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Understanding Regional Branching
Knowledge Diversification via Inventor Collaboration Networks

Adam Whittle, Balázs Lengyel and Dieter F. Kogler

Utrecht University Human Geography and Planning

UNDERSTANDING REGIONAL BRANCHING

KNOWLEDGE DIVERSIFICATION VIA INVENTOR COLLABORATION NETWORKS

ADAM WHITTLE [a]

BALÁZS LENGYEL [b,c]

DIETER F. KOGLER [a,d]

[a] Spatial Dynamics Lab, University College Dublin; adam.whittle@ucd.ie , dieter.kogler@ucd.ie
[b] Agglomeration and Social Networks Lendület Research Group, Centre for Economic and Regional Studies; lengyel.balazs@krtk.mta.hu
[c] Corvinus University Budapest
[d] Insight Centre for Data Analytics, University College Dublin

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Abstract

The diversification of regions into new technologies is driven by the degree of relatedness to existing capabilities in the region. However, in such case where the necessary skills for diversification are missing, the importation of external knowledge from neighbouring regions or from further away is necessary. Despite the importance of interregional knowledge flows through collaborative work, we still have a very limited understanding of how collaboration networks across regions facilitate diversification processes. The present study investigates the diversification patterns of European NUTS2 regions into new knowledge domains via CPC technology classes reported in patent applications to the European Patent Office. The findings indicate that externally oriented inventor collaboration networks increase the likelihood that a new technology enters a region. The influence of interregional ties is higher if the external knowledge sourcing is based on a diverse set of regions and if collaboration is intense within entities located in distinct regions. Further, the results demonstrate that interregional collaboration networks in general provides the final push into related diversification activities. At the same time, internal collaboration promotes entry into knowledge domains that are weakly related to already present technologies in the region. Finally, evidence shows that diverse external connections and intense collaboration within companies across distant sites compensate for missing related skills in the region.

Keywords

Economic Diversification, Regional Knowledge Networks, Inventor Collaboration Networks, Firm Linkages, Knowledge Sourcing, Specialisation, Patent Data Analysis

JEL: O33, O52, R11

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1. Introduction

Throughout the diversification literature, the concepts of *technological relatedness* and *regional branching* have been used in tandem to describe how the emergence of new economic activities can be understood as a function of the regions pre-existing knowledge base and relatedness structure (Boschma and Frenken, 2012, Kogler *et al.*, 2013; Boschma *et al.*, 2015; Hidalgo *et al.*, 2018). Economic geographers have developed various measures of technological relatedness in order to capture complementarities between firms, industries, skills and technologies and in doing so have shown that regions have a tendency to diversify gradually and into related areas of the knowledge space (Kogler *et al.*, 2017; Whittle and Kogler, 2020). Consequently, technological relatedness is regarded by many to be the primary mechanism that underscores these branching processes (Essletzbichler, 2015). On an empirical level, the branching thesis has been adopted at various spatial scales throughout Europe to investigate the emergence of fuel cell technologies (Tanner, 2014), patterns of structural change (Neffke *et al.*, 2011), radical technologies (Tanner, 2016) and key enabling technologies (Montresor and Quatraro, 2017), amongst others.

At the same time, however, the aforementioned studies have also recognized the concept's infancy and in parallel have called for future work to continue disentangling the mechanisms, *i.e.*, firm diversification, entrepreneurial spin-offs, labour mobility, and networking activities, which drives these diversification processes (Tanner, 2014). Against this backdrop, the present study enters the above discussions by focusing explicitly on the network dimensions of the regional branching thesis which has been largely unexplored to date, and in particular aims to investigate how interregional collaborations facilitate regional diversification processes.

There are two specific and persisting research problems that motivate the presented work. First, despite the recent contributions of Lengyel and Eriksson (2017) and Eriksson and Lengyel (2019) there is still a significant lack of understanding in terms of how external connections promote regional diversification.[1] Eriksson and Lengyel (2019) have examined how different types of network structures influence regional productivity in Sweden finding that regions with links that are diverse, *i.e.* to many other regional economies, are more beneficial for growth. While highly informative a pan-European regional analysis in this regard is still missing. Second, there is a consensus throughout the relevant literatures, and in particular in economic geography, that an upper echelon exists limiting the extent to which a single region can rely solely on its internal technological structure (Boschma and Frenken, 2012). In this capacity, new innovations are likely to depend on the interplay between a region's existing knowledge base, *i.e.* existing specialisations and relatedness structure, and the types of collaborations it has with other regions. Based on these insights a crucial research question emerges that has yet to be addressed in both the diversification and branching literatures. What are the characteristics and trajectories of interregional collaboration patterns that lead to networks that have the potential to compensate for missing knowledge in a region?

The present investigation aims to systematically analyse how external collaborations with other regions facilitates these diversification processes, with a particular focus on the interplay between interregional collaborations and local technological relatedness. The analysis is based on patent data provided by the European Patent Office (EPO) PATSTAT database in order to explain the branching

[1] There are a series of case study examples focusing on specific industries or regions (Isaksen, 2015), but as Boschma (2017) highlights no studies yet exist that compare the intensity and type of diversification in many regions simultaneously and in a systematic way. Fitjar and Rodríguez-Pose (2011) echo these concerns noting that the potential for quantitative methods to uncover the mechanisms through which knowledge is created and diffused in regions (clusters) remains largely overlooked.

patterns of 249 NUTS2 regions over the period 1981–2015. More explicitly, the relationship between inventor-networks and regional relatedness is captured by three distinct social network indicators as well as the relatedness density index (Balland, 2017). The network indicators include a modified external-internal index that measures whether regional knowledge production in a specific technology domain leans more towards internal (intraregional) or external (interregional) collaborations (Krackhardt and Stern, 1988). The second network index aims to capture the diversity of extra-regional knowledge pools, and the third measures how intensively inventors are involved in generating knowledge flows via collaborations within companies, but across locations. The findings can be summarised under three headings.

First, and in line with previous contributions (Kogler *et al.,* 2017), an increasing technological relatedness score between knowledge domains in a region boosts the rate of entry. In fact, the probability of entering a new specialisation changes by almost an order of magnitude along the spectrum of weak to strong technological relatedness. Second, external collaborations are especially efficient when regions establish technological capabilities suitable to branch out into related areas of the local knowledge space. In such cases, interregional linkages as indicated by an inventor network that spans two or more regions appears to provide the final push for related diversification to take place. However, and equally important, this should not deny or downplay the relative importance of internal collaborations. The results indicate that when an emerging technology is weakly related to the existing knowledge base in a region then knowledge sourcing across unrelated technologies can be realized through intraregional collaborations that foster entry. Next, in order to control for sectoral differences, we aggregate the 650 distinctive knowledge domains (4-digit CPC patent classes) into eight main technology categories. Even at this aggregate level, the finding that interregional collaboration drives technological entry prevails. Third, and final, the influence of diversity found in external linkages and the importance of within-company collaboration across regions were found to facilitate the entry of new technologies to the region. These sort of co-inventor networks appear to compensate for a present lack of technological relatedness in a region.

The remainder of this paper is organised as follows. In Section 2, we provide a novel conceptual angle on the buzz-pipeline debate (Bathelt *et al.,* 2004) in the context of network dimensions and their role in regional branching processes. Section 3 describes the use of patent data as well as how the variables where created. Expanding on this, Section 4 explores the investigation's main research questions and discusses the results. Finally, Section 5 provides concluding remarks and offers directions for future research in this line of inquiry.

2. Knowledge Production Networks and Regional Branching

Increasingly viewed as a recombinant and interactive process, the production of economically valuable knowledge is known to underscore the long-term survival of both firms and regions alike (Schumpeter 1942). From this perspective, regions evolve by collectivizing an increasingly larger array of knowledge and by experimenting with how this knowledge can be recombined in novel ways to form new products and processes. These processes of experimentation through industrial mutation are at the core of Schumpeter's *creative destruction* thesis, which is considered by many to be the engine of innovation and a vital component for regional diversification and associated growth (Boschma and Martin, 2007). More recently, the intertwining of these processes has given rise to the evolutionary turn in economic geography (Grabher, 2009; Kogler, 2016) which propagates the evolutionary belief that diversification is an endogenous, dynamic process conditioned upon a set of localized capabilities (Maskell and Malmberg, 2006).

The central tenants of the regional branching thesis champion the idea that learning processes, innovation and technological change are inescapably geographic in nature suggesting that the location – country, region, city, etc. – where these processes take place may provide strategic advantages to these innovative activities (Bathelt *et al*., 2004). It describes how the emergence of new activities in the region can be understood as a function of how related the emerging activity is to the regions existing knowledge base (Neffke *et al.,* 2011). This thesis has been adopted widely by policy-makers (Montresor and Quatraro, 2017) and has become a key pillar of the European Union's Smart Specialisation Strategies (S3) framework (Boschma, 2014).

Grounded in a path dependent logic, the regional branching thesis builds on two very prominent ideas in economic geography. Firstly, that the production of knowledge is still very much a localized process despite noticeable advances in ICT and communication technologies (Feldman and Kogler, 2010). Second, that knowledge will primarily "spillover between sectors that are related and only to a limited extent among unrelated sectors" (Frenken *et al.,* 2007, p. 688). In evolutionary approaches to regional economic development, it is generally well accepted that some baseline level of proximity is required for learning to take place, whilst too much proximity can have a negative effect (Boschma, 2005). According to Neffke *et al.* (2011) this is because technologically related industries combine cognitive distance with cognitive proximity and in doing so bring together the positive aspects of variety and relatedness.

2.1 Regional Branching and Knowledge Transfer Mechanisms

Boschma and Frenken (2012) outline four channels through which these branching processes can operate – firm diversification, entrepreneurial spin-offs, labour mobility, and social networking – and throughout the diversification literature they have been applied to examine the technological evolution of countries and regions alike (Whittle and Kogler, 2020).

Utilizing trade data, Hidalgo *et al.* (2007) were among the first to show that countries typically expand their export structure into products that are related to their current export basket. They also show that those countries which populate denser sections of the product space have a greater opportunity to diversify into new products. Intuitively this makes sense and provides additional weight to the Jacobian claim that the greater the sheer number of varieties already achieved in an economy, "the greater the economies inherent capacity of adding more kinds of goods and services" (Jacobs, 1969, p. 59).

Focusing on the emergence of fuel cell technologies throughout European region, Tanner (2014) explains how these branching processes can also be driven through firm diversification whilst also recognising the importance of spin-off firms, universities and research institutes. Turning to entrepreneurial spin-offs, Klepper and Simons (2000) provide clear evidence on how new sectors grow out of old sectors. Their study on the US television industry demonstrated how entrants with a background in radio significantly outperformed their nonradio counterparts a process they metaphorically labelled "dominance by birth right". More recently, Morrison and Boschma (2018) reveal similar patterns for the Italian motorcycle industry.

Lastly, the importance of labour mobility as a conduit of knowledge exchange has a long tradition in economic geography (Almeida and Kogut, 1999) but has only recently been applied to investigate regional branching (Boschma *et al.*, 2009). Noticeable here are the contributions of Eriksson and Lindgren (2008), Eriksson (2011) and Boschma *et al.* (2014) which analysed for Swedish regions how the mobility of skilled workers affects plant performance. Also, for Sweden, Neffke *et al.* (2018) found that structural change, which is synonymous with regional branching, is primarily driven through the influx of entrepreneurs (and firms) from outside of the region. This last finding is extended by Elekes *et al.* (2019) who showed that foreign-owned firms induce more unrelated diversification than domestic firms.

Lastly, in an attempt to combine the spatial and cognitive proximity dimensions as explanatories within one model of technological knowledge diversification, Feldman *et al.* (2015) test the spatial diffusion and adoption of rDNA methods across US metropolitan areas. Findings reiterate the importance of spatial proximity, as demonstrated previously (Glaeser *et al.*, 1992), as a significant driver of knowledge diffusion patterns. However, results also point to the need of cognitive proximity, measured as the technological distance to the new rDNA technology. In addition to the spatial and cognitive dimensions, the Feldman *et al.* (2015) study also tests the role of social proximity as a conduit for knowledge flows that lead to the adoption of initial rDNA knowledge in a region. Findings indicate that interregional collaboration networks of rDNA inventors with individuals who might have not been exposed to that specific technology previously significantly explain the diffusion patterns of rDNA methods in space, and thus hints on the importance of social networks for regional branching processes; something that will be subsequently discussed in more detail.

2.2 Social Networks and Regional Branching

From a technological or scientific point of view, there is a wealth of research focusing on the dynamism within regions and how relatedness between existing technologies drives diversification into related areas of the knowledge space (Kogler *et al.*, 2013, 2017; Boschma *et al.*, 2015; Rigby, 2015; Kogler and Whittle, 2018; Whittle, 2020). Further, whilst these studies provide additional support for the branching thesis, they themselves do not discern who the actual drivers of these diversification processes are, and as such relatedness remains encased in somewhat of a black-box (Boschma, 2017; Kogler, 2017); a notable exception is regard is the contribution by Kogler *et al.* (2017) who decompose regional structural change into processes of entry, exit and selection.

Using this research gap alongside the above contributions as a guidepost, a discussion that focuses explicitly on the social network dimensions of regional branching activities seems needed in order to further investigate how external collaborations with other regions facilitate regional diversification. Theory suggests that successful innovations require a mixture of region specific knowledge and perhaps also external capabilities. Bathelt *et al.* (2004) first formalised these ideas whilst discussing the relational dimensions of knowledge creation in a buzz-pipeline framework. Here, ‘buzz’ is synonymous with cohesive local connections and is known to promote learning opportunities of a Marshallian nature. For instance, Asheim (1996) suggests that tight social cliques enhance certain types of Marshallian externalities for specialised industrial districts, thus fostering incremental innovation and productivity. Similarly, Funk (2014) has shown for nanotechnology firms in the United States, that learning between firms in specialised agglomerations is facilitated if the internal networks are cohesive. This is because cohesive local networks based on repeated socialisation and trust enable the transmission of complex, non-proprietary and sensitive knowledge (Sorenson *et al.,* 2006). However, in network related learning cohesive ties also carry the risk that actors will rely too heavily on the knowledge of their immediate peers thus ignoring more optimal solutions (Perry-Smith and Shalley, 2003).

On the other end of the spectrum, external collaborations (pipelines) ensure that the region is kept abreast of ideas developed elsewhere (Fitjar and Rodriguez-Pose, 2011; Morrison *et al.*, 2013; Neffke *et al.*, 2018). For Bathelt *et al.* (2004) pipelines are associated with multiple selection environments which permit external sources of knowledge to be brought into the region through deliberate action. In the context of the present investigation, two forms of pipelines are particular noteworthy, namely: *the diversity of links to other regions* and *intra-firm collaborations across regions*. Branching studies have hinted at the limitations of individual regions (Boschma and Frenken, 2012). Bathelt *et al.* (2004, p. 46) already understood this reality outlining how “even world-class clusters (regions) cannot be permanently self-sufficient in terms of state-of-the-art knowledge creation. New and valuable knowledge will always be created in other parts of the world and firms who can build pipelines to such sites of global excellence gain competitive advantage”. In this regard there are two noteworthy arguments that require further clarifications.

Firstly, the *diversity of links to other regions* reinforces the aforementioned Jacobian claim that variety increases the likelihood of successful recombination as actors can benefit from the cross-fertilization of knowledge and ideas from multiple localities. Translating this argument to the level of interregional collaborations suggest that the diversity in regional connections is a crucial component through which non-redundant sources of knowledge can be brought into the region (Moodysson, 2008). In this capacity, Kemeny *et al.* (2016) have shown that the number of connections an incoming manager has helps to explain variations in firm performance. They argue that high-degree managers *i.e.* those who are “unusually well connected in the local social network” are better equipped and therefore more likely to channel external sources of information into the firm (Kemeny *et al.*, 2016, p. 1). In a similar context, Tóth and Lengyel (2019) found hiring new employees that have diverse linkages facilitates company innovation; whereas Fitjar and Rodríguez-Pose (2011) demonstrate that Norwegian firms with a greater diversity of international partners were more innovative than those who are primary embedded in a local or national context. However, for the same reasons as outlined in Frenken *et al.* (2007) it may also be the case that the diversity of interregional networks is not sufficient to explain knowledge creation simply because there are a lot of technologies that cannot be meaningfully recombined in the first place. To account for this, what matters more than diverse linkages per se, is having linkages to other regions that can compensate for missing related skills in the region *(cf.* Eriksson and Lengyel, 2019).

Secondly, despite noteworthy advances in the field of information and communication technologies physical distance, *i.e.* geographic proximity, still remains the greatest impediment to knowledge sharing (Boschma, 2005). While recent evidence has suggested that firms can overcome this geographical distance by exploiting benefits of other types of proximities; this is often easier said than done (Fitjar and Rodríguez-Pose, 2011). Thus, interregional collaborations are often seen as a desirable pathway for a region given their association with unrelated diversification and technological breakthroughs (Whittle and Kogler, 2020). At the same time, however, a significant portion of interregional collaboration occurs within the boundaries of a single firm making it difficult to emulate (Singh, 2008).[2] In the business management literature, these individuals are known as *boundary spanners* and are said to create knowledge-sharing-connections which have been shown to increase performance at both the project (Cummings, 2004) and individual level (Cross and Cummings, 2004). Moving to a regional perspective, the benefits of intrafirm and interregional collaborations are twofold. Firstly, they limit the potential for duplication of research efforts and thus save resources as technical

[2] For instance, an employee working for Microsoft Dublin collaborating with their counterpart working for Microsoft Budapest.

challenges faced by a subsidiary located in one region might have already been mastered by their counterpart in another. Secondly, if these interactions are sufficiently intense, which is likely in an environment where individuals share the same overall firm association then these connections have the potential to enact entirely new growth trajectories in the region, *i.e.* unrelated diversification. Following these lines of reasoning, the present investigation now turns to the methodological approach that is deemed suitable to conduct such a multifaceted analysis of regional economic branching processes.

3. Methodological Approach

3.1 Patent Data and Inventor Networks

The empirical analysis of this article uses patent data from the European Patent Office (EPO) PATSTAT database for seven non-overlapping 5-year periods (1981-85, …, 2011-2015) and covers 249 NUTS2 regions.[3] Patent data have an established record throughout the economic geography literature and have become a staple metric for those interested in the evolution of regional knowledge spaces (Kogler *et al.*, 2013), regional collaboration networks (Tóth *et al.*, 2018), knowledge complexity (Whittle, 2019), and regional branching (Tanner, 2014). Patents, which are applied for novel products and processes of economic value, provide a wealth of information. In addition to the names and addresses of inventors and assignees they also contain CPC codes which are used to reflect the patents underlying novelty. A patent document will contain at least one CPC class, but in most cases more than that, which in turn allows for an analysis of how particular knowledge domains are related to each other. While most useful for the purpose of regional economic analysis, the limitations of patents are equally well-known (Kogler, 2015). For instance, they are not uniformly distributed across sectors and their legal protection frequently favours larger firms. Nevertheless, prior research along similar lines have demonstrated the fruitfulness of patents with Acs *et al.* (2002) arguing that they provide a good indication of the processes of knowledge creation and diffusion especially on a regional level, which is the primary concern of the present investigation.

As has become commonplace, individual patent applications are regionalised using inventors' addresses, which is frequently at the NUTS2 spatial aggregation level if the focus is on European regional economies (Kogler *et al.*, 2017). Further, as the majority of patents are now the result of collaborative networks spanning multiple inventors and possibly regions, we employ a standardized technique and fractionally split those patents to reflect the geographic distribution of co-inventors. Next, in order to construct the regional inventor network, we make use of the aforementioned inventor addresses and the 650 CPC 4-digit patent classification codes. Utilizing this information, we closely follow the approach outlined in Toth *et al.*, (2018) and derive interregional and intraregional inventor collaboration networks through aggregating individual level ties to their NUTS2 counterparts.

3.2 Knowledge Space and Network Indicators

Echoing the central tenants of the regional branching thesis our main variable of interest focuses on the emergence of new technological specialisations in European NUTS2 regions. Throughout the extant literature, these diversification processes have most frequently been investigated using a measure

[3] The utilized PATSTAT database was developed via the ERC TechEvo project (https://cordis.europa.eu/project/id/715631) and includes all EPO patent applications that feature at least one inventor who resided in one of the 249 NUTS2 regions at the time of invention. Further, this TechEvo database features inventor name disambiguated, and assignee name harmonized, information. For further information about the ERC TechEvo database please get in touch with: dieter.kogler@ucd.ie.

of Revealed Comparative Advantage or a spatial derivative thereof (Whittle and Kogler, 2020). In its capacity and the way it is employed in the present investigation, RTA $_{i,r,t}$ captures a regional technological specialisation in a given knowledge domain and time period. Once an RTA $_{i,r,t}$ reaches a value of 1 or above, which we trace period by period over the entire timeframe (1981-2015) and for each region, it signifies a branching event, *i.e.* the regional economy managed to branch out into a new knowledge domain in which it has become specialised above the pan-European average.[4]

In order to capture the network dimensions of the regional branching thesis two core indicators are developed. The first is a measure of technological relatedness, which gauges how close an emerging technology is to the existing knowledge space of the region (Balland, 2017). The knowledge space is a network-based representation that captures the levels of technological relatedness based on the co-occurrence of technology classes listed on patent documents (Whittle, 2020). Originally popularized by the proximity index of Hidalgo *et al.,* (2007), its general schema has recently been adapted by various economic geographers and regional scientists to analyse the diversification patterns of economic activities at the subnational level (Kogler *et al.,* 2013; 2017; Boschma *et al*., 2015; Kogler and Whittle, 2018). In this approach, relatedness $\varphi_{i,j,t}$ between technologies i and j is computed as the minimum pair-wise conditional probability of regions patenting in technology i while also patenting in technology j at time t. Or:

$$\varphi_{i,j,t} = \min\{P(RTAx_{i,t} | RTAx_{j,t}), \{P(RTAx_{j,t} | RTAx_{i,t})\}\} \quad (1)$$

As has become commonplace, we only focus on those regions that are a substantial producer of a given technology. Otherwise stated, $RTA_{r,t}(i) = 1$ if:

$$\frac{patents_{r,t}\ (i)/\Sigma_i\ patents_{r,t}\ (i)}{\Sigma_c\ patents_{r,t}\ (i)/\Sigma_c\ \Sigma_i\ patents_{r,t}\ (i)} > 1 \quad (2)$$

However, more than just focusing on the region's relatedness structure in terms of individual patents, we are particularly interested in how close an emerging technology is to the existing knowledge base of the region. Or from a branching perspective, how new technologies emerge from the region's pre-existing technological structure (Tanner, 2014). Following Boschma *et al.* (2015) and Balland *et al.* (2018), we develop a relatedness density index in which the density of a specific technology i in region r at time t is calculated using the corresponding relatedness index of technology i to the technologies in region r that have an RTA ≥ 1 in time t, divided by the sum of technological relatedness of technology i to all the other technologies in region r at time t:

$$Relatedness\ Density_{i,r,t} = \frac{\sum_{j \in r, j \neq i} \varphi_{ij}}{\sum_{j \neq i} \varphi_{ij}} \times 100 \quad (3)$$

By design, this index can take a value between 0% and 100%. A value equal to 0% would indicate that there is no technology related to technology i in region r at time t. Conversely, a value of 100% would

[4] Although the most frequently used indicator of diversification, RTAs are not without limitations and these limitations are becoming increasingly well-known. For instance, because RTA is a revealed measure of specialisation it is possible for a technology to emerge in a region without any increase in inventive activity. By the same token, a region can also lose a specialisation if other regions begin patenting more frequently in that technology class.

indicate that all the technologies related to i are present in region $r's$ knowledge space. Table 1 provides some descriptive statistics for each of the seven time periods as well as providing information over the entire period of analysis. Here it is important to note that over the previous thirty-five years the average density index as a whole has increased markedly from just over 10% in 1981-85 to over 20% in the period 2011-15. This process is indicative of regions becoming more specialised in their respective areas of the knowledge, *i.e.* areas of excellence and has also been reported for both EU15 (Kogler *et al.*, 2017) and metropolitan regions in the US (Kogler *et al.*, 2013).

Table 1. Relatedness Density Summary Statistics

	1981-85	**1986-90**	**1991-95**	**1996-00**	**2001-05**	**2006-10**	**2011-15**	**1981-15**
Min	0	0	0	0	0	0	0	0
Max	100	100	100	100	100	100	100	100
Mean	11.01	14.72	15.46	17.53	19.04	20.77	21.23	23.06
Median	11.11	14.18	15.95	18.52	19.31	20.95	20.92	25.01
SD	10.56	11.07	11.18	10.96	10.67	10.11	9.66	12.05

Our second independent variable is the External-Internal Index (EI Index) that investigates the role of inter- and intra-regional inventor collaboration in regional branching.[5] Originally a social network measure (Krackhardt and Stern, 1988), this index quantifies the relative density of internal connections for a given entity (firm, organisation, region, etc.) compared to the number of connections that entity has to the external world in the following manner:

$$External\ Internal - Index_{i,r,t} = \frac{EL_{i,r,t} - IL_{i,r,t}}{EL_{i,r,t} + IL_{i,r,t}} \qquad (4)$$

where *EL* is the number of external linkages (pipelines) to other regions and *IL* is the number internal linkages (buzz) within the same region. The index can take a value from -1 (all connections are intern to the region) to +1 (all connections are with external entities). For economic geographers, a balanced EI-index moves the discussion beyond the simple "local = tacit versus global = codified" debate recognising that real learning opportunities and true knowledge exchange often take place when these types of knowledge occur in unison (Isaksen, 2015). Along these lines, Oinas (1999, p. 365) has argued that the "creation of new knowledge might be best viewed as a result of a "combinations" of close and distant interactions". In the present investigation, *close interactions* capture those network dimensions where co-inventors are located in the same NUTS2 region, whereas *distant interactions* capture co-inventors residing in multiple regions.

The diversity of links in a network captures the pool of information that can be accessed directly through first connections (Granovetter, 1985). A diverse set of links provides the opportunity to combine distinct pieces of knowledge and to come up with innovative ideas (Burt, 2004). In that sense, the geographical diversity in social and collaborative networks captures the pool of knowledge that

[5] Henceforth referred to as an EI-index.

resides in various locations. For example, individuals that have spatially diverse communication networks and connections to many places are typically wealthier than those who do not (Eagle *et al.*, 2010). On a more aggregate level, Eriksson and Lengyel (2019) have found that spatially diverse co-worker links facilitate the growth of those industry-region pairs that have a low degree of specialisation.

In our specific inventor-collaboration case, we quantify the spatial diversity of the technology-region pairs by aggregating the co-inventor links that a technology-region has to other regions. By definition, this is a weighted network in which the weights are the number of individual co-inventorships. Then, for every technology-region $i \in r$ we calculate the entropy of the weights distributed across connections to other regions q following the formula:

$$Diversity_{i,r,t} = \frac{-\sum l_{rq} \times \log(l_{rq})}{\log(k)} \quad (5)$$

where l_{rq} is the proportion of co-inventor links from $i \in r$ to q among the total co-inventorship volume of r and k is the number of q regions $i \in r$ is connected to. The indictor takes a high value if the co-inventor links of $i \in r$ are equally distributed across q and low values if links of $i \in r$ are concentrated to specific q.

We quantify intensity of within firm collaboration to other regions by calculating the density of collaboration ties within firms as the ratio of observed within firm collaboration in all possible within firm collaboration. The indicator is formulated by:

$$Intensity_{i,r,t} = \frac{\sum_q L_{f \in i,r = f \in q}}{\sum_{q, f \in i,r = f \in q} N_{f \in i,r} \times N_{f \in q}} \quad (6)$$

where L refers to the observed number of co-inventor links between the inventors resided in $i \in r$ and inventors working for the same firm in other regions, $N_{f \in i,r}$ is the number of inventors in $i \in r$ and $N_{f \in q}$ is the number of inventors working for the same firm in other regions. The indicator takes a high value if the inventors in $i \in r$ are collaborating with most of their colleagues in the firm in other regions and a low value means that inventors in $i \in r$ are isolated from distant colleagues in the same firm.

A series of additional control variables are employed. *Number of Inventors*$_{r,t}$ and *Urban Density* $_{r,t}$ are designed to reflect underlying agglomeration externalities. *CPC Diversity*$_{r,t}$ captures the Jacobian externalities by measuring how diverse the patent portfolio of a region is. As mentioned earlier, this variable speaks to the Jacobian claim that the greater the sheer number of varieties already achieved in an economy, "the greater the economies inherent capacity of adding more kinds of goods and services" (Jacobs, 1969, p. 59). The *Number of Firms*$_{i,r,t}$ captures degree of absolute specialisation in a given technology in the region (Kemeny and Storper, 2015) and *Firm Concentration*$_{i,r,t}$ measures the distribution of patents across assignees in the region. We have also considered further indicators representing the overall inventive capacity of a region, such as the sum of patent applications in a given region, the number of technological specialisation and the number of CPC classes the region is currently active in. However, these were very highly correlated with one or more of the variables specified above. Table 2 provides a summary of all the variables used with the correlation matrix provided in Table 3.

Table 2. Description of Variables and Data Sources

Variable	Definition	Source
$Entry_{i,r,t}$	Binary variable donated as 1 if region r develops a new specialisation i since the previous time period $t_{-1}$and 0 otherwise	EPO PATSTAT Database
Relatedness $\text{Density}_{i,r,t}$	Measure of how close an emerging technology i is to region $r's$ existing knowledge base at time t.	EPO PATSTAT Database
$External - Internal\ Index_{r,t}$	The relative density of region $r's$ internal and external connections at time t.	EPO PATSTAT Database
Diversity	Entropy of the co-inventor link distribution to other regions.	EPO PATSTAT Database
Intensity	The ratio of observed links within the firm to other regions among all possible such links.	EPO PATSTAT Database
Number of Inventors $_{r,t}$	Total number of inventors present in region r at time t.	EPO PATSTAT Database
$Urban\ Density_{r,t}$	Population density for region r at time t.	EPO PATSTAT Database & Cambridge Econometrics – European Regional Database
CPC Diversity$_{r,t}$	Entropy of patent number distribution across CPC classes in the region.	EPO PATSTAT Database
Firm Concentration$_{i,r,t}$	The Hirshman-Herfindahl index of patent concentration in firms in the region.	EPO PATSTAT Database
Number of Firms$_{r,t}$	Total number of firms assigning patents in the region *r* and time *t*.	EPO PATSTAT Database
GDP per Capita	GDP over population of region *r* in time *t*.	Cambridge Econometrics – European Regional Database

Table 3. Correlation Matrix

Relatedness Density	1								
External-Internal Index	0.037	1							
Diversity	0.329	-0.15	1						
Intensity	0.324	-0.239	0.662	1					
Number of Inventors	0.598	0.116	0.226	0.177	1				
GDP per capita	0.533	0.123	0.172	0.156	0.763	1			
Urban Density	0.151	-0.043	0.058	0.064	0.06	0.241	1		
CPC Diversity	0.736	0.01	0.221	0.237	0.363	0.424	0.128	1	
Firm Concentration	0.226	-0.082	0.331	0.636	0.073	0.084	0.038	0.182	1
Number of Firms	0.28	0.068	0.496	0.296	0.316	0.249	0.026	0.175	0.112

4. Results and Discussion

4.1. The role of external connections in related diversification

Figure 1 illustrates how entry probabilities change along the spectrum of technological relatedness. To ease with interpretation, we binned technological relatedness along a spectrum of 1 to 10 where 1 donates weakly related and 10 highly related. Firstly, we find that the probability of entry (red line) increases sharply with technological relatedness. In fact, the probability that a region develops a new specialisation, *i.e.* enters a new technology class, increases by almost an order of magnitude along the spectrum of weak to strong technological relatedness. As such, our results corroborate those of earlier studies, including Boschma *et al.* (2015), Rigby (2015) and Kogler *et al.* (2017), and demonstrate that entry is more likely when an emerging activity is highly related to the region's existing knowledge base (Whittle and Kogler, 2020). However, while this finding provides additional empirical evidence to the branching thesis, it does not discern who the actual drivers of these diversification processes are, and as such relatedness as a driver of regional economic diversification remains encased in somewhat of a black-box (Boschma, 2017).

To begin engaging with these questions and to better understand the underlying network dimensions of the regional branching thesis, we deconstruct technological relatedness with the EI-index discussed earlier. Recall that index can take a value from -1 (all connections are internal to the region) to +1 (all connections are with external jurisdictions). In order to implement this, all the observed entries (red line) in regions at each particular bin (relatedness) are examined to determine whether entry was driven primarily by intraregional collaborations *i.e.* within the same region (blue line in case EI-index < 0) or interregional collaborations *i.e.* with multiple regions (green line in case EI-index ≥ 0). Our results indicate that when a technology is weakly related to the regions existing knowledge base then technological entry is mainly driven by intraregional collaborations.

There are a few logic explanations for the observed trend based on insights derived from the relevant literature. One would be based on the notion that it requires frequent face-to-face interactions that facilitates high-level tacit knowledge exchanges in order to tackle more complex problem-solving tasks. Essentially, only spatial proximity enables the sort of 'buzz' (Storper and Venables, 2004) that provides the opportunity for frequent socialization and learning, the psychological motivation, the trust, and exploitation of absorptive capacity opportunities that are difficult to replicate in long-distance collaborations. Thus, in order to overcome technological knowledge barriers in the recombination of current specialisations with new domains, *i.e.* low technological relatedness, it basically requires the high degree of spatial proximity found in intraregional co-inventor networks.

Conversely, moving along the horizontal axis, we see that the rate of entry increases (red line), but this entry is primarily driven through collaborations with other (NUTS2) regions. These results show that at higher levels of relatedness extra regional collaborations give the region a 'final push' towards related diversification. In such instances, external orientation complements relatedness meaning that if there are related technologies in the region then external knowledge is easier to absorb. Again, there are a few possible explanations. For example, it is possible that endogenously driven increasing specialisation, *i.e.* branching out in new specialisations that are already close to the current knowledge base found in a region, might be subject to decreasing returns. In other words, in order to even further branch out into related knowledge domains than what already exists in a particular locality it requires inputs from more distant knowledge pools and thus interregional collaborations.

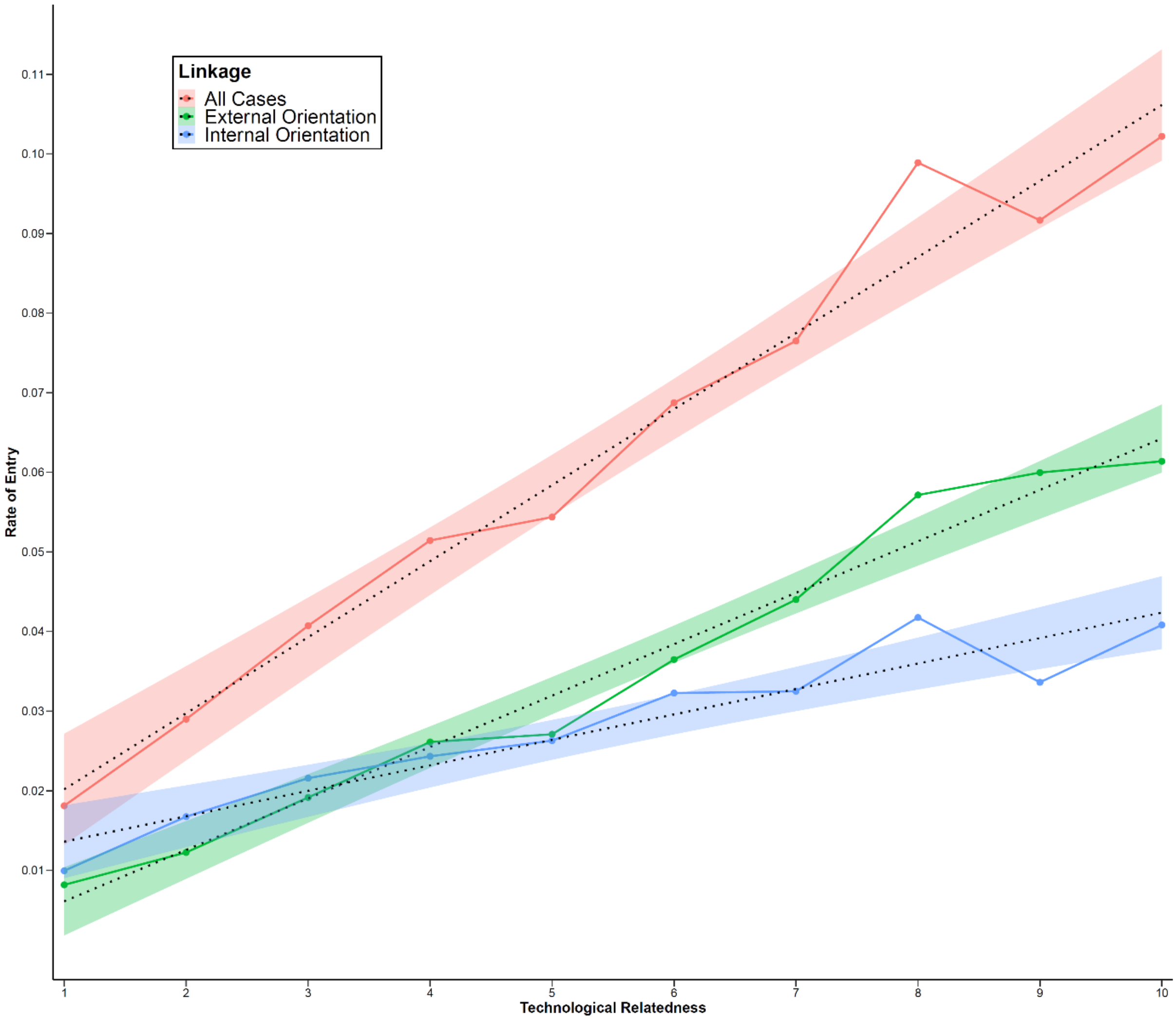

Figure 1. Probability of Entry by Technological Relatedness and External-Internal Index.

Notes: Markers denote the number of entries over all possible entry options binned into Technological Relatedness categories (deciles of Relatedness Density). Red markers denote probability calculated from all cases, Green denote probability of entry in case External-Internal Index is greater or equal to zero, Blue denote probability of entry in case External-Internal Index is lower than zero. Shaded areas denote 95% confidence interval.

The literature does indeed hint on this phenomenon referring to buzz-pipelines dynamics (Bathelt *et al.*, 2004) and the internationalization of ventures' R&D activities around centres of excellence (Chiesa, 1995). A further argument is provided by the tacit *vs.* codified knowledge debate (Gertler, 2003) that highlights that codified knowledge, which is more likely to be present within a community that operates along similar standards and speaks a common 'technical' language (Amin and Cohendet, 1999), and thus is characterized by high relatedness, is much easier to exchange over long distances.

The results provided thus far provide sound support for the increasing importance of interregional collaborations. However, as a robustness check, and in order to provide further support

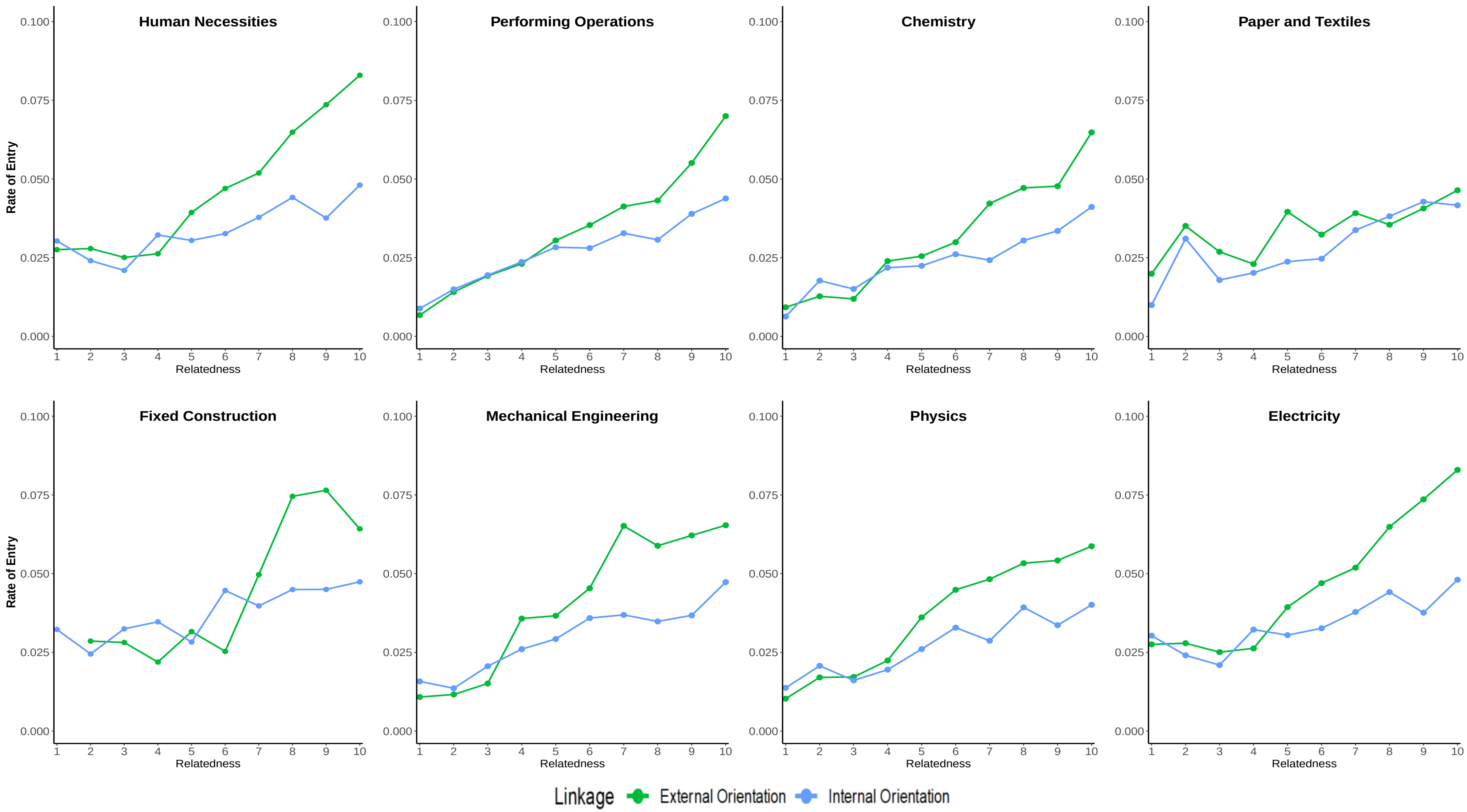

Figure 2. Probability of Entry by Aggregate Technology Class. Green denote probability of entry in case External-Internal Index is greater or equal to zero, Blue denote probability of entry in case External-Internal Index is lower than zero.

for our primary hypothesis, we aggregated the 650 individual knowledge domains (4-digit CPC patent classes) into eight main technology categories. In doing so, we are able to investigate more directly whether or not there are any sectoral differences to the patterns observed in Figure 1. Indeed there is strong evidence - anectodical and otherwise – that the pace of innovation differs by industry (Gordon, 2000; Kogler, 2015) with certain types of industries requiring more frequent interaction (Powell *et al.*, 1996). Once again, the rDNA technology described in Section 2.1 provides a detailed example of this. Biotechnology is an area of the knowledge space where the scientific frontier is continually being reshaped and thus where interregional collaboration is paramount (Feldman *et al.*, 2015). Focusing on the role of interorganisational collaborations, Almeida *et al.* (2011) found the extent to which a firm's scientists collaborate externally on scientific journal articles with other biotech firms positively influences their own innovation performance. Similarly, Powell *et al.* (1996, p.1) has argued that "when an industry is both complex and expanding and the sources of expertise are widely dispersed, the locus of innovation will be found in networks of learning, rather than in individual firm". Against this backdrop, Figure 2 clearly demonstrates that whilst there are technological differences the overarching hypothesis holds irrespectively. Consistent with the extant literature, the areas of *Chemistry*, *Electricity* and *Physics* demonstrate the proclivity of interregional collaboration particularly well. These are areas of the knowledge space which are commonly associated with the knowledge-base or learning economy (Asheim, 1996). Most recently, Balland *et al.* (2019) have also demonstrated that these technologies are also the most 'complex' and underscore the European Union's smart specialisation strategies for the coming decade (*c.f.* Montresor and Quatraro, 2017).

At the same time, however, whilst Figure 2 echoes the overarching findings of Figure 1, namely: that externally oriented inventor collaboration networks increase the likelihood that a new closely related technology enters a region, there is one notable expectation which provides further support to the arguments developed thus far, *i.e.* Paper and Textiles. As an industry, Paper and Textiles consistency ranks as one of the least complex industries and therefore would not necessarily require the same level of interregional collaboration to be kept up to date with changing practices of specialisation.

4.2 The role of diverse interregional knowledge pools and intra-firm connections

We analyse the role of interregional co-inventor collaboration on technological diversification with a logistic regression approach by estimating the log-odds ratio that a new technology enters a region:

$$log_e\left(\frac{P_{r,t}^{entry}}{1-P_{r,t}^{entry}}\right) = \alpha + \beta X_{r,t} + \gamma Z_{r,t} + \mu_t + \varepsilon_{r,t} \qquad (7)$$

where $X_{r,t}$ are region control variables including *Number of Inventors*, *GDP per Capita*, *Urban Density*, *CPC Diversity*, *Firm Concentration*, and *Number of Firms*, $Z_{r,t}$ denote region and time specific explanatory variables including *Relatedness Diversity*, *External-Internal Index*, *Diversity*, and *Intensity* and their interactions, μ_t is period fixed effect and $\varepsilon_{r,t}$ is the error term. Regressions are run on a panel of technology-regions in which observations are traced only until the event of entry.

In this specification, we include the levels of independent variables at the time of technology entry instead of lagging variables. This is important since most of the technologies that are new to the region have no co-inventorship history. Consequently, we can only evaluate the type of knowledge-sourcing through co-inventorship at that time of patent application that also coincides with the event of diversification. By including period fixed effects, we control for the unobserved time-variant heterogeneity of technological evolution. For the reasons of effective computing, we let all regressions run until 20 iterations.

In Table 4, we introduce the results in a stepwise manner. Control variables introduced in Model 1 all have significant co-efficients as expected. However, their relationship with the probability of entry cannot be assessed from this table, since some of them are strongly correlated (eg. *Number of Inventors* and *GDP per Capita*). Furthermore, when *Relatedness Density* is introduced in Model 2, the coefficient sign of most control variables changes. Nevertheless, regression fit improves from Model 1 to Model 2 meaning that Relatedness Density significantly adds to the quality of estimation. In Models 3-9, when we include the network measures, neither the sign of controller coefficients changes nor model statistics deviate remarkably, which in turn enables us to evaluate the role of co-inventor collaboration in a meaningful and statistically robust manner.

In line with the previous literature, the positive and significant coefficient of *Relatedness Density* is stable across Models 2-9. This confirms that technological relatedness to the existing knowledge that is present in the region facilitates diversification into new technologies (Hidalgo *et al.,* 2007, Kogler *et al.,* 2017).

In Model 3, the *External-Internal Index* has a weak but significant and positive coefficient. This finding implies that technologies are more likely to enter a region in case they pull external knowledge to the region through co-inventor collaboration. The result is in line with the previous literature claiming the need of external knowledge sources for diversification (Neffke *et al.,* 2018) and with the claim on global pipelines (Bathelt *et al.,* 2004). Going further in Model 4, we introduce the interaction of *Relatedness Density* and *External-Internal Index*. In line with our findings presented in Section 4.1, we find a positive and significant coefficient, meaning that external knowledge complements related diversification.

The direct coefficient of the *External-Internal Index* takes a negative value when regressed together with its interaction with *Relatedness Density* in Model 4. Recall that the *External-Internal Index* is bounded by [-1, 1] and that the negative values mean more intensive collaboration within the region than with other regions. The negative coefficient therefore indicates that intra-region collaboration shows importance after controlling for its relationship with technological relatedness. This change in the coefficient sign from Model 3 to Model 4 even allows us to deduce that controlling for the complementary relations between external collaborations and related diversification, there is room left for internal co-inventor collaborations that significantly increase the likelihood of unrelated diversification. The finding is intuitive because co-location facilitates face-to-face meetings that can be used to combine unrelated knowledge (Feldman and Kogler, 2010; Storper and Venables, 2004).

Diversity is found to increase the likelihood of Entry in Model 5. This is because the combination of knowledge pooled from many locations increases the potential to combine them in a way, in this case the combination of technological classes listed in patent documents that describe novel inventions of economic value, that is new to the region. Further, the negative coefficient of *Relatedness Density* and *Diversity* in Model 6 suggests a supplementary relation between diverse external knowledge access and local technological relatedness. In other words, in case inventors in a region can collaborate with co-inventors located in a variety of regions the lack of relatedness to the local knowledge base can be compensated for.

Table 4. The role of extra-regional ties in technological diversification

	1	2	3	4	5	6	7	8	9
Number of Inventors	0.083***	-0.434***	-0.435***	-0.441***	-0.433***	-0.416***	-0.433***	-0.420***	-0.417***
	(0.005)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
GDP per Capita	-0.052***	0.102***	0.101***	0.098**	0.108***	0.105***	0.104***	0.105***	0.099***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Urban Density	0.052***	-0.028***	-0.027***	-0.027***	-0.030***	-0.033***	-0.030***	-0.033***	-0.032***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
CPC Diversity	0.808***	-0.342***	-0.341***	-0.340***	-0.341***	-0.357***	-0.344***	-0.365***	-0.362***
	(0.007)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
Firm Concentration	0.211***	0.139***	0.140***	0.138***	0.124***	0.112***	0.093***	0.074***	0.079***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)	(0.004)	(0.004)
Number of Firms	0.098***	0.059***	0.058***	0.057***	0.031***	0.043***	0.048***	0.048***	0.035***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)	(0.002)	(0.002)	(0.003)
Relatedness Density (REL)		1.448***	1.448***	1.454***	1.423***	1.460***	1.428***	1.481***	1.474***
		(0.008)	(0.008)	(0.008)	(0.008)	(0.009)	(0.008)	(0.009)	(0.009)
External-Internal Index (EI)			0.011***	-0.104***					0.009
			(0.003)	(0.011)					(0.011)
REL × EI				0.108***					0.025*
				(0.010)					(0.010)
Diversity (DIV)					0.0824***	0.306***			0.176***
					(0.003)	(0.011)			(0.015)
REL × DIV						-0.227***			-0.118***
						(0.011)			(0.015)
Intensity (INTENS)							0.088***	0.324***	0.237***
							(0.004)	(0.011)	(0.015)
REL × INTENS								-0.225***	-0.165***
								(0.010)	(0.014)
CONSTANT	-2.488***	-2.646***	-2.647***	-2.650***	-2.647***	-2.648***	-2.650***	-2.656***	-2.659***
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
PERIOD FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
N	819,496	819,496	819,496	819,496	819,496	819,496	819,496	819,496	819,496
AIC	525,014.8	491,873.6	491,862.1	491,756.6	491,366.4	490,991.6	491,418.5	490,987.0	490,589.6
LL	-262,496.4	-245,924.8	-245,918.1	-245,864.3	-245,670.2	-245,481.8	-245,696.2	-245,479.5	-245,276.8
CHI2	36,387.1	69,530.3	69,543.8	69,651.3	70,039.5	70,416.3	69,987.4	70,420.9	70,826.3

Intensity of co-inventor collaboration with colleagues within the same company, but located elsewhere, is found to increase the likelihood of *Entry* in Model 7. Knowledge transfer within firm boundaries can bring new knowledge to the region, which is in line with previous research on multinational companies and knowledge transfer mechanisms (Cummings, 2004). In Model 8, the negative coefficient of the interaction between *Relatedness Density* and *Intensity* even demonstrates that intra-firm co-inventor links can compensate for missing technological relatedness to the knowledge base of the region and thus facilitate unrelated diversification (Elekes *et al.,* 2019).

Results hold when all co-inventor network variables are introduced into the estimation in Model 9. To comply with previous research on diversification, we have run regressions by lagging Relatedness Density but not the other variables. This left our findings related to Diversity and Intensity unchanged. However, the interaction between Related Density and the External-Internal Index loses significance.

5. Concluding Remarks and Future Research Direction

According to a consensus achieved in economic geography and related literatures, the diversification of regions into new economic activities is driven by the degree of relatedness to existing capabilities in the region. In such instances where the capabilities for diversification are missing, external sources of knowledge can be imported from neighbouring regions and beyond via collaboration or by inventive agents that move between regions. Despite the importance of interregional collaborations for knowledge flows, we still have a very limited understanding about how collaboration networks across regions facilitate diversification processes. Owing up to this shortcoming, the objective of the present investigation was to examine the network dimensions of the regional branching thesis in order to analyse how external collaboration may facilitate regional diversification. Our findings can be summarised under two headings.

First and foremost, we find that externally oriented inventor collaboration networks increase the likelihood that a new and technology enters a region. Results indicate that interregional collaborations provide regions with a 'final push' towards more related diversification processes. In such instances, collaborations with inventors residing in other regions complements relatedness, implying that external knowledge is easier to absorb if closely related technologies are present in a region. At the same time, however, this finding should not downplay or diminish the importance of intraregional collaboration which is shown to promote entry into new knowledge domains especially at lower levels of relatedness. Similarly, we find that although there are sectoral differences to these patterns that the overarching relationship holds irrespective of aggregate technology class. Consistent with the extant literature, the areas of Chemistry, Electricity and Physics demonstrate the proclivity of interregional collaboration particularly well. These are global sectors where the scientific frontier and new modes of best practice are continually reshaped. Thus, in order for them to be constantly kept abreast of new ideas developed elsewhere they are highly dependent on interregional collaboration.

Second, we show that a lack of local technological relatedness can be overcome if the region maintains a high number of diverse connections to other regions or through intense intrafirm-interregional collaborations. In such instances, the likelihood a region will diversify into a distant (unrelated) technology increases by virtue of the fact that when inventors collaborate with colleagues in different localities, it exposes them to sources of knowledge that are not currently present in their region. Similarly, the same practice holds for collaborative projects involving the same firm in multiple locations which is also shown to facilitate unrelated diversification.

Turning to policy, the regional branching thesis discussed at length here has recently been adopted by policy-makers as a roadmap guiding the EU's smart specialisation strategy (Montresor and Quatraro, 2017; Whittle, 2020). Indeed, as the pace of innovation increases and the processes of knowledge production become more of a *team sport* there is a burgeoning need to collaborative with distance actors. With this in mind, the present study demonstrates the increasing importance of inventor collaboration for regional branching. Differentiating between intraregional and interregional inventor networks, results hint to what degree internal and external collaboration settings might lead to distinct diversification patterns in terms of further specialisation or a push into new areas of the knowledge space. However, although engaging in collaborations seems to become increasingly necessary, it is not easy to directly steer co-invention networks and perhaps the best option policy-makers might have in this regard is to ensure that their region appears as a desirable place to connect with. Our results suggest that intra-firm interregional collaborations may be one potential avenue for policy to more directly initiate branching processes via place-based R&D and innovation policy instruments, in particular at the supranational EU level.

Whilst the present study has addressed a number of missing links between inventor collaboration and regional branching it has also brought an equal number of additional research questions in focus. For instance, beyond (related) regional branching future work should begin disentangling the effects different types of network formation, *i.e.* intra/interregional, have on the creation of specific regional pathways, *e.g.* unrelated diversification. The results presented here provide a first look at the necessary conditions required for unrelated diversification pathways to manifest in a region, but clearly more work is necessary to fully disentangle such complex processes. Furthermore, subsequent work should begin to consider more explicitly the types of connections to other regions. For instance, is it more advantageous to connect with a technologically diverse or specialised region? Or should collaboration focus more narrowly on either specific firms or so-called centres of excellence? Similarly, at what stage of the technology's lifecycle is it most optimal to collaborate?

Finally, there is a tendency throughout the relevant literature to discuss regional diversification from a primarily entry-driven perspective suggesting that technological change is exclusively driven through the addition of new (related) technologies (for an exception *cf.* Kogler *et al.,* 2017). However, this singular focus does not consider how diversification is a two-tailed process including the addition of new technologies and the abandonment old. Indeed, Schumpeter's (1942) *gales of creative destruction thesis* reconciles that the development of new industries (technologies) frequently happens at the expense of abolishing old and outdated products and processes. With this in mind, it would be very insightful to study how the collapse of ties within/between regions impacts knowledge production and technological change.

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