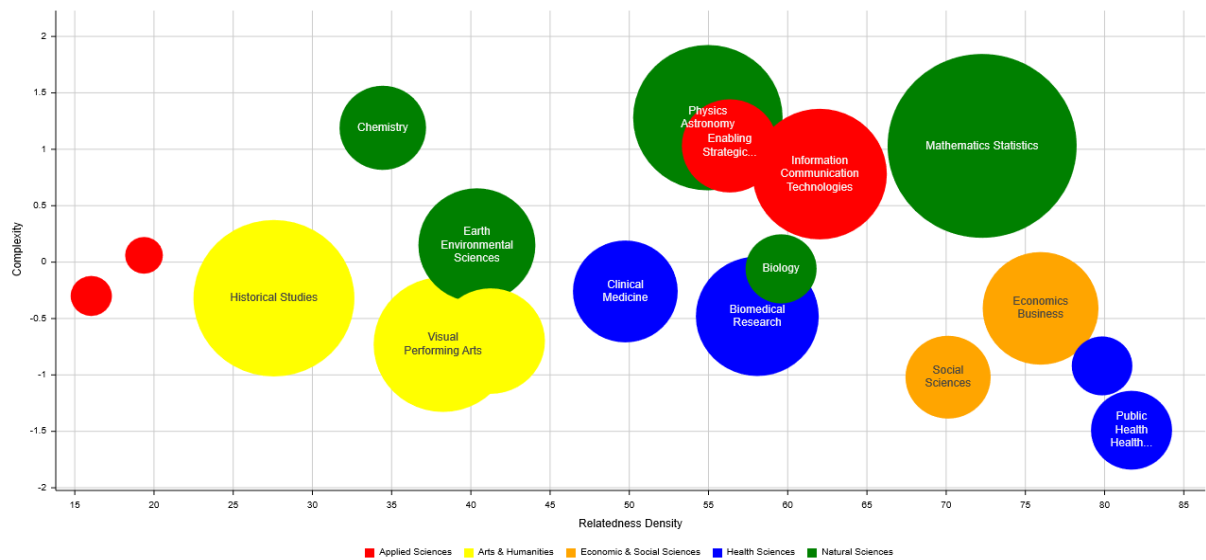


Figure 4 represents the case of Silesia which tells a very different story. Silesia has the highest potential to develop new technologies in Chemistry and Earth & Environmental Sciences because the region scores relatively high on all three indicators: it shows scientific excellence, the local presence 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.

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

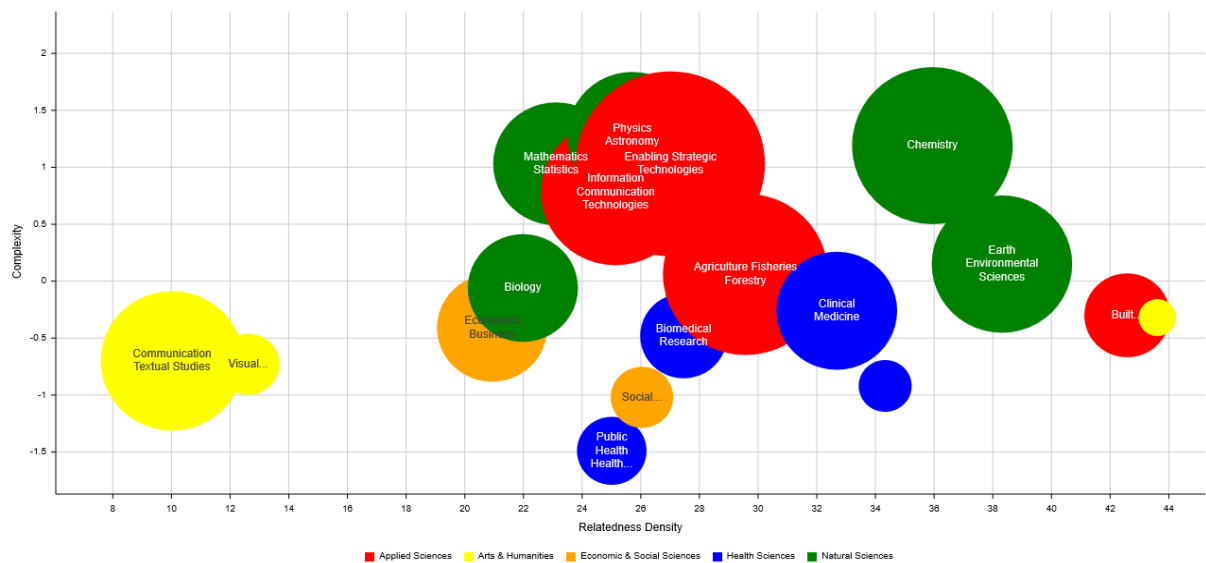
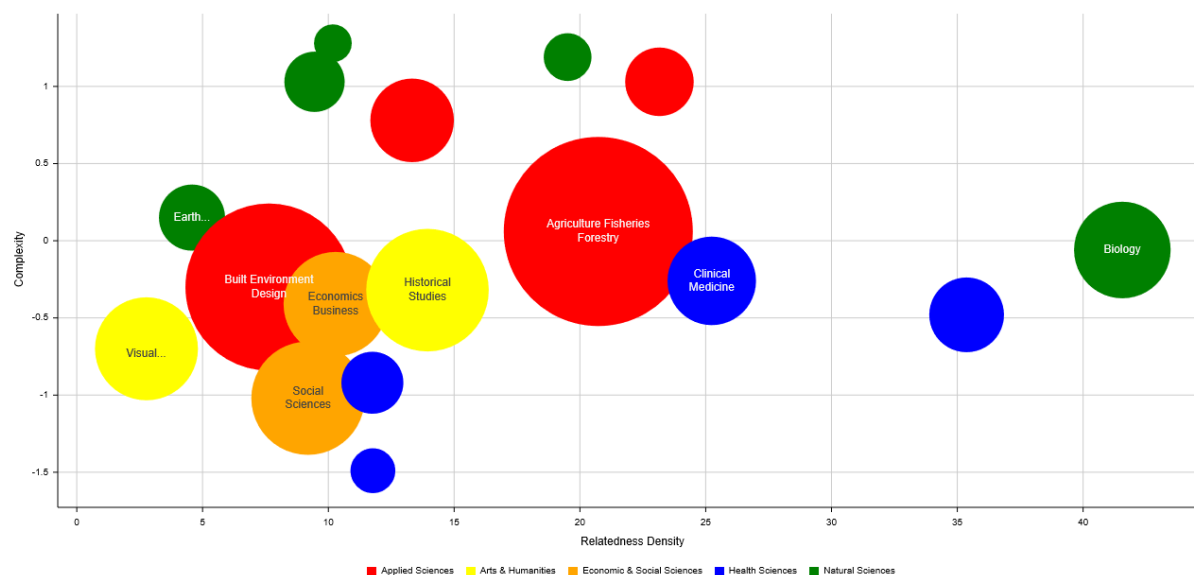


Figure 5 presents the Spanish region of Extremadura, again a very different case. This peripheral region shows potential to develop new technologies in domains like Biology, Clinical Medicine and Agriculture, Fisheries & Forestry, because these domains show some complexity, and the region shows a strong 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.

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



Regional diversification model

To dynamically 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 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 9,995 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. It assesses the possible effect of the degree of specialization in a scientific domain in a region on the entry probability of new technologies in that same domain in a region. 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.

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 Figure 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. 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 variables of interest, while the overall fit of the models increases.

Figure 6. Diversification model

| | (1) | (2) | (3) | (4) | (5) | (6) |
|----------------------------------|--------------------------------|---------------------------------|---------------------------------|----------------------------------|----------------------------------|----------------------------------|
| Scientific specialization | 0.014*** | | 0.013*** | 0.014*** | 0.013*** | 0.014*** |
| | (0.004) | | (0.004) | (0.004) | (0.004) | (0.004) |
| Relatedness density | | 0.002*** | 0.002*** | 0.002*** | 0.004*** | 0.004*** |
| | | (0.0003) | (0.0003) | (0.0003) | (0.0005) | (0.001) |
| Period FE | yes | yes | yes | yes | yes | yes |
| Region FE | no | no | no | yes | no | yes |
| Industry FE | no | no | no | no | yes | yes |
| Constant | 0.162*** | 0.151*** | 0.139*** | 0.076 | 0.092*** | 0.023 |
| | (0.007) | (0.007) | (0.008) | (0.060) | (0.020) | (0.062) |
| Observations | 9,995 | 9,995 | 9,995 | 9,995 | 9,995 | 9,995 |
| R² | 0.001 | 0.005 | 0.006 | 0.074 | 0.021 | 0.091 |
| Adjusted R² | 0.001 | 0.004 | 0.006 | 0.047 | 0.019 | 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) |
| 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) |
| Note: | * p ** p *** p<0.01 | | | | | |

6. conclusions and implications

This paper compared the scientific and technological capabilities of 285 European regions in 18 domains. First, we explored which of the 18 domains share similar capabilities. It turned out that the domains of Information & Communication Technologies, Mathematics & Statistics and Physics & Astronomy are the most related ones, sharing capabilities with many other domains. We also developed a measure to determine the level of complexity of the 18 domains. Our findings suggest that the most complex domains are Physics & Astronomy, Chemistry, Mathematics & Statistics, Enabling & Strategic Technologies, and Information & Communication Technologies.

When exploring the degree of overlap between the scientific and technological base of regions in Europe in the 18 domains, 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 regions 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.

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 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 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.

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 et al. 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 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, 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). 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 source of inspiration (Kenney and Mowery 2014; Lehman and Menter 2015).

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References

- Acs, Z. J., Anselin, L. and Varga, A. (2002) Patents and innovation counts as measures of regional production of new knowledge, *Research Policy* 31 (7), 1069–1085.
- Alshamsi, A., F. Pinheiro and C. Hidalgo (2018) Optimal diversification strategies in the networks of related products and of related research areas. *Nat. Commun.* 1–7. <https://doi.org/10.1038/s41467-018-03740-9>.
- Anselin, L., A. Varga and Z. Acs (1997) Local geographic spillovers between university research and high technology innovations. *Journal of Urban Economics* 42 (3), 422–48.
- Atkinson A. B. and Stiglitz J. E. (1969) A new view of technological change, *Economic Journal* 79, 573–578.
- Audretsch, D. B. and M. P. Feldman (1996) R&D spillovers and the geography of innovation and production. *The American Economic Review* 86 (3), 630–40.
- Autant-Bernard, C. (2001) Science and knowledge flows: evidence from the French case. *Research Policy* 30, 1069–1078.
- Azagra-Caro, J. M., F. Archontakis, A. Gutiérrez-Gracia, and I. Fernández-de-Lucio (2006) Faculty support for the objectives of university–industry relations versus degree of R&D cooperation: The importance of regional absorptive capacity, *Research Policy* 35, 37–55.
- Balland, P. and R. Boschma (2021) Complementary inter-regional linkages and Smart Specialization. An empirical study on European regions, *Regional Studies*, forthcoming.
- Balland, P.A., R. Boschma, J. Crespo and D. Rigby (2019) Smart specialization policy in the EU: Relatedness, knowledge complexity and regional diversification, *Regional Studies* 53(9), 1252-1268.
- Balland, P.A., Jara-Figueroa, C., Petralia, S., Steijn, M., Rigby, D., and Hidalgo, C. (2020) Complex economic activities concentrate in large cities, *Nature Human Behavior* 4, 248–254.
- Balland, P.-A. and D. Rigby (2017) The geography of complex knowledge. *Economic Geography* 93(1), 1–23.
- Bikard, M. and M. Marx (2020) Bridging academia and industry: how geographic hubs connect university science and corporate technology, *Management Science* 66(8), 3425-3443.

Bonaccorsi, A. (2017) Addressing the disenchantment: universities and regional development in peripheral regions, *Journal of Economic Policy Reform* 20 (4), 293-320.

Boschma, R. (2017) Relatedness as driver behind regional diversification: a research agenda, *Regional Studies* 51 (3), 351-364.

Boschma, R., P.A. Balland and D.F. Kogler (2015), Relatedness and technological change in cities: The rise and fall of technological knowledge in U.S. metropolitan areas from 1981 to 2010, *Industrial and Corporate Change* 24 (1), 223-250.

Boschma, R., G. Heimeriks, and P.A. Balland (2014) Scientific knowledge dynamics and relatedness in biotech cities. *Research Policy* 43 (1), 107–14.

Boschma, R., Minondo, A., and Navarro, M. (2013) The emergence of new industries at the regional level in Spain: A proximity approach based on product relatedness. *Economic Geography* 89 (1), 29–51.

Boyack, K. W., Klavans, R., & Börner, K. (2005). Mapping the backbone of science. *Scientometrics* 64 (3), 351–374.

Callaert, J., M. Pellens and B. Van Looy (2014) Sources of Inspiration? Making Sense of Scientific References in Patents, *Scientometrics* 98 (3), 1617–29.

Catalána, P. C. Navarretec and F. Figueroae (2020) The scientific and technological cross-space: Is technological diversification driven by scientific endogenous capacity?, *Research Policy* forthcoming, doi.org/10.1016/j.respol.2020.104016

Cohen, W. M., Nelson, R. R., Walsh, J. P. (2002) Links and impacts: the influence of public research on industrial R&D. *Management Science* 48, 1–23.

Dasgupta P. and P.A. David (1994) Toward a new economics of science. *Research Policy* 23, 487–521.

Davies, B. and D.C. Mare (2019) *Relatedness, complexity and local growth*, Institute of Labor Economics DP, no. 12223.

D'Este, P., F. Guy and S. Iammarino (2013) Shaping the formation of university–industry research collaborations: what type of proximity does really matter?, *Journal of Economic Geography* 13 (4), 537-558.

Dosi G. (1982) Technological paradigms and technological trajectories. A suggested interpretation of the determinants and directions of technical change, *Research Policy* 11, 147–162.

Etzkowitz H. and L. Leydesdorff (2000) The dynamics of innovation: From National Systems and “Mode 2” to a Triple Helix of university–industry–government relations. *Research Policy* 29, 109–123.

Feldman, M. P. (1994) *The Geography of Innovation*, Boston: Kluwer Academic.

- Fleming, L. and O. Sorenson (2004) Science as a map in technological search, *Strategic Management Journal* 25 (8–9), 909–28.
- Foray, D., P.A. David, and B.H. Hall (2009) Smart specialization. The concept (Knowledge Economists Policy Brief No. 9, June). Brussels: European Commission.
- Foray, D. (2015) *Smart Specialisation: Opportunities and Challenges for Regional Innovation Policy*. London: Routledge.
- Fritsch, M. and V. Slavtchev (2007) Universities and innovation in space, *Industry and Innovation* 14 (2), 201–218.
- Gittelman M and B. Kogut (2003) Does good science lead to valuable knowledge? Biotechnology firms and the evolutionary logic of citation patterns. *Management Science* 49, 366–382.
- Goddard, J., L. Kempton, and P. Vallance (2013) Universities and Smart Specialisation: Challenges, Tensions and Opportunities for the Innovation Strategies of European Regions, *Ekonomiaz* 83 (2), 82–101.
- Guevara, M.R., D. Hartmann, M. Aristarán, M. Mendoza and C.A. Hidalgo (2016) The research space: using career paths to predict the evolution of the research output of individuals, institutions, and nations, *Scientometrics* 109, 1695–1709.
- Heimeriks, G. D. Li, W. Lamers, I. Meijer and A. Yegros (2019) Scientific knowledge production in European regions: patterns of growth, diversity and complexity, *European Planning Studies*, 27 (11), 2123–2143.
- Hidalgo, C., Balland, P.A., Boschma, R., Delgado, M., Feldman, M., Frenken, K., Glaeser, E., He, C., Kogler, D., Morrison, A., Neffke, F., Rigby, D., Stern, S., Zheng, S., and Zhu, S. (2018) The principle of relatedness, *Springer Proceedings in Complexity*, 451–457.
- Hidalgo, C. and R. Hausmann (2009) The building blocks of economic complexity, *Proceedings of the National Academy of Sciences* 106, 10570–10575.
- Hidalgo, C.A., Klinger, B., Barabasi, A.L. and Hausmann, R. (2007) The product space and its consequences for economic growth, *Science* 317, 482–487.
- Hoekman, J. (2012) *Science in an age of globalisation: the geography of research collaboration and its effect on scientific publishing*, PhD thesis, Technische Universiteit Eindhoven. <https://doi.org/10.6100/IR735405>
- Jaffe, A. B. (1989) Real effects of academic research, *American Economic Review* 79 (5), 957–970.
- Jaffe, A. B. and M. Trajtenberg (1996) Flows of knowledge from universities and federal laboratories: Modeling the flow of patent citations over time and across institutional and geographic boundaries. *Proceedings of the National Academy of Sciences* 93 (23), 12671–77.
- Jaffe, A. B., Trajtenberg, M., Henderson, R. (1993) Geographic localization of knowledge spillovers as evidenced by patent citations. *Quarterly Journal of Economics* 108, 577–598.

- Jones, B. F. (2009) The burden of knowledge and the death of the Renaissance Man: Is innovation getting harder? *Review of Economic Studies* 76 (1), 283–317.
- Kenney, M., and D. C. Mowery (eds.) (2014) *Public Universities and Regional Growth. Insights from the University of California*. Stanford: Stanford University Press.
- Klevorick, A. K., Levin, R. C., Nelson, R. R., Winter, S. G. (1995) On the sources and significance of interindustry differences in technological opportunities. *Research Policy* 24, 185–205.
- Kogler, D.F., D.L. Rigby and I. Tucker (2013) Mapping knowledge space and technological relatedness in US cities, *European Planning Studies* 21(9), 1374-1391.
- Kogut, B., and U. Zander (1993). Knowledge of the firm and the evolutionary theory of the multinational corporation. *Journal of International Business Studies* 24, 625–645.
- Laursen, K. and A. Salter (2004) Searching high and low: What types of firms use universities as a source of innovation? *Research Policy* 33 (8), 1201–15.
- Lehmann, E. E., and M. Menter (2015) University-industry collaboration and regional wealth, *Journal of Technology Transfer* 40, 1–24.
- Leten, B., P. Landoni, and B. Van Looy (2014) Science or graduates: How do firms benefit from the proximity of universities? *Research Policy* 43 (8), 1398–1412.
- Leydesdorff, L. and I. Rafols (2009) A global map of science based on the ISI subject categories. *Journal of the American Society for Information Science and Technology* 60(2), 348–362.
- McCann P. and R. Ortega-Argilés (2015) Smart Specialisation, Regional Growth and Applications to EU Cohesion Policy, *Regional Studies* 49 (8), 1291-1302.
- McKelvey, M., Alm, H., Riccaboni, M. (2003) Does co-location matter for formal knowledge collaboration in the Swedish biotechnology–pharmaceutical sector? *Research Policy* 32, 483–501.
- Mewes, L. and T. Broekel (2020) Technological complexity and economic growth of regions. *Regional Studies*, <https://doi.org/10.1016/j.respol.2020.10415>.
- Moodysson, J. (2008) Principles and practices of knowledge creation: On the organization of "buzz" and "pipelines" in life science communities, *Economic Geography* 84 (4), 449-469.
- Moreno, R., Paci, R. and Usai, S. (2005) Spatial spillovers and innovation activity in European regions, *Environment and Planning A* 37, 1793–1812.
- Muneepeerakul, R., Lobo, J., Shutters, S. T., Gomez-Lievano, A., and Qubbaj, M. R. (2013). Urban economies and occupation space: Can they get ‘there’ from ‘here’? *PLoS ONE*, 8(9), e73676. doi:10.1371/journal.pone.0073676
- Narin, F., K.S. Hamilton and D. Olivastro (1997) The increasing linkage between U.S. technology and public science, *Research Policy* 26 (3), 317–30.

- Neffke F., M. Henning and R. Boschma (2011) How do regions diversify over time? Industry relatedness and the development of new growth paths in regions, *Economic Geography* 87 (3), 237–265.
- Nelson, R. R. and Winter S. G. (1982) *An Evolutionary Theory of Economic Change*. Harvard University Press, Cambridge, MA.
- Patelli, A., G. Cimini, E. Pugliese and A. Gabrielli (2017) The scientific influence of nations on global scientific and technological development. *Journal of Infometrics* 11(4), 1229–37.
- Pavitt, K. (1984) Sectoral patterns of technical change: towards a taxonomy and a theory. *Research Policy* 13, 343–373.
- Petralia, S., Balland, P.A., Morrison, A. (2017) Climbing the ladder of technological development. *Research Policy* 46, 956–969.
- Pezzoni, M., R. Veugelers and F. Visentin (2019) How fast is this novel technology going to be a hit? Antecedents predicting follow-on inventions, working papers of Department of Management, Strategy and Innovation, Leuven.
- Pintar, N. and T. Scherngell (2020) The complex nature of regional knowledge production: Evidence on European regions, *Research Policy*, doi.org/10.1016/j.respol.2020.104170.
- Ponds, R., F. van Oort and K. Frenken (2007) The geographical and institutional proximity of research collaboration, *Papers in Regional Science*, 86 (3), 423-443.
- Ponds, R., F.G. van Oort and K. Frenken (2010) Innovation, spillovers and university-industry collaboration: an extended knowledge production function approach, *Journal of Economic Geography* 10, 231-255.
- Power, D., and A. Malmberg (2008) The contribution of universities to innovation and economic development: In what sense a regional problem? *Cambridge Journal of Regions, Economy and Society* 1, 233–245.
- Pugliese, E., G. Cimini, A. Patelli, A. Zaccaria, L. Pietronero and A. Gabrielli (2019) Unfolding the innovation system for the development of countries: Coevolution of science, technology and production, *Sci. Rep.* 9, 1-12.
- Rigby, D. (2015) Technological relatedness and knowledge space. Entry and exit of US cities from patent classes, *Regional Studies* 49 (11), 1922-1937.
- Rodríguez-Pose, A. (2001) Is R&D investment in lagging areas of Europe worthwhile? Theory and Empirical evidence, *Papers in Regional Science* 80, 275–295.
- Roper, S. and J.H. Love (2006) Innovation and regional absorptive capacity: the labour market dimension. *Annals of Regional Science* 40 (2), 437–447.
- Sánchez-Barrioluengo, M. (2014) ‘Turning the tables’: Regions shaping university performance, *Regional Studies, Regional Science* 1 (1), 276–285.
- Tran, T. (2020) *Three essays on how regions’ knowledge expertises affect the innovative performance*, Doctoral Thesis, Nice.

Varga A. (2000) Local academic knowledge spillovers and the concentration of economic activity, *Journal of Regional Science* 40, 289–309.

Waltman, L., van Eck, N. J., and Noyons, E. C. M. (2010) A unified approach to mapping and clustering of bibliometric networks. *Journal of Informetrics*, 4(4), 629–635.

Wuchty, S., Jones, B. F. and Uzzi, B. (2007) The increasing dominance of teams in production of knowledge. *Science* 316, 1036–1039.