Research Article

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Science space: the evolution of scientific knowledge specialisations across European regions

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Abstract: This study extends evolutionary economic geography to science by mapping how regional scientific capabilities emerge and evolve across Europe. Using Web of Science publications (2000–2017) geo-coded to 1,216 regions in 35 countries and classified into 228 subjects, we construct a pan-European "Science Space" based on subject co-occurrence and relatedness, and test whether relatedness density, i.e., the embeddedness of a subject in a region's existing portfolio, predicts subsequent entry (Revealed Scientific Advantage ≥ 1). Network evidence shows Europe's science system becoming more interdisciplinary, with technology-adjacent subjects (e.g., nanoscience, robotics, computer science) gaining centrality, while Life Sciences & Biomedicine remain dominant by volume. Econometric results (pooled OLS and GLM for binary entry, with region/subject/period fixed effects and controls for the regional economy and knowledge base) indicate that higher relatedness density significantly raises the likelihood of scientific entry. The effect is stronger in non-metropolitan regions and when a subject's initial RSA is very low, consistent with relatedness seeding new capabilities rather than merely consolidating near-threshold strengths. These findings generalise the principle of relatedness from technology to science and advise regional innovation policy to prioritise adjacent scientific opportunities, invest in bridging infrastructures, and design interdisciplinary platforms where relatedness density is high but specialisation has not yet emerged.

Keywords: scientific knowledge; science space; evolutionary economic geography; knowledge relatedness density and entry; regional knowledge specialisation; smart specialisation strategies

JEL Classifications: O33; R11; R58

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1 Introduction

Regions continuously evolve, reshaping their economic structures from within, an idea central to the Evolutionary Economic Geography (EEG) theoretical framework (Kogler et al. 2023a). This perspective builds on two foundational insights from the Geography of Innovation literature (Feldman and Kogler 2010): innovation is geographically concentrated (Feldman 1994, 1999), and knowledge flows are spatially localised (Bottazzi and Peri 2003; Jaffe et al. 1993; Maurseth and Verspagen 2002; Soon and Storper 2008). Knowledge is widely considered an important input for innovation and growth, and in many cases, regional performance is shaped by the type and quantity of knowledge generated locally. Close interactions among regional actors foster not only knowledge diffusion but also exposure to diverse perspectives that fuel creativity (Cowan and Jonard 2004). The seminal contributions by Gertler (1995, 2003) emphasise that much of the spatial stickiness of valuable knowledge can be attributed to its tacit nature. Essentially, it is tacit knowledge, deeply embedded in people and place and reliant on face-to-face interaction, and thus particularly difficult to transfer across space, which creates persistent barriers to knowledge flows. Consequently, knowledge accumulation unfolds unevenly over space and time due to regional unique histories of resource use, industrial development, institutional structures, and production systems (Rigby and Essletzbichler 1997; Saxenian 1994; Storper 1997). It is then those regional knowledge production and utilisation trajectories that give rise to specialised techno-industrial clusters, where long-standing capabilities and skills reinforce path dependency and institutional inertia in knowledge production (Asheim and Gertler 2006).

Investigations into regional development trajectories indeed find that places tend to expand and diversify into economic activities that are closely aligned to their pre-existing local capabilities (Boschma et al. 2015, 2017; Kogler 2015a). This path-dependent logic implies that there are potential opportunities for regional economies to branch out into closely related knowledge domains that drive specific capabilities, but less so in very distant ones (Kogler 2017). Thus, long-term investigations into the underpinnings that determine structural change in patterns of regional knowledge production, which by extension define competitive advantages vis-à-vis other localities, are important to understand the mechanisms behind these structural transformations along with anticipated future sustainability and growth prospects.

Following this call, and building on the regional 'knowledge space' methodology by Kogler et al. (2013, 2017), which employs earlier proposed measures of knowledge proximity from patent data proposed by Engelsman and van Raan (1994), numerous empirical studies have shown a strong positive correlation between technological relatedness and regional knowledge development, as reflected in patterns of specialisation and diversification (Antonietti and Montresor 2021; Boschma et al. 2015; Feldman et al. 2015; Kogler et al. 2017; Rigby 2015; Tanner 2014). In these studies, patents are treated as proxies for knowledge production and resulting innovative outputs, and in general many studies have utilised patent data as a device to indicate main properties and trends of industrial or governmental research and development (R & D) activities (Acs et al. 2002). Accordingly, the use of patent data was also approved by studies regarding regional technological domains: it enables to represent regional technological competences, demonstrate knowledge recombinant process and change, illustrate patterns of geographical concentration, and indicate intangible assets of regions or organisations (Belenzon and Schankerman 2013; Breschi et al. 2003).

While patent data is widely perceived as a reliable proxy for regional knowledge production, it might only offer a partial view (Engelsman and van Raan 1994). Not all innovations are patented, and patents typically reflect only the most successful technological outcomes, and therefore only reveal the upper end of the knowledge landscape. Furthermore, the propensity to patent varies greatly among industry sectors, and once accounted for patent metrics might be more reflective of regional patterns of specialisation rather than being directly indicative of general innovative performance (Kogler 2015b). As a complement, publication data captures a broader range of scientific activity, documenting the state-of-the-art in research and the foundational stages of innovation (Acs et al. 2002; Fleming and Sorenson 2004). It is widely accepted that scientific research has an essential role in technological innovation and economic growth. Scientific knowledge provides fundamental understanding, and the cumulative knowledge accelerates practical applications for technological advancements and growth (Ahmadpoor and Jones 2017). It is therefore worthwhile to investigate the scientific knowledge landscape since it provides a foundation for ultimate technological applications. Indeed, according to Jefferson et al. (2018), a large magnitude of patents includes references to scientific publications in their description of prior art, and that the number of citations to the scientific literature found in patents has grown dramatically over time.

A related line of argument emphasises that economic agents beyond firms, such as universities and research institutions, play a substantial role in producing economically valuable knowledge and facilitating spillovers, yet their contributions are often underrepresented in patent-based analyses. For instance, Belenzon and Schankerman (2013) estimate that only about 10 % of scientific findings at universities are patented. Given the importance, but often unobserved scale, of knowledge transfer from science to technology (Jefferson et al. 2018; Patelli et al. 2017), it is highly likely that regional capabilities are built on a much broader spectrum of knowledge foundations than is typically captured by patent-focused investigations (Kogler et al. 2024). In this context, scientific publications can provide a more accurate reflection of underlying local-global learning dynamics and knowledge transfer processes than patent-based co-inventor networks, which tend to be largely intra-organisational and mainly driven by profit motives (Wanzenböck et al. 2025). This distinction is crucial, as regional knowledge production ecosystems operate at the interface of local and global influences, often shaped by internationally connected scientific and professional communities (Bathelt and Cantwell 2025; Wolfe and Gertler 2004). Therefore, the extensive literature on the geography of knowledge flows and innovation spillovers, primarily grounded in patent data (Buzard et al. 2020; Murata et al. 2014), may significantly underestimate the indirect yet pivotal role of globally accessed scientific knowledge in driving regional knowledge diversification.

To address this significant research gap, the objective of this study is to extent the knowledge relatedness framework in accordance with EEG theoretical insights to investigate the underlying processes that drive structural change in scientific knowledge production patterns across European regional economies. At the onset, the most fundamental research question to be answered is if regional scientific knowledge follows the same principles that drive technical knowledge development trajectories: Do advancements in existing, and the emergence of new, regional scientific capabilities mainly result from the recombination of knowledge that is already present in a place? Following prior research efforts, the study introduces the concept of the "Science Space", which is a research field co-occurrence representation of regional scientific knowledge based on publication data. This methodological approach enables us to model the evolution of regional scientific knowledge spaces, and in parallel to evaluate the overall spatial configuration of the state-of-the-art in science. Thus, the spatial configuration of a region's existing knowledge base along with the dynamics resulting in patterns of specialisation/diversification over time will be explored in detail.

For this purpose, data from the Web of Science (WoS) and the European Regional Database (ERD), covering the scientific publications and regional indicators of the European regions from 2000 to 2017 will be utilised. To the best of our knowledge, this study is the first of a kind that employs a large-scale geo-coded publication database to explore how regional scientific knowledge production processes unfold. The analysis proceeds along two steps: first, the Science Space will be constructed to highlight changes in the overall structure of scientific knowledge production trajectories, and second a an econometric analysis that features a scientific knowledge-entry model will be conducted, in order to determine if new regional scientific capabilities are indeed related to the existing scientific base as it would be the case with regional patterns of technical knowledge evolution. Finally, we will also engage in sensitivity exercise where the base model is tested and compared across short- and long-term periods, as well as between less-specialised and least-specialised science subjects.

This study is organised as follows. Section 2 highlights the relevant literature that speaks to the concept of knowledge spaces and how these can be utilised to determine regional relatedness and knowledge entry patterns. The following section introduces the data and methodology in more detail, while the subsequent section presents the results along with a discussion. Section 5 offers some concluding remarks.

2 Knowledge in space – conceptual and empirical insights towards the mapping of scientific knowledge

2.1 The Science Space

Science Space refers to a networked representation of scientific knowledge in which research fields are nodes and the links between them capture patterns of relatedness inferred from co-occurrence across publications. Mapping Science Space enables the analysis of how regional scientific capabilities emerge and evolve over time and across places, thereby extending the Evolutionary Economic Geography (EEG) perspective, which emphasises path dependency conditioned by local stocks of knowledge and technology (Kogler 2015a; Kogler et al. 2023a). Essentially, pre-existing knowledge sets, experiences, and capabilities established in particular places, together with the localised nature of tacit and institutionally embedded knowledge (Gertler 2004), shape current configurations and future pathways of regional knowledge trajectories (Feldman and Kogler 2010).

An intuitive way to test these theoretical underpinnings and trace the evolution of knowledge in space and over time is the 'knowledge space' methodology (Kogler et al. 2013). This framework offers a clear approach for tracking structural changes in innovation over time (Kogler et al. 2017; Whittle and Kogler 2020). Built on patent data, it leverages the co-occurrence of patent classification codes to map the structure of technological activity (Engelsman and van Raan 1994). By identifying technologies that frequently appear together in patents, the approach captures technological relatedness, placing closely related technologies near each other in the knowledge space. Because patents are often assigned to multiple classes, they provide strong evidence of links between those technologies. In addition, patent documents are legally standardised, detailed, and offer relevant geo-references (via inventor and assignee addresses), while their patent classification systems enable longitudinal analyses of the evolution of technical knowledge production (Joo and Kim 2010).

The networked representation of knowledge domains, globally and at specific localities, rests on the principle of relatedness (Hidalgo et al. 2018). Knowledge domains that require similar cognitive capabilities, skills, and inputs, or that complement one another, are located close together in the knowledge space (Boschma 2017; Kogler 2017). Over the longer term, novelty in the space often arises from the recombination of existing, frequently locally present, technological capabilities, i.e., combining knowledge domains that have not previously appeared together in a single invention (Fleming and Sorenson 2001; Strumsky and Lobo 2015; Weitzman 1998).

Early measurements of technological relatedness based on patent class co-occurrence were used to assess firms' competencies to detect techno-economic paradigm changes (Breschi et al. 2003, Engelsman and van Raan 1994). Subsequent work combined the relatedness and evolutionary perspectives to analyse structural change in observed spatial patterns of specialisation and diversification along dimensions such products, technologies, and skills (Whittle and Kogler 2020).[1] Initial national-level attempts by Hausmann and Klinger (2007) and Hidalgo et al. (2007) used international trade data to measure product relatedness through co-export patterns, introducing the product spaces as a network-based representation in which links reflect the frequency with which product categories co-occur in a country's exports. In similar spirit at the subnational level, Neffke et al. (2011) derived industry relatedness from the co-occurrence of products in manufacturing of Swedish regions (1969–2002), while Boschma et al. (2013) analysed the industrial dynamics of Spanish regions (1988 and 2008) based on product relatedness.

Following the same analytical framework, many studies have investigated technological relatedness in regional economic structures by identifying knowledge/technology spaces from patent data. Kogler et al. (2013) used patent co-classification to measure relatedness between technologies and to examine the evolution of the US knowledge space, both nationally and for metropolitan areas, during 1975–2005. Boschma et al. (2015) showed entry and exit dynamics of technological knowledge in US cities for 1981–2010. For Europe, the evolution of regional knowledge spaces has been traced by Balland et al. (2019), Kim et al. (2024), and Kogler et al. (2017), linking long-term technological relatedness to regional diversification patterns and the Smart Specialisation Strategy (Foray 2015).

By contrast, relatively few attempts have mapped the evolution of scientific knowledge using scientific publication databases. Until recently, a limiting factor was the lack of large-scale publication databases with precise spatial information on the origin of scientific work. While patent data reflects inventive technological developments, publication data represents the state-of-the-art in science (Engelsman and van Raan 1994). Mapping regional knowledge spaces based on publication field co-occurrence, i.e., Science Space, would therefore allow analysis of scientific knowledge dynamics in a spatial context, analogous to prior work on technological knowledge. Compared with the technological focus, mapping scientific knowledge has been less common, partly because large-scale publication databases with precise spatial information were less accessible until recently. While patent data reflects inventive technological developments, publication data represents the evolving state of the art in science (Engelsman and van Raan 1994). A Science Space, constructed from publication field co-occurrence, therefore provides an analogue to technology spaces for studying the spatial dynamics of scientific knowledge.

The mapping of publication data has been explored in a few studies. Tijssen and Van Raan (1994) highlight several avenues for mapping scientific knowledge: co-citation analysis between articles and journals, co-word analysis (co-occurrence of keywords), and co-classification analysis. While co-citation analysis can reveal clusters of research specialties, it is prone to time lags inherent in citation practices and may overlook relevant non-cited publications. Co-word analysis indicates networks of conceptual and intellectual content but can suffer from inconsistencies over time. By contrast, co-classification analysis appears advantageous, as assigned classification systems are well defined and consistent in meaning across the scientific domain over time. In line with these methodological considerations, more recent efforts have mapped scientific knowledge using large-scale publication databases, most commonly by constructing maps from co-citation links between articles (Börner et al. 2012) or journals (Leydesdorff and Rafols 2009). Such co-citation maps aim to represent knowledge flows between academic fields. As an alternative to flow-based science maps, Guevara et al. (2016) introduced a 'research map' that traces scholars' career trajectories to predict future research output of countries, organisations, and individuals. In these representations, nodes denote research fields and links indicate the likelihood of collaboration between fields, resembling measures of skill relatedness derived from labour flows and mobility among industries in knowledge space to illustrate regional industrial evolution (Neffke and Henning 2013). Although spatial elements are embedded in these prior attempts to map the Science Space, a comprehensive regional analysis of the evolutionary paths of scientific knowledge production across localities and over extended periods, using what appears the

1 For a detailed overview of the relevant recent literature concerning the relatedness framework, including details on associated measurements and empirical evidence, see Whittle and Kogler (2020).

most reasonable methodological approach, namely relatedness measures based on the co-occurrence of research fields, remains largely absent. The Science Space method addresses this gap directly.

2.2 Science relatedness and knowledge entry

Knowledge exchange depends on shared frameworks of understanding, yet the transfer of knowledge, especially complex and tacit forms (Gertler 2003), is constrained by cognitive, social, and geographical distances between individuals and organisations (Boschma 2005; Nooteboom 2000). Consequently, knowledge flows more readily between similar or related domains. Because knowledge flows and spillovers are localised, places develop distinctive stocks of knowledge over time, which in turn shape their future evolutionary trajectories (Kogler et al. 2023a). This path-dependent logic implies that branching into new domains is most viable when those domains are closely related to a region's existing portfolio (Kogler 2015a; Martin and Sunley 2006, 2022).

The regional diversification literature emphasises the benefits of expanding into emerging, complex industries while recognising path dependence. Concepts such as regional branching (Boschma and Frenken 2011), path creation (MacKinnon et al. 2019), and path development (Grillitsch et al. 2018; Hassink et al. 2019) all highlight that new competencies are shaped by pre-existing capabilities; a finding supported by extensive empirical evidence (Boschma et al. 2015; Essletzbichler 2015; Kogler et al. 2017). In short, regional branching tends to occur where existing industries share technological relatedness with emerging sectors, rooted in common or complementary knowledge bases (Breschi et al. 2003; Frenken and Boschma 2007; Tanner 2014).

The relatedness–entry relationship was first shown at the national level by Hidalgo et al. (2007), who introduced the product space, a network of product relatedness based on co-export patterns, demonstrating that countries expand exports around products in which they already have comparative advantage. Hausmann and Klinger (2007) similarly found that nations are more likely to develop new export products related to their existing capabilities, and that greater variety and density of related products expand growth opportunities. Regional extensions by Neffke et al. (2011) showed that technological relatedness between manufacturing industries predicts the emergence of new sectors in Swedish regions. Consistent findings appear for Spanish regions (Boschma et al. 2013) and US metropolitan areas (Essletzbichler 2015), confirming that higher relatedness raises the probability of industry entry. Patent-based studies reinforce this view: Rigby (2015) showed US metros diversify into technologies related to existing strengths, while Boschma et al. (2015) quantified that, on average, a 10 % increase in relatedness raises the likelihood of technology entry by 30 % at the city level. European case studies of emerging sectors, e.g., fuel cells (Tanner 2014) and nanotechnology (Colombelli et al. 2014), corroborate these patterns.

The broader principle of relatedness (Hidalgo et al. 2018), coupled with the advantages of knowledge diversification, aligns with Smart Specialisation Strategy initiatives (Kim et al. 2024). Regional competitiveness stems from leveraging intrinsic knowledge assets to enter related, high-value domains (Balland et al. 2019; European Commission 2014). Simply adding new knowledge domains is insufficient; what matters is how well new capabilities integrate with existing structures to unlock broader benefits. Because regional knowledge spaces reflect unique evolutionary trajectories, the entry potential of any given domain varies by place, making a region–knowledge–time level of analysis essential for identifying optimal branching opportunities (Kogler et al. 2022, 2023b).

In summary, across products, industries, and technologies, the probability that new activity enters a region is positively conditioned by relatedness to existing capabilities. Extending this logic, we expect science (field) relatedness to similarly influence a region's ability to develop new scientific specialisations, an expectation we test in the subsequent sections.

3 Data and methodology

3.1 Data

In this study, the WoS and ERD databases are employed.[2] First, regional scientific knowledge measures are obtained from the WoS database covering the 2000 to 2017 timeframe and grouped into 3-year time periods (2000–2002, 2003–2005, 2006–2008, 2009–2011, 2012–2014, 2015–2017). The WoS provides information of publications including publication year, title, journal title, author, institution, institution's address, subheading, subject, funding,

2 Restrictions apply to the publication dataset used in this paper. The Web of Science data is owned by Clarivate Analytics. To obtain the bibliometric data in the same manner as authors (i.e., by purchasing them), readers can contact Clarivate Analytics at https://clarivate.com/webofsciencegroup/solutions/web-of-science/contact-us/in order to gain access to the following Web of Science bibliographic databases: '1980–2017 – Annual Science Citation Index Expanded and Proceedings-Science Combined'.

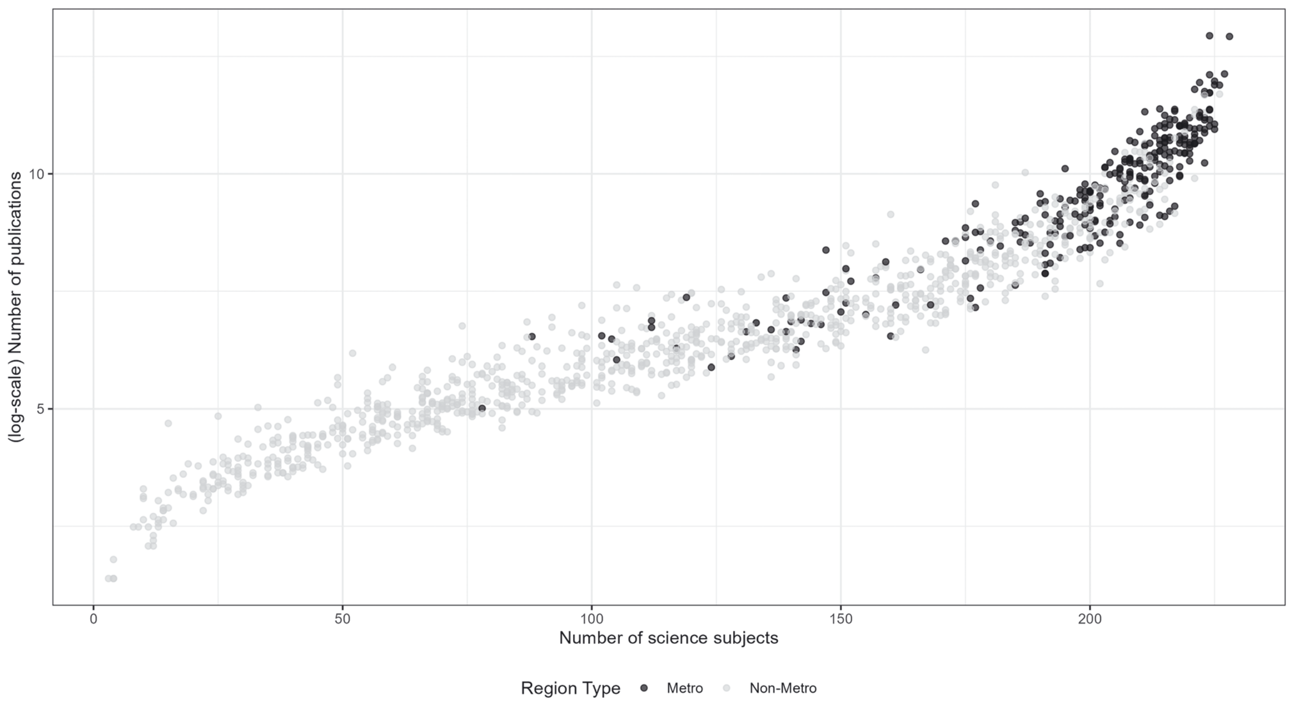

Figure 1: Number of science subjects and publications by region.

citation, etc. It covers five main research areas (labelled "subheading"): Arts & Humanities, Life Sciences & Biomedicine, Physical Sciences, Social Sciences, and Technology. Among them, our sample is restricted to publications that fall into the category of Life Sciences & Biomedicine, Physical Sciences, and Technology which are related to technological or industrial activities. Further, the WoS database also provides a lower-tier classification of science (labelled "subject"), which includes 265 disciplines. Utilising this information, the Science Space is then constructed to discuss how regional science is structured and has changed over time.

We restrict our scope to scientific activities in European regions; in other words, publications that are published from institutions located in European regions are selected. Following the retrieval of institutional address' information, additional data processing tasks were required to correct for errors and duplications, e.g., multiple database entries that referred to a single institution, and to supplement the data with geo-location information. All data processing and geo-coding tasks were completed in data preparation stage, and subsequently all publications originating from European regions could be filtered accordingly. For the spatial definition of regions, we apply the metropolitan and non-metropolitan (NUTS3) classification that is based on EUROSTAT's Urban Audit's Functional Urban Area.[3] In alignment with the established regional classification and time periods schema in our final dataset, regional-level economic variables were retrieved from ERD.[4] Here, we took the summation of the values of NUTS3 regions that belong to the metropolitan regions, and then employed the average values of the 3-year periods that are used.

Our final sample includes 6,977,525 publications from 228 science subjects, originating from 1,216 European regions including 274 metropolitan and 942 non-metropolitan regions across 35 countries.[5] Figure 1 illustrates the

3 https://ec.europa.eu/eurostat/statistics-explained/index.php?title=Glossary:Metro_regions.

4 The European Regional Database (ERD) was a service provided by Cambridge Econometrics that contains information on regional employment, level of output, and population; see: https://www.camecon.com/european-regional-data/. More recent data is available at the Annual Regional Database of the European Commission (ARDECO) website: https://urban.jrc.ec.europa.eu/?lng=en.

5 The list of countries whose regions are the focus of the present analysis includes: AT – Austria; BE – Belgium; BG – Bulgaria; CH – Switzerland; CY – Cyprus; CZ – Czech Republic; DE – Germany; DK – Denmark; EE – Estonia; EL – Greece; ES – Spain; FI – Finland; FR – France; HR – Croatia; HU – Hungary; IE – Ireland; IS – Iceland; IT – Italy; LI – Liechtenstein; LT – Lithuania; LU – Luxembourg; LV – Latvia; ME – Montenegro; MK – North Macedonia; MT – Malta; NL – Netherlands; NO – Norway; PL – Poland; PT – Portugal; RO – Romania; SE – Sweden; SI – Slovenia; SK – Slovakia; TR – Türkiye (Turkey); and the UK – United Kingdom.

number of science subjects and number of publications across European regions. Each dot indicates a region with colour difference differentiating metro (black) and non-metro (grey) regions. As expected, we can locate metropolitan regions primarily in the top-right corner of the graph, which indicates that they have greater numbers of publications and cover more diverse science subjects compared with non-metropolitan regions. On average across each of the two types of regions, metropolitan regions produce 31,818 publications in 198 science subjects, while non-metropolitan regions on average produce only 2,878 publications in 115 science subjects.

3.2 Science space methodology

Following the concept of regional knowledge spaces constructed with patent information (Kogler et al. 2013; Rigby 2015; Vlčková et al. 2018; Whittle 2019), this study introduces regional Science Spaces based on publication and science classification information. Utilising our dataset that contains the entire list of publications published by institutions located in European regions, the pan-European Science Space can be constructed. As a first step, a pair matrix presenting a combination of subjects of a publication is constructed. Here, the weight of each combination equals the number of articles published in a certain period and subject (or science field). For instance, if a publication contains three science subjects, i.e., subject A, B, and C, then the pair set has a total three rows (A-B, A-C, B–C) with all having an equal weight of 1. Once the processes of calculating those pair sets and associated weights was completed, it was then possible to construct the subject co-occurrence network by creating the nodes and edges based on subject co-occurrence pairs and number of publications. Considering the relationship between subjects but also the duplication of subject pairs, undirected and weighted network measures are employed.

3.3 Econometric specifications

3.3.1 Research model

The objective of this study is to explore the effect of science relatedness on the potential entry of new regional scientific knowledge with comparative advantages. The research model is specified in equation (1) as follows:

$$\begin{aligned}\text{Entry}_{r,i,t} &= \text{RelDen}_{r,i,t-1} + \textbf{RegEcon}_{r,i,t-1} \\ &\quad + \textbf{RegKnow}_{r,i,t-1} + \varphi_r + \rho_i + \alpha_t + \varepsilon_{r,i,t} \qquad (1)\end{aligned}$$

where r, i, and t identify region, science field, and time period, respectively, **RegEcon** is a matrix of regional economic variables, including total employment (Emp), non-market service employment intensity (NMS), and GDP per capita (GDP). **RegKnow** indicates a matrix of regional knowledge variables, including the revealed comparative advantage of science (RSA), knowledge complexity (KC), scientific coherence (SC), and the number of publications (Pub). φ, ρ, α are region, science field, and period fixed effects. All independent variables are lagged by one period to avoid potential endogeneity.

The dependent variable of our model is the knowledge entry, in other words, the entry into a new specialised scientific activity in a region. The first step is to calculate the revealed comparative advantage in a science field in each region and period. Following previous approaches that measured the revealed technological advantage (RTA) of regions via patent data (Balland et al. 2019, Boschma et al. 2015, Kogler et al. 2013, Whittle 2019), a new measure labelled Revealed Scientific Advantage (RSA) that utilises regionalised publication data is adopted (Equation (2)).

$$\text{RSA}_{r,i,t} = \frac{\text{publication}_{r,t}(i)/\Sigma_i \text{publication}_{r,t}(i)}{\Sigma_r \text{publication}_{r,t}(i)/\Sigma_r \Sigma_i \text{publication}_{r,t}(i)} \qquad (2)$$

RSA tells us whether a region r has a comparative advantage in science i compared to other regions based on a threshold of ≥1. Precisely, an RSA equal and above one means that a region has an equal or greater share of knowledge specialisation in a certain scientific field than the average of all other regions in aggregate. Ceteris paribus, in the cases where the value is below that threshold, a region would be less specialised than the collective average. To operationalise the proposed analysis that follows a binary of RSA values is produced, i.e., one where RSA values are ≥ 1, and 0 when RSA values are < 1. Subsequently, RSA values between two consecutive time periods are compared to determine whether an entry event has occurred. In other words, if there has been a switch from RSA < 1 in one time period to RSA ≥ 1 in the subsequent period, an entry event has occurred. Figure 2 provides an example and illustrates how science subject #3 in Region A and science subject #2 in Region B are the only two cases where an entry event is observed.

Related density, our key variable, refers to the embeddedness of a science produced within a region to its core science subjects. Following Balland et al. (2019), Boschma et al. (2015), and Hidalgo et al. (2007), the relatedness density of science i in region r at time t is measured by dividing the summation of scientific relatedness ($\emptyset_{ijt}$) of science i to all other sciences j with RSA in region r to the summation of all other sciences j in all other regions (Equation (3)). Scientific relatedness is measured based on co-occurrence of

t	**Science 1**	**Science 2**	**Science 3**	…
Region A	1	0	0	…
Region B	0	0	1	…
…	…	…	…	…

t+1	**Science 1**	**Science 2**	**Science 3**	…
Region A	0	0	1	…
Region B	0	1	1	…
…	…	…	…	…

t → t+1	**Science 1**	**Science 2**	**Science 3**	…
Region A	(1 → 0) = **0**	(0 → 0) = **0**	(0 → 1) = **1**	…
Region B	(0 → 0) = **0**	(0 → 1) = **1**	(1 → 1) = **0**	…
…	…	…	…	…

Figure 2: Entry into a new regional science specialisation (transition from RSA < 1 to RSA ≥ 1). Note: Values “0” and “1” refer to a science subject’s RSA; RSA $< 1 =$ “0” and RSA $\geq 1 =$ “1”, respectively. Entry into a newly acquired regional science subject specialisation is indicated by $=$ “1” in lower panel.

subjects in publications; in other words, measuring the frequency of the two subjects appearing in the same publication (Equation (4)). The greater value of relatedness density indicates that a science is closely linked to the sciences with RSA in a region, and this can be interpreted as a potential of such a science to be developed or applied with other sciences.

$$\text{RelDen}_{i,r,t} = \frac{\sum_{j\in r, j\neq i}\emptyset_{ij}}{\sum_{j\neq i}\emptyset_{ij}} *100 \tag{3}$$

$$\emptyset_{ij} = \frac{N_{ij}}{\sqrt{N_i^2 * N_j^2}} \tag{4}$$

Two types of control variables are included: regional economic and knowledge variables. Regional economic variables, all obtained from ERD, include Emp, NMS, GDP. To control the level of regional science activity, regional knowledge variables of RSA, KC, SC, and Pub are included. First, KC is captured by a knowledge complexity index based on an extended bimodal network model by Hidalgo and Hausmann (2009), and further deployed by Balland and Rigby (2017). From the original method, patent classifications and the unit of regions are converted into publication classifications and the European NUTS level. KC reveals the degree of whether local knowledge developed in a region to also be reproduced in other regions. Regarding the spatial unevenness of regional knowledge, KC allows us to capture the regional difference relate to the quality aspect of local knowledge (Balland and Rigby 2017; Whittle 2019). Next, SC is also included as a control variable. The concept of coherence is adopted to scientific publication data to measure the degree to what extent different subjects of publications are complementary to an existing scientific knowledge base of a region (Rocchetta and Mina 2019). In case of technological coherence, when measured by patent, it has been found to favour knowledge spillovers (Frenken et al. 2007) and adaptive resilience of regional economies (Rocchetta and Mina 2019). In a similar sense, we expect that SC controls the region’s scientific capability of producing new publications. Lastly, number of publications (Pub) is included to control the size effects of publications.

List of variables and descriptive statistics are represented in Table 1 and 2.

3.3.2 Estimation strategies

For econometric estimation, three different estimation strategies are used to confirm robustness of our finding. First, pooled OLS estimation including different combinations of variable sets is used without and with fixed effects of region, science field, and period. This allows us to observe whether the coefficients of our key variable change by the

Table 1: Variables.

Variable	**Description**
Entry	Entry of science *i* in region *j* at period *t*
RelDen	Relatedness density of science *i* in region *j* at period *t*
Emp	Total employment in region *j* at period *t*
NMS	Non-market service employment intensity in region *j* at period *t*
GDP	GDP per capita in region *j* at period *t*
RSA	Revealed comparative advantage of science *i* in region *j* at period *t*
KC	Knowledge complexity in region *j* at period *t*
SC	Scientific coherence in region *j* at period *t*
Pub	Number of publications of science *i* in region *j* at period *t*

Note: NMS includes NACE Rev.2 classification, O-Q (Public administration, defence, education, human health, and social work activities) and R–U (Arts, entertainment, and recreation; other service activities; activities of household and extra-territorial organizations and bodies).

Table 2: Descriptive statistics.

	RelDen	Emp	NMS	GDP	RSA	KC	SC	Pub
Emp	0.364							
NMS	0.334	0.002						
GDP	0.404	0.189	0.460					
RSA	0.011	−0.004	0.003	0.004				
KC	−0.047	−0.045	0.190	0.199	−0.002			
SC	0.111	0.040	0.015	0.035	−0.011	−0.135		
Pub	0.140	0.264	0.036	0.090	0.006	0.003	0.007	
Mean	21.5	196.3	0.29	0.02	1.15	0.00	16.69	2.31
SD	12.2	355.1	0.08	0.01	13.1	0.01	2.15	22.8

existence of other control variables. As a second part of estimation, generalised linear model (GLM) estimation is conducted. Since our dependent variable, entry, is dichotomous, logit and probit model with GLM is used. In addition, regional disaggregation is considered to check whether our result holds for both large and small regions. Subsamples are divided into metropolitan and non-metropolitan regions by using metropolitan dummy. Lastly, two different cases of RSA values are estimated to check whether different levels of RSA show consistent results. On the one hand very low RSA values (<0.7) are considered as an indicator of least specialised science subjects in a region, while on the other hand RSA values ranging from 0.7 to <1 are employed to signify science field that are somewhat close to a level of specialisation. Since the probability of knowledge entry is expected to be higher when an RSA of a region's science is close to 1, the impact of relatedness density may differ depending on the RSA value. Further, these two cases are compared in short-term and long-term scenarios which follows the work of Perruchas et al. (2020). In sum, short-term effect is tested with the subsample where RSA is very low or close to specialisation in the previous period $\left(\mathrm{RSA}_{r,i,t-1} < 0.7 \text{ or } 0.7 \leq \mathrm{RSA}_{r,i,t-1} < 1\right)$, and long-term effect is tested with the subsample where RSA is again very low or almost at the level of specialisation in the first period of the sample ($\mathrm{RSA}_{r,i,t} < 0.7$ or $0.7 \leq \mathrm{RSA}_{r,i,t} < 1$ where t = 2000–2003).

4 Results and discussion

The study set out with the objective to investigate if the evolution of regional scientific knowledge production capabilities follows the same principles that drive technical knowledge development trajectories that have been highlighted in the relevant literature (Boschma et al. 2015; Colombelli et al. 2014; Kogler et al. 2013, 2017; Rigby 2015). Specifically, the critical research question in this regard is: Do advancements in existing, and the emergence of new, regional scientific capabilities mainly result from the recombination of knowledge that is already present at a place? The summary of results and accompanied discussion considering this objective follows in turn.

4.1 The evolution of regional Science Spaces in the Europe

In this section, the evolution of the overall European Science Space is highlighted and discussed. Initially, and by means of a network visualisation, we compare the European Science Space in period 1 (2000–2002) with that in period 6 (2015–2017); see Figures 3 and 4. The node sizes are determined by their respective eigenvector centrality values. The eigenvector centrality value indicates how well a certain node is connected, and by extension shows how "important" a node, i.e., science subject, is in the overall Science Space. Thus, a subject with a larger node size compared to other nodes is indicative of its relative importance in the entire science network. For illustrative purposes, and to reduce confusion and emphasise key findings, only 40 % of the two overall networks are shown in both figures. The node colours represent the science subheadings (i.e., the clustering of subjects): pink = Life Sciences & Biomedicine (LSB), light green = Technology (TECH), orange = Physical Sciences (PS), blue = Social Sciences (SS), and dark-green = Arts & Humanities (AH).[6] Although or sample does not focus on publications in the Social Sciences and Art & Humanities science domains per se, there are few nodes from those research areas that appear in the two networks due to multidisciplinary science outputs.

In the first observed period (2000–2002), a fairly clear separation between our three main subjects and their associated subheadings can be observed. Although PS and TECH associated subjects are perhaps more intermingled with each other compared to LSB subjects that are quite isolated on their own in the left section of Figure 3. Thus, most of the subjects belonging to the same subheading

6 The Web of Science provides a list of subject classifications for all databases. Most subjects are assigned to a subheading category, whereas some subjects needed to be assigned to one for the purpose of presentation in Figures 3 and 4. A full list of all subjects and assigned subheadings that are utilized in the analysis that follows is featured in Table A1 in the Appendix. For further information, please refer to: https://support.clarivate.com/ScientificandAcademicResearch/s/article/Web-of-Science-List-of-Subject-Classifications-for-All-Databases?language=en_US.

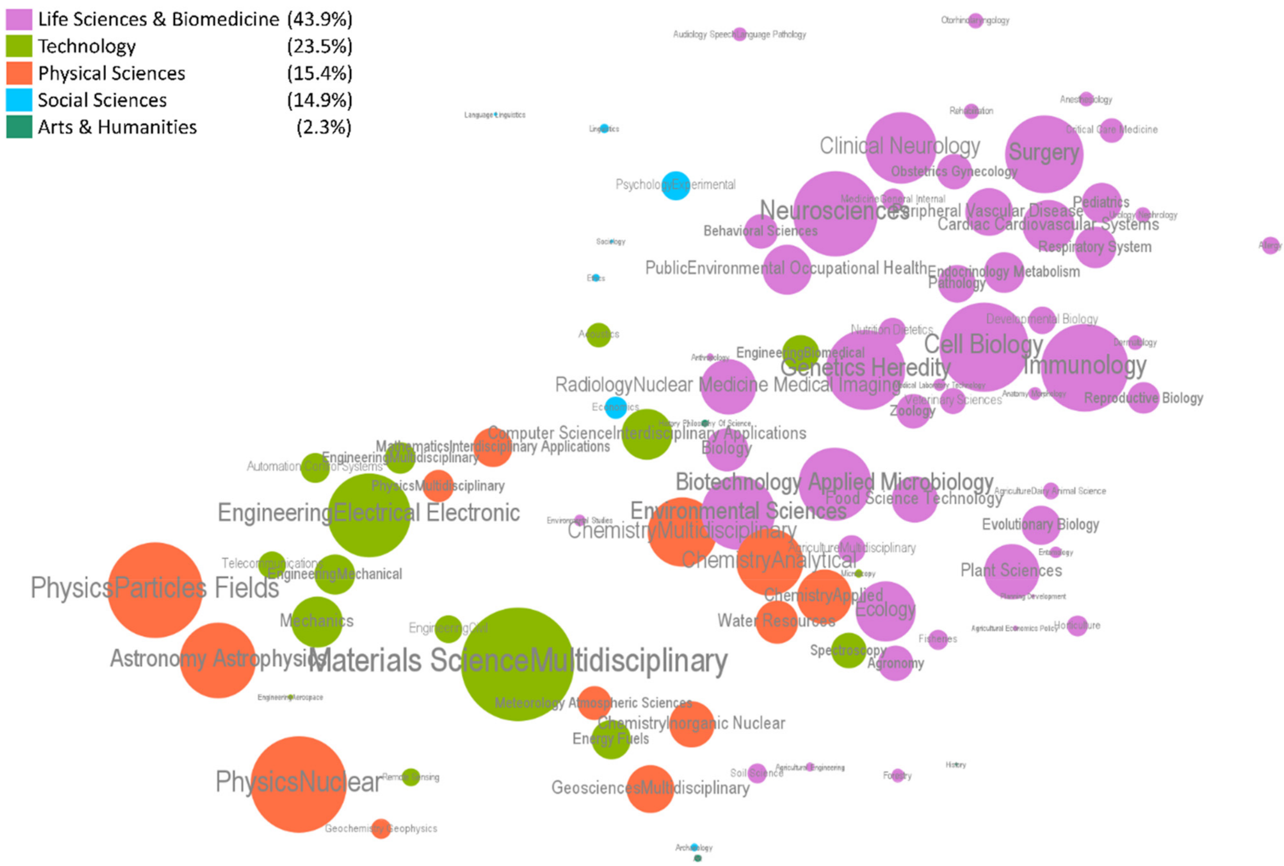

Figure 3: The european science space in 2000–2002. Note: The nodes represent the subjects, and their respective colour refers to the corresponding subheading. The size of the node was determined by the eigenvector centrality value. Percentage values in the legend correspond to the share of each science subheading in the entire network.

are located closely to each other, which indicates a certain scientific homogeneity in scientific knowledge production where most scientific outputs drew on inputs from within their core research area. In contrast, in the last observed period (2015–2017) a much more heterogeneous picture emerges where subheadings belonging to the same research subject area do not necessarily form clearly distinguishable clusters within the overall network anymore. It is plausible to suspect that the observed structural differences are the result of increasing inter-disciplinary research efforts, i.e., in the later period scientific outputs are much more likely to recombine knowledge from several subjects belonging to different rather than the same research area. Furthermore, and again in the latter period (Figure 4), we observe an increasing number of nodes that represent SS and AH subjects, which provides additional support for an increasing shift towards, and growth of, interdisciplinary research outputs across the entire European Science Space. In both periods, LSB turns out to be the most prevailing science subjects in the European regions as it includes not only many nodes but also subjects that are with greater node size. LSB associated nodes represent 43.9 % 42.8 % of all subheadings that are represented in the first and last observed period, respectively. This aligns with the observations from knowledge spaces based on patents that showed the strong presence and clustering of chemistry and biology associated technical knowledge domains (Kogler et al. 2017). Another observation is the TECH subheadings, that were already more scattered across the entire network compared to other subjects in the initial period, have become very central nodes in the contemporary Science Space (Figure 4). Perhaps no surprise given that TECH related subheadings that represent scientific knowledge production in subjects such as nanotechnology or robotics, many of which are considered general purpose technologies, have been applied to a diverse range of subjects across the entire science spectrum. Further TECH related advancements, such as the wide diffusion and application of information, communication, and computer sciences, which have become central to knowledge discovery processes in non-TECH subjects, has further accelerated this trend.

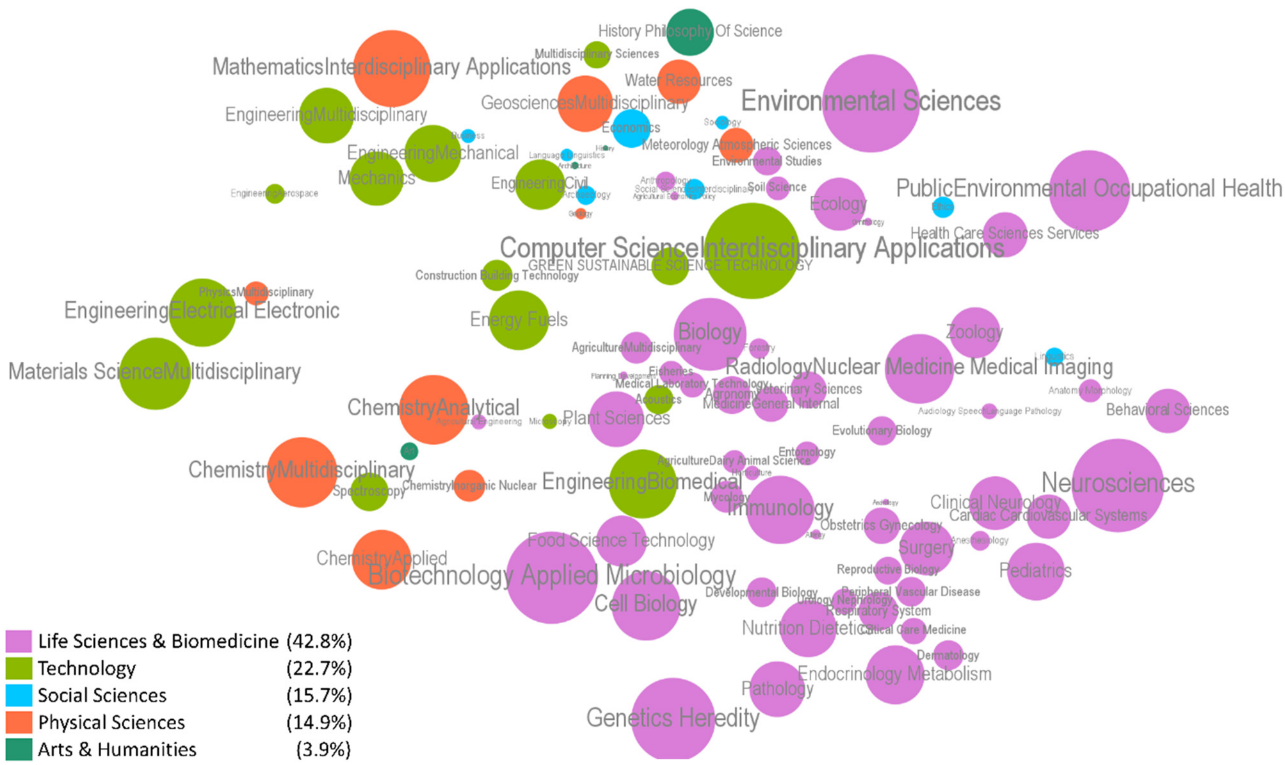

Figure 4: The european science space in 2015–2017. Note: The nodes represent the subjects, and their respective colour refers to the corresponding subheading. The size of the node was determined by the eigenvector centrality value. Percentage values in the legend correspond to the share of each science subheading in the entire network.

Although insights into the overall evolution of scientific knowledge production at the pan-European level are very informative, the relevant follow-up question is then how this might vary across regional settings that most likely are characterised by distinct knowledge bases and development trajectories (Asheim and Coenen 2005). Considering this task, Table 3 lists the top 10 scientific knowledge producing European metropolitan regions, determined by their overall number of publications produced in the 2000–2002 time period. Furthermore, the table also indicates the most prominent science subject, again in terms of publication output, in each of these metropolitan regions. At the onset, it is noticeable that the top science subjects appear to repeat themselves across these top producing regions in both time periods. In the 2000–2002 period publications related to Biochemistry & Molecular Biology are amongst the most produced ones across these top regions, whereas in the 2015–2017 period the momentum had shifted towards the subjects of "Multidisciplinary Sciences" and "Astronomy & Astrophysics". In the context of the earlier

Table 3: Major metropolitan region's top science subjects.

Region	2000–2002		2015–2017	
	Science subject	Pub	Science subject	Pub
Paris	Biochemistry & molecular biology	4,163	Astronomy & astrophysics	4,945
London	Biochemistry & molecular biology	3,481	Multidisciplinary sciences	6,524
Berlin	Physics, condensed matter	1,658	Multidisciplinary sciences	2,542
Munich	Biochemistry & molecular biology	1,265	Astronomy & astrophysics	3,072
Stokholm	Biochemistry & molecular biology	1,249	Multidisciplinary sciences	2,048
Madrid	Chemistry, physical	1,217	Multidisciplinary sciences	2,277
Rome	Biochemistry & molecular biology	1,114	Astronomy & astrophysics	2,435
Milan	Oncology	1,106	Oncology	2,222
Copenhagen	Biochemistry & molecular biology	1,072	Multidisciplinary sciences	2,012
Barcelona	Biochemistry & molecular biology	792	Multidisciplinary sciences	2,270

discussion concerning the overall European Science Space, it should be noted that top science subjects present in major metropolitan regions that account for a large share of the overall scientific knowledge production output strongly determine the overall observed European Science Space configuration.

4.2 Summary and discussion of the insights derived from the regression analysis

In this section, the econometric results of the impact of relatedness density on the scientific changes in European regions from 2000 to 2017 are discussed. Table 4 summarises the estimation results from multiple regression models that incorporate different sets of control variables. Column (1) in Table 4 presents the baseline model including only the key independent variable, *RelDen*. In turn, column (2) adds regional economic controls, column (3) then also includes regional knowledge variables, while column (4) is the full model that incorporates both socio-economic and regional science variables. Finally, column (5) reports the most stringent specification by employing a three-way fixed effects model that controls for all time-invariant regional, technological, and period-specific effects.

Across all model specifications, relatedness density (*RelDen*) consistently reports a positive and statistically significant coefficient. This robust finding indicates that science subjects embedded in a denser network of related fields are more likely to undergo scientific transformation towards specialisation. In other words, when a scientific field is surrounded by more related and scientifically proximate disciplines within a region, it can benefit from knowledge spillovers and potential knowledge recombination processes that facilitate innovation and a structural restructuring in the overall scientific activity present at a place. This result is consistent with the EEG literature highlighted previously, which also emphasises the role of relatedness in fostering regional diversification and technological upgrading.

Turning to the control variables, most coefficients show consistent signs across specifications, with a few notable exceptions. In the model excluding regional knowledge variables (column 2), total employment (*EMP*), non-market service employment intensity (*NMS*), and *GDP*, all display negative coefficients. This may initially appear counterintuitive, as one might expect regions with larger labour markets to foster more emergence on scientific activity. However, this result likely reflects a saturation or maturity effect: highly developed regions may already have fully formed scientific systems with limited room for further diversification. In contrast, smaller or less-developed regions may still possess untapped potential for scientific restructuring and thus exhibit higher rates of change towards scientific specialisation. A similar interpretation applies to the negative coefficient of number of publications (Pub). Regions with higher existing publication output tend to be mature in terms of their scientific development. These regions are likely to have already consolidated their positions in key scientific subjects, reducing the opportunity for further specialisation into new or emerging areas.

Table 4: Emergence of new specialised science in European regions.

	(1)	(2)	(3)	(4)	(5)
RelDen	0.004*** (0.00004)	0.004*** (0.0001)	0.003*** (0.0005)	0.003*** (0.0001)	0.009*** (0.0001)
Emp		−0.0000*** (0.00000)		−0.0000*** (0.00000)	0.00000 (0.00003)
NMS		−0.010 (0.008)		0.020*** (0.008)	−0.004 (0.038)
GDP		−0.269*** (0.057)		−0.203*** (0.057)	0.683* (0.411)
RSA			0.324*** (0.003)	0.316*** (0.004)	0.294*** (0.004)
KC			0.572*** (0.048)	0.657*** (0.051)	0.044 (0.074)
SC			−0.001*** (0.0002)	−0.001*** (0.0002)	−0.0005** (0.0002)
Pub			−0.064*** (0.001)	−0.061*** (0.001)	−0.062*** (0.001)
Constant	0.018*** (0.001)	0.022*** (0.002)	0.036*** (0.003)	0.045*** (0.004)	−0.196*** (0.029)
Region FE	No	No	No	No	Yes
Science FE	No	No	No	No	Yes
Period FE	No	No	No	No	Yes
R^2	0.03	0.03	0.06	0.05	0.10
Adjusted R^2	0.03	0.03	0.06	0.05	0.07
Observation	352,153	309,526	352,153	309,526	309,526

Notes: The dependent variable entry = 1 if a given technology enters the technological portfolio of a given region during the corresponding 5-year window, and 0 otherwise. All time-varying covariates are lagged by one period, with standard errors noted in parentheses; * $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$.

In case of regional knowledge variables (see results displayed in column 3 an onwards), RSA shows positive effects, which is an expected observation, showing the greater possibility of specialisation to occur in well-developed science subjects in a particular region. This is indicative of a cumulative advantage mechanism, where already strong scientific disciplines continue to attract resources and attention. The positive coefficient of *KC* shows the importance of a region's capability on producing better quality, or more complex, scientific knowledge. This suggests that high-performing regions in terms of research productivity are more likely to evolve their scientific portfolio, likely due to better infrastructure, talent pools, and institutional support. The coefficient of *SC* reports the negative and significant impact, meaning less coherent scientific activities enhance regional science specialisation. This implies that regions with a less coherence across scientific subjects may be better placed to develop new science specialisations. A possible explanation is that a loosely connected scientific structure provides more opportunities for novel combinatory knowledge production and interdisciplinary exploration, which are key drivers in enabling emerging scientific directions.

In Table 5, the robustness of our findings is tested with a different estimation strategy and disaggregated subsamples. These tests are designed to verify whether the observed positive effect of relatedness density on scientific change as reported in Table 4 also holds under different model specifications and across varying regional contexts. First, in column (1) and (2), GLM estimation results based on logit and probit model confirm the positive and significant effect of relatedness density on the probability of science entry. In both models, relatedness density continues to exhibit a positive and statistically significant effect on the probability of science entry. This finding confirms that even when switching from linear probability models to more appropriate nonlinear specifications for binary outcomes, the relationship between relatedness density and regional scientific transformation remains robust. In particular, the consistent significance across both logit and probit models enhances confidence in the general validity of our results.

Second, in Column (3) and (4), the results estimated by the subsamples divided into metropolitan and non-metropolitan regions are presented. The results reveal that the coefficient of relatedness density is statistically significant in both subsamples, but notably larger in non-metropolitan regions than in metropolitan ones. This suggests that relatedness plays a more critical role in shaping scientific change in less-developed areas. One possible explanation is that metropolitan regions typically enjoy a wider array of resources for scientific advancement, such as large universities, research centres, and highly skilled labour pools. These regions may rely less on relatedness-driven recombination and more on institutional or agglomeration advantages when it comes to scientific specialisation. In contrast, non-metropolitan regions, which often lack these structural advantages, may depend more heavily on the knowledge spillovers and cross-field synergies facilitated by relatedness density. Thus, the local knowledge structure could be a particularly vital mechanism for

Table 5: Emergence of new specialised science in European regions (robustness-check).

	GLM specifications		**GLM specifications (logit) & regional disaggregation**	
	(1)Logit	**(2)Probit**	**(3)Metro**	**(4)Non-metro**
RelDen	0.043*** (0.000)	0.023*** (0.000)	0.035*** (0.002)	0.055*** (0.001)
Emp	−0.0002*** (0.00002)	−0.00008*** (0.00001)	−0.00003 (0.00003)	−0.001*** (0.000)
NMS	−0.219** (0.101)	−0.088* (0.051)	−1.18*** (0.226)	−0.331*** (0.117)
GDP	−3.742*** (0.743)	−1.770*** (0.377)	−6.36*** (1.42)	−3.733*** (0.884)
RSA	2.227*** (0.031)	1.260*** (0.018)	2.96*** (0.053)	1.964*** (0.041)
KC	9.370*** (0.711)	4.600*** (0.353)	3.91* (2.23)	8.307*** (0.765)
SC	−0.001 (0.004)	−0.004** (0.002)	−0.165*** (0.025)	−0.005 (0.004)
Pub	−0.478** (0.011)	−0.275*** (0.006)	−0.486*** (0.015)	−0.569*** (0.020)
Constant	−3.095*** (0.067)	−1.730*** (0.032)	−0.052 (0.458)	−3.116*** (0.072)
Region FE	Yes	Yes	Yes	Yes
Science FE	Yes	Yes	Yes	Yes
Period FE	Yes	Yes	Yes	Yes
Log-likelihood	−87,960	−87,874	−21,553	−65,965
Observation	309,526	309,526	64,274	242,252

Notes: The dependent variable entry = 1 if a given technology enters the technological portfolio of a given region during the corresponding 5-year window, and 0 otherwise. All time-varying covariates are lagged by one period, with standard errors noted in parentheses; * $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$.

Table 6: Emergence of new specialised science in European regions (short- and long-term).

	Short-term		Long-term	
	(1) **(RSA < 1 & RSA ≥ 0.7 prior period)**	**(2)** **(RSA < 0.7 prior period)**	**(3)** **(RSA < 1 & RSA ≥ 0.7 first period)**	**(4)** **(RSA < 0.7 first period)**
RelDen	0.015** (0.005)	0.049*** (0.001)	0.014*** (0.003)	0.048*** (0.0009)
Emp	0.00001 (0.00005)	−0.0005*** (0.00006)	0.00002 (0.00004)	−0.0004*** (0.00005)
NMS	−0.820 (0.679)	−0.434*** (0.139)	−0.74* (0.436)	−0.231** (0.116)
GDP	−8.130* (4.450)	−4.85*** (1.03)	−1.06 (2.93)	−6.23*** (0.866)
RSA	4.500*** (0.460)	2.36*** (0.085)	2.73*** (0.132)	2.12*** (0.043)
KC	14.4** (6.36)	7.69*** (0.875)	3.32*** (4.94)	8.15*** (0.807)
SC	0.327*** (0.105)	−0.026*** (0.005)	0.123** (0.051)	−0.017*** (0.004)
Pub	−0.291*** (0.032)	−1.11*** (0.035)	−0.321*** (0.023)	−0.687*** (0.018)
Constant	−9.64*** (1.96)	−2.74*** (0.091)	−4.79*** (0.941)	−2.88*** (0.076)
Region FE	Yes	Yes	Yes	Yes
Science FE	Yes	Yes	Yes	Yes
Period FE	Yes	Yes	Yes	Yes
Log-likelihood	−2,053	−49,585	−4,564	−69,100
Observation	3,819	210,252	10,287s	266,218

Notes: The dependent variable entry = 1 if a given technology enters the technological portfolio of a given region during the corresponding 5-year window, and 0 otherwise. All time-varying covariates are lagged by one period, with standard errors noted in parentheses; * $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$.

driving scientific diversification in less resource-endowed regions.

Table 6 reports estimates that distinguish short-term from long-term effects of relatedness density on regional scientific specialisation. The key question is whether the effect of relatedness density holds irrespective of prior RSA values and how it differs over time. In the short term, relatedness density has a positive and significant impact in both specifications. The long-term estimates are also significant, indicating that the influence of relatedness density endures, consistent with a path-dependent process shaped by the structural proximity of knowledge domains. Comparing fields with very low RSA to those close to specialisation (RSA≈1), the impact of relatedness density is larger at very low RSA. Put differently, fields already near RSA = 1 are more likely to specialise and are less sensitive to relatedness density, as they have almost reached specialisation and thus additional policy support may yield limited gains. By contrast, for fields with very low RSA, future specialisation is uncertain, and relatedness density plays a more important role.

5 Concluding remarks

The present paper advances the evolutionary economic geography (EEG) literature by shifting the lens from technological invention (as proxied by patents) to scientific knowledge production (as proxied by publications), and by asking whether regional science specialisation evolves through mechanisms analogous to those documented for technology in the context of relatedness, recombination, and path dependence. Building a pan-European Science Space from Web of Science data (2000–2017), we show that the relatedness density of a scientific field within a region robustly predicts the probability that the region will subsequently enter that field (attain an RSA ≥ 1). This result holds across pooled OLS and GLM specifications even once an extensive set of regional economic and knowledge controls, as well as fixed effects, are included.

The effect is consistently positive and statistically significant, stronger in non-metropolitan regions, and present in both short- and long-term horizons. Moreover, the marginal influence of relatedness is larger when a field's initial RSA is very low, suggesting that relatedness is particularly consequential for seeding new scientific specialisations rather than merely consolidating near-threshold strengths. Beyond the econometric evidence, our network analyses indicate that Europe's scientific landscape has become more inter-disciplinary over time: clear sub-domain clusters visible in the early 2000s give way to denser cross-field connectivity by 2015–2017. Technology-adjacent subjects (e.g., nanoscience, robotics, computer science) become increasingly central to the Science Space, consistent with their role as general-purpose enablers. Life Sciences & Biomedicine remain a dominant presence in terms of volume and centrality, but the permeability of boundaries among broad subjects has grown, underscoring the salience of recombinant knowledge production in scientific advance.

Empirically, we provide the first large-scale, geo-coded evidence that the principle of relatedness extends from technology to science at the regional level: regions are more likely to develop comparative advantage in scientific subjects that are embedded in their existing portfolios. Conceptually, we connect the literatures on product/technology/skill spaces (Whittle and Kogler 2020) to the scientific domain, highlighting that scientific capabilities, and not only inventive capacities, are structured, cumulative, and place-specific. Methodologically, we adapt the knowledge space methodology and associated tools to publication data, demonstrating a tractable way to model subject co-occurrence and to derive relatedness density measures for science.

For policy, the findings validate that the logic behind Smart Specialisation Strategies also holds in the scientific knowledge domain. Prioritising adjacent or cognate scientific subjects, those most related to a region's incumbent strengths, can raise the probability of successful entry and, by extension, accelerate capability formation (European Commission 2014). This is especially pertinent for smaller and non-metropolitan regions, where relatedness appears to substitute, at least in part, for agglomeration advantages, i.e., denser research infrastructures and large talent pools. In practical terms, regional authorities along with education and training focused entities can use the proposed "Science-Space" methodology to: (i) identify adjacent scientific opportunities; (ii) target bridge investments (centres, doctoral programmes, shared facilities) that connect core subjects with promising neighbours; and (iii) design interdisciplinary platforms that deliberately increase cross-field co-authorship and co-funding where relatedness density is high but specialisation has yet to emerge.

A set of limitations need to be considered as they may impact upon our derived inferences. First, the geo-coding that was carried out on metadata that concerns the close to 7 m publication documents in our final sample relies on institutional addresses rather than individual author residences. This is standard in publication analytics but potentially could blur the spatial locus of knowledge creation for multi-campus or cross-border institutions. Second, our analysis covers European regions, and one needs to be careful to generalise those to other geographies, e.g., North America or Asia where funding regimes, institutional incentives, and field compositions differ. Third, while we include extensive controls, fixed effects and lag structures, unobserved shocks such as science field specific funding waves directed by EU framework priorities, may still correlate with both relatedness measures and entry. Fourth, the employed classification system, i.e., WoS subheadings/subjects, is broad and therefore results could vary with alternative taxonomies or with finer-grained field definitions. Finally, although publication data capture a broader slice of knowledge than other indicators, e.g., patents, they still might omit other potential highly relevant aspects, such as tacit knowledge exchange processes, and thus our measures most likely understate informal, but important knowledge flows that impact on regional outcomes.

There are a multitude of potential research avenues stemming from this analysis, but it is especially three that stand out. First, it would be useful to extend the dynamic analysis with panel estimators tailored to binary transitions, e.g., dynamic random-effects or correlated random-effects probit with initial-conditions corrections, and also to test exogenous instruments for relatedness exposure, e.g., shift–share designs based on exogenous field-level shocks or international co-authorship diffusion, all geared towards mitigating remaining endogeneity concerns. Second, it would be valuable to link regional Science Space trajectories to technology space outcomes to quantify science-to-technology translation lags, spillovers, and complementarities. For example, knowing whether scientific entry in photonics might predict subsequent patent entry in opto-electronics would offer ample insights for the design of more effective place-bases science, technology and innovation policy instruments. Third, ideally one would also incorporate funding, infrastructure, and mobility data, e.g., EU research priorities, significant core facilities only available in certain places, or data on the mobility of researchers, which in turn could further open the "black box" of the mechanisms through which relatedness is activated.

To conclude, the provided evidence highlights that where science is done, what science is done, and with whom it is connected, are all mutually constitutive. Regions do not become scientifically competitive by leaping into distant subjects; rather, they build outward from their existing knowledge bases, and especially when interdisciplinary bridges shorten the cognitive distance to new opportunities. By providing a scalable way to map those bridges, our study offers both an analytical tool and a strategic compass for regional research and science policy and institutional decision-making. In a period of tightening budgets and widening spatial disparities, aligning scientific priorities with relatedness-informed opportunities can improve the odds of durable capability formation, particularly in places that lack the structural advantages that are more readily present in major metropolitan hubs. The Science Space thus enables a shift away from potentially fashionable scientific disciplines that are too far to reach in a particular regional setting, to a portfolio strategy grounded in each region's evolving endowments, enabling more credible, equitable, and effective pathways to scientific, and ultimately technological and economic, advance.

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Table A1: WoS subjects listed across the ca. 7 million publications that were analysed.

WoS Subject	WoS Subject	WoS Subject
Acoustics (TECH)	Entomology (LSB)	Nutrition & dietetics (LSB)
Agricultural economics & policy (LSB)	Environmental sciences (LSB)	Obstetrics & gynecology (LSB)
Agricultural engineering (LSB)	Environmental studies (LSB)	Oceanography (PS)
Agriculture, dairy & animal science (LSB)	Ergonomics (TECH)	Oncology (LSB)
Agriculture, multidisciplinary (LSB)	Ethics (SS)	Operations research & management science (TECH)
Agronomy (LSB)	Ethnic studies (SS)	Ophthalmology (LSB)
Allergy (LSB)	Evolutionary biology (LSB)	Optics (PS)
Anatomy & morphology (LSB)	Family studies (SS)	Ornithology (LSB)
Andrology (LSB)	Fisheries (LSB)	Orthopedics (LSB)
Anesthesiology (LSB)	Food science & technology (LSB)	Otorhinolaryngology (LSB)
Anthropology (LSB)	Forestry (LSB)	Paleontology (LSB)
Archaeology (SS)	Gastroenterology & hepatology (LSB)	Parasitology (LSB)
Architecture (AH)	Genetics & heredity (LSB)	Pathology (LSB)
Art (AH)	Geochemistry & geophysics (PS)	Pediatrics (LSB)
Astronomy & astrophysics (PS)	Geography (SS)	Peripheral vascular disease (LSB)
Audiology & speech-language pathology (LSB)	Geography, physical (PS)	Pharmacology & pharmacy (LSB)
Automation & control systems (TECH)	Geology (PS)	Philosophy (AH)
Behavioral sciences (LSB)	Geosciences, multidisciplinary (PS)	Physics, applied (PS)
Biochemical research methods (LSB)	Geriatrics & gerontology (LSB)	Physics, atomic, molecular & chemical (PS)
Biochemistry & molecular biology (LSB)	Gerontology (LSB)	Physics, condensed matter (PS)
Biodiversity conservation (LSB)	Green & Sustainable Science & Technology (TECH)	Physics, fluids & plasmas (PS)
Biology (LSB)	Health care sciences & services (LSB)	Physics, mathematical (PS)
Biophysics (LSB)	Health policy & services (LSB)	Physics, multidisciplinary (PS)
Biotechnology & applied microbiology (LSB)	Hematology (LSB)	Physics, nuclear (PS)
Business (SS)	History (AH)	Physics, particles & fields (PS)
Business, finance (SS)	History & philosophy of science (AH)	Physiology (LSB)
Cardiac & cardiovascular systems (LSB)	History of social sciences (SS)	Planning & development (LSB)
Cell & tissue engineering (LSB)	Horticulture (LSB)	Plant sciences (LSB)
Cell biology (LSB)	Hospitality, leisure, sport & tourism (LSB)	Polymer science (PS)
Chemistry, analytical (PS)	Humanities, multidisciplinary (AH)	Primary health care (LSB)
Chemistry, applied (PS)	Imaging science & photographic technology (TECH)	Psychiatry (LSB)
Chemistry, inorganic & nuclear (PS)	Immunology (LSB)	Psychology (SS)
Chemistry, medicinal (LSB)	Infectious diseases (LSB)	Psychology, applied (SS)
Chemistry, multidisciplinary (PS)	Information science & library science (TECH)	Psychology, biological (SS)
Chemistry, organic (PS)	Instruments & instrumentation (TECH)	Psychology, clinical (SS)
Chemistry, physical (PS)	Integrative & complementary medicine (LSB)	Psychology, developmental (SS)
Clinical neurology (LSB)	Language & linguistics (SS)	Psychology, educational (SS)
Communication (SS)	Law (SS)	Psychology, experimental (SS)

Table A1: (continued)

WoS Subject	WoS Subject	WoS Subject
Computer science, artificial intelligence (TECH)	Limnology (LSB)	Psychology, mathematical (PS)
Computer science, cybernetics (TECH)	Linguistics (SS)	Psychology, multidisciplinary (SS)
Computer science, hardware & architecture (TECH)	Logic (TECH)	Psychology, psychoanalysis (SS)
Computer science, information systems (TECH)	Management (SS)	Public, environmental & occupational health (LSB)
Computer science, interdisciplinary applications (TECH)	Marine & freshwater biology (LSB)	Radiology, nuclear medicine & medical imaging (LSB)
Computer science, software engineering (TECH)	Materials science, biomaterials (TECH)	Rehabilitation (LSB)
Computer science, theory & methods (TECH)	Materials science, ceramics (TECH)	Religion (AH)
Construction & building technology (TECH)	Materials science, characterization & testing (TECH)	Remote sensing (TECH)
Criminology & penology (SS)	Materials science, coatings & films (TECH)	Reproductive biology (LSB)
Critical care medicine (LSB)	Materials science, composites (TECH)	Respiratory system (LSB)
Crystallography (PS)	Materials science, multidisciplinary (TECH)	Rheumatology (LSB)
Demography (SS)	Materials science, paper & wood (TECH)	Robotics (TECH)
Dentistry, oral surgery & medicine (LSB)	Materials science, textiles (TECH)	Social issues (SS)
Dermatology (LSB)	Mathematical & computational biology (LSB)	Social sciences, biomedical (SS)
Developmental biology (LSB)	Mathematics (PS)	Social sciences, interdisciplinary (SS)
Ecology (LSB)	Mathematics, applied (PS)	Social sciences, mathematical methods (SS)
Economics (SS)	Mathematics, interdisciplinary applications (PS)	Social work (SS)
Education & educational research (SS)	Mechanics (TECH)	Sociology (SS)
Education, scientific disciplines (SS)	Medical ethics (LSB)	Soil science (LSB)
Education, special (SS)	Medical informatics (LSB)	Spectroscopy (TECH)
Electrochemistry (PS)	Medical laboratory technology (LSB)	Sport sciences (LSB)
Emergency medicine (LSB)	Medicine, general & internal (LSB)	Statistics & probability (PS)
Endocrinology & metabolism (LSB)	Medicine, legal (LSB)	Substance abuse (LSB)
Energy & fuels (TECH)	Medicine, research & experimental (LSB)	Surgery (LSB)
Engineering, aerospace (TECH)	Metallurgy & metallurgical engineering (TECH)	Telecommunications (TECH)
Engineering, biomedical (TECH)	Meteorology & atmospheric sciences (PS)	Thermodynamics (PS)
Engineering, chemical (TECH)	Microbiology (LSB)	Toxicology (LSB)
Engineering, civil (TECH)	Microscopy (TECH)	Transplantation (LSB)
Engineering, electrical & electronic (TECH)	Mineralogy (PS)	Transportation (TECH)
Engineering, environmental (TECH)	Mining & mineral processing (PS)	Transportation science & technology (TECH)
Engineering, geological (TECH)	Multidisciplinary sciences (TECH)	Tropical medicine (LSB)
Engineering, industrial (TECH)	Music (AH)	Urban studies (SS)
Engineering, manufacturing (TECH)	Mycology (LSB)	Urology & nephrology (LSB)
Engineering, marine (TECH)	Nanoscience & nanotechnology (TECH)	Veterinary sciences (LSB)
Engineering, mechanical (TECH)	Neuroimaging (LSB)	Virology (LSB)
Engineering, multidisciplinary (TECH)	Neurosciences (LSB)	Water resources (PS)
Engineering, ocean (TECH)	Nuclear science & technology (TECH)	Women's studies (SS)
Engineering, petroleum (TECH)	Nursing (LSB)	Zoology (LSB)

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