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Abstract
Novel combinations of technologies are generated from existing knowledge embedded in collaborative work. Albeit inventors tend to develop specialized skills and participate in specialized work, it is their collaboration with peers with varied experience that facilitates the production of radical novelty. While this is of key importance, we lack full understanding on how the evolution of inventor collaborations is related to the nature of technological combination. In this paper, we analyse how the role of technological specialization and variety in evolving co-inventor networks is related to the creation of 'atypical' inventions in European NUTS2 regions. By analysing the community structure of co-inventor networks in each region, we find that the share of atypical patents is growing where co-inventor communities are strongly specialized in certain technologies and these communities are also bridged by collaborations. Evidence suggests that linking communities of dissimilar technological profiles favours atypical knowledge production the most. Our work implies that to produce radical innovative outcomes, regions must support knowledge production in specialized inventor communities and sponsor the bridging of collaborations to induce diversity.

Keywords: patents, novelty, network communities, technological similarity, network of places

JEL codes: L14, O33, O52, R11, R58

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1. Introduction

Innovation requires collaborative work (Burt, 2004; Wuchty et al., 2007). This in turn makes co-inventor networks essential tools in order to understand how the transfer and combination of knowledge takes place (Sorenson et al., 2006; Tóth and Lengyel, 2019). Previous research in the geography of innovation literature has therefore extensively looked at co-inventor networks in regions and found statistical relationships between their structural properties and the number, or growth rate, of patents produced in regions (Bergé et al., 2018; Breschi and Lenzi, 2016; Fleming et al., 2007; Li et al., 2014; Lobo and Strumsky, 2008). Co-inventor networks in regions are not independent from the technological dimension of knowledge production. Instead, the variety of technologies available in a region conditions the structure of inventor collaboration (van der Wouden and Rigby, 2019) and determines the potentials for radical new combinations in the region (Castaldi et al., 2015). However, the empirical questions, i.e. whether and how co-inventor ties between similarly specialized inventors or across technological varieties facilitate the quality of regional innovative performance, have been largely overlooked.

To address these questions, we take an evolutionary perspective and argue that network formation and new co-inventor collaboration links offer new combinations of knowledge. According to Glückler (2007), network formation in regions is however mostly a path dependent process because the creation of new co-inventor ties depends strongly on earlier realizations of the network (i.e. the retention mechanism). Since similar knowledge is easier to combine (Boschma, 2005; Hidalgo, 2018) and because triadic closure is a trait of collaboration networks (Newman, 2001), collaboration network dynamics tend to drive regional innovation towards specialization and lock-in (Boschma and Frenken, 2010; Giuliani, 2013). Following from this logic, a path-breaking new variation is most likely to be achieved when new links bridge previously separated parts of the network where dissimilar technological expertise lie (Glückler, 2007; Juhász and Lengyel, 2017).

Our empirical approach rests on network communities of co-inventor collaboration within regions. Such communities are dense segments of the network that are only loosely linked to each other (Girvan and Newman, 2002; Palla et al., 2005). In the situation where technological similarity and triadic closure are major driver of co-inventor link formation, co-inventor communities are evolving towards technological specialization. Bridging new links between such specialized communities might facilitate radical innovation (Burt, 2004; Ter Wal, 2014).

Following Uzzi et al. (2013), we measure radical innovation by identifying atypical combinations of technologies in patents using the EPO PATSTAT database over three decades (1980-2014). The co-inventor network is constructed for NUTS2 regions (EUROSTAT, 2018) in a cumulative fashion that enables us to estimate the correlation between new link formation and regional level outcomes in a fixed-effect regression framework (Eriksson and Lengyel, 2019). We apply the 'network of places' method to remedy biases caused by projecting bipartite networks (Lucena-Piquero and Vicente, 2019) and detect co-inventor communities over five-year time windows (Blondel et al., 2008). Finally, we measure the degree of communities' technological specialization, the fraction of co-inventor links that bridge communities, and the technological similarity of communities that are bridged by such links. The share of atypical patents in each region's innovation output in the subsequent five-year time-window is estimated by these three explanatory variables.

Our results suggest that the share of atypical patents is growing in those regions where co-inventor communities are increasingly specialized in certain technologies. The increasing share of bridging collaborations across communities are positively correlated with atypical patents. The finding is robust compared against other network variables suggested in previous research. Finally, new evidence suggests that linking communities with dissimilar technological profiles favours atypical knowledge production the most. These results imply that to produce radical innovations, regions must support the technological specialization of a diverse set of inventor communities and facilitate the collaboration among them.

2. Literature and Hypotheses

In the pursuit for new opportunities, progress, and impact, actors of knowledge creation combine existing pieces of previously explored knowledge (Nelson and Winter, 1982; Schumpeter, 1911). Combinations that have rarely been made before or that are completely new – both referred to as atypical combinations – are inputs of radical novelty generation and are necessary ingredients for technological breakthroughs and future impact (Kim et al., 2016; Uzzi et al., 2013; Wang et al., 2017). It has been shown recently that such atypical combinations in scientific publications greatly overlap with interdisciplinarity, implying that distinct knowledge domains are put together in atypical new knowledge (Fontana et al., 2020).

Innovative knowledge generation is not evenly distributed around the globe. Instead, innovation – either captured by product developments or by patents – concentrates in urban areas (Audretsch and Feldman, 1996; Bettencourt et al., 2007). Recent evidence suggests that atypical innovation is even more concentrated in large cities (Mewes, 2019). In the past, the standard explanation of this stylized fact was that the diverse pool of knowledge in urban areas (Feldman and Audretsch, 1999; Florida et al., 2017; Glaeser et al., 1992; Jacobs, 1961) allows for atypical combinations (Berkes and Gaetani, 2020). However, a growing body of literature questions this claim by finding support for specialization facilitating innovation that is due to a critical mass of expertise in some regions (Beaudry and Schiffauerova, 2009; Lobo and Strumsky, 2008; Ó Huallacháin and Lee, 2010). Knowledge transfer mechanisms between local critical masses are thought to foster novel combinations (Berkes and Gaetani, 2020), especially when the specializations contain different knowledge domains (Castaldi et al., 2015). Nevertheless, such knowledge transfer mechanisms across local specializations have remained largely hidden.

Anecdotal evidence exists to support the role of diverse knowledge combinations in creating completely new technologies. For example, the Boston biotechnology cluster has emerged from local skills that have been accumulated before into a local critical mass in engineering and biology (Cooke 2002). Focusing on the birth of biotechnology in Boston, the seminal paper of Powell et al. (1996) emphasises the role of social interactions. Individual collaboration enables the combination of distinct knowledge domains by combining knowledge of the collaborating parties, and facilitating atypical innovations (Cowan and Jonard, 2004; Kogut, 2000; Kogut and Zander, 1992; Owen-Smith and Powell, 2004).

However, how the dynamics of specialization and diversity happens in local collaboration networks and how these processes describe local capacities in generating radical novelty, is still largely hidden. A recent piece of research in quantitative anthropology suggests that cycles of social interaction dynamics, alternating between segregation and mixing, favour such combinations by balancing specialization and diversity. For example, Migliano et al. (2020) describe that drug discoveries in hunter-gatherer tribes demanded experimentation with plants separated by camps before these plants could be combined into a better drug through the interactions across camps. Nevertheless, systematic evidence on how diverse knowledge is combined into atypical innovations through the collaboration of inventors is still missing. In the following section, we argue that atypical combinations in regions are facilitated by similar mechanisms and demand segregated knowledge generation around specific technologies and also their mixing through the bridging of individual collaborations.

Co-inventor networks, defined by links between inventors by way of collaboration on at least one patent, have been put forward as an analytical tool to further understand innovative differences across spatial units (Lobo and Strumsky, 2008). The major underlying reason is that collaboration creates social relationships that provide grounds for effective knowledge transfer, even after the project, which the inventors co-worked on, has already finished (Breschi and Lissoni, 2009). Contradicting earlier approaches that argue for the importance of isolated inventors (Lobo and Strumsky, 2008), a few recent studies show that the structure of co-inventor networks is informative in evaluating the effectiveness of knowledge combination (Bergé et al., 2018). For example, Breschi and Lenzi (2016) showed that both diverse knowledge, being accessible through inter-regional collaborations, and effective knowledge shared in dense local co-inventor networks, favour innovation in regions.

An optimal balance between specialized groups and accessible diversity in innovation networks have been put forward in sociology and management science (Aral, 2016). Following the seminal works of Granovetter (1973) and Burt (2004), this line of literature claims that most information and knowledge circulation happens in strongly knit cliques in the networks, and that novelty emerges through diverse connections across cliques that are often called weak ties or bridges. Aral and van Alstyne (2011) claim a trade-off between strong and weak ties and their pay-off depends on information overlap and the knowledge of involved parties and the rapidity of changes in the business environment. Analysing inter-firm inventor mobility, Tóth and Lengyel (2019) illustrate that firms that produce high impact patents hire inventors who can channel-in new information through diverse links, and that this is paired with strongly-knit co-inventor networks within the firm that can effectively process novel and diverse information.

In an economic geographic approach to network dynamics, Glückler (2007) argues for a similar balance between two counteracting mechanisms that drive regions towards specialization and diversity. These mechanisms are network retention and network variation. Network retention – the tendency for earlier structure of the network to determine the later structure – is thought to drive networks towards specialization in case where technological similarity and triadic closure increase the likelihood of co-inventing (Abbasiharofteh and Broekel, 2020; Boschma and Frenken, 2010; Broekel and Boschma, 2012; Cantner and Graf, 2006; Giuliani, 2013; Grabher, 1993; Ter Wal, 2013). Such mechanisms are posing a threat to radical knowledge generation especially in specialized regions where inventors tend to partner with co-inventors of similar technological profiles to a greater extent than inventors in technologically diverse cities (van der Wouden and Rigby, 2019). Network variation – when otherwise loosely knit clicks of the network are bridged by few collaborations – is argued to create momentum for radical combination (Glückler, 2007).

Here, based on the literature discussed above, we argue that both retention and variation in regional co-inventor networks are needed to create atypical patents in regions and formulate our hypotheses around this claim. Our focus is on network communities – densely connected subnetworks that are loosely connected to each other – which are widely analysed in network science (Girvan and Newman, 2002; Palla et al., 2005). Due to micro-mechanisms of the network retention mechanism – homophily and triadic closure – qualities tend to diverge into separate communities (DiMaggio and Garip, 2011; Tóth et al., 2019). For instance, if cognitive proximity is a key driver of co-inventor collaboration and inventors are likely to work with partners of partners, then co-inventor network communities tend to increasingly specialize around certain technologies. We argue that when a critical mass of knowledge accumulates in such cliques of technological specialization thus can facilitate atypical innovations through two ways. First, the likelihood that someone in the community can combine the technology with an unrelated technology increases as the community grows in the number of inventors. Second, the depth of knowledge accumulated in the community increases the capacity to absorb technologies external to the community and combine with internal knowledge. The argument is formalized into Hypothesis 1 as follows.

H1: The growing technological specialization of co-inventor communities is positively related to the fraction of atypical patents in the region.

Network variation materializes in links that connect segregated communities. These links function as weak ties and bridge previously separated sources of knowledge (Granovetter, 1973). Such ties that connect otherwise loosely connected structural holes in networks are thought to have comparative advantage in knowledge combination (Burt, 2004). We formulate these widely accepted ideas in social and collaboration networks into Hypothesis 2 to discuss atypical patenting in regions.

H2: The growing fraction of inter-community ties of co-inventor networks is positively related to the fraction of atypical patents in the region.

Finally, we postulate that the influence of network variation on atypical patenting intensifies as the overlap of the technological profiles of communities decreases. In other words, novel combinations are more likely when co-inventor communities accumulate knowledge in different domains. This expectation is formalized into Hypothesis 3.

H3: Technological similarity across bridged inventor communities is negatively related to the fraction of atypical patents in the region.

3. Materials and Methods

3.1. Data

Innovation scholars have widely used patent databases to study collaboration networks, technological change, knowledge spaces and economic complexity (Balland et al., 2020; Castaldi et al., 2015; Jaffe, 1986; Jaffe, 1993; Kogler et al., 2013). While the limitation of these type of data has been discussed in the literature (Archibugi and Planta, 1996; Kogler, 2015), patent data indeed provide a very valuable source of information to undertake empirical studies where the temporal dimension of inventive activities is under scrutiny.

We use the European Patent Office (EPO) PATSTAT database and follow the common practice of aggregating collaborative ties in seven non-overlapping 5-year time-windows (Fleming et al., 2007; Menzel et al., 2017; Ter Wal, 2014).[1] Inventor and assignee names are disambiguated and harmonised, and the database also contains the region of the home location of inventors. Collaborative inventor-inventor ties are distributed within and across 249 NUTS2 regions (see Appendix A). We assign interregional collaborative ties to both NUTS2 regions involved in the development of a patented invention in order to ensure that regional networks are not biased by the so-called modifiable areal unit problem (Scholl and Brenner, 2014). Also, in the spirit of the Schumpeterian view on innovation (Schumpeter, 1911; Strumsky and Lobo, 2015; Weitzman, 1998), we utilize the information on technological knowledge domains listed in individual patent documents to identify what technology codes were combined for each invention. We make use of these data to create a proxy for the degree of atypicality that each patent introduces, something we return to and explain further later in this section.[2]

[1] Seven time-windows: (1) 1980-1984, (2) 1985-1989, (3) 1990-1994, (4) 1995-1999, (5) 2000-2004, (6) 2005-2009, and (7) 2010-2014. It is important to note that we do not dissolve created ties. This implies that once a collaborative tie is established, it is also present in the subsequent time-windows. Thus, the sheer number of ties increases over time.

[2] To identify the distinct technological knowledge domains that characterize individual inventions we employ the Cooperative Patent Classification scheme that contains 650 individual codes at the 4-digit level.

3.2. Projecting bipartite networks and networks of places

Collaboration networks observed in patents are detected by the co-presence of inventors in one or several common patents (Broekel and Graf, 2012; Li et al., 2014; Menzel et al., 2017; Stefano and Zaccarin, 2013; Ter Wal, 2014). These observations constitute a bipartite network based on an inventor-by-patent matrix that one can transform to a unipartite network representation based on an inventor-by-inventor matrix.

While numerous empirical studies have used this method in innovation studies to generate and analyse collaboration networks, there are concerns that this introduces a bias that affects communities detected in collaboration networks (Newman, 2001; Zhou et al., 2007). The projection of a bipartite network normally provides a high degree of network clustering in the unipartite network if collaborations include more than three participants, something that is increasingly the case in patenting (Broekel, 2019; van der Wouden, 2018). Also, the projection introduces technology biases for clustering-related indices because the average team size differs substantially across sectors (Kogler et al., 2013).

To deal with the projection bias, we follow the method developed by Pizarro (2007) and create a new network (hereafter, network of places) in which new nodes (hereafter, places) will be created to replace a set of neighbouring nodes in the collaboration network that share similar structural properties (for a review, see Lucena-Piquero and Vicente, 2019). 'Structural equivalence' is a social network concept developed by Lorrain and White (1971) and Burt (1987). Nodes in a network are claimed to be structurally equivalent in case they are identical in terms of location, relation, and embeddedness patterns, which provide them with access to identical resources in the network (Gnyawali and Madhavan, 2001; Stuart and Podolny, 1996).

Figure 1 demonstrates how networks of places are created from the co-inventor network.[3] In case A, the collaboration of six inventors on a single patent is transformed to a single node in the network of places because all inventors have similar structural properties. In case B, where three inventors are connected in two collaborations, no modification has been made in the transformation. Case C contains two projects bridged by one inventor. Thus, the algorithm groups inventors involved only in one project into two separated nodes conceded by the bridging inventor. Case D is a complex composition, in which one can find all above-mentioned pairings of inventors and projects such that some of the inventors are structurally equivalent and some are different. A higher share of isolated nodes in the network of places

[3] To implement this method, we used the Places R-package developed by Lucena (2017).

reflects the fact that most inventors take part in one or few projects rather than being involved in numerous collaborations.

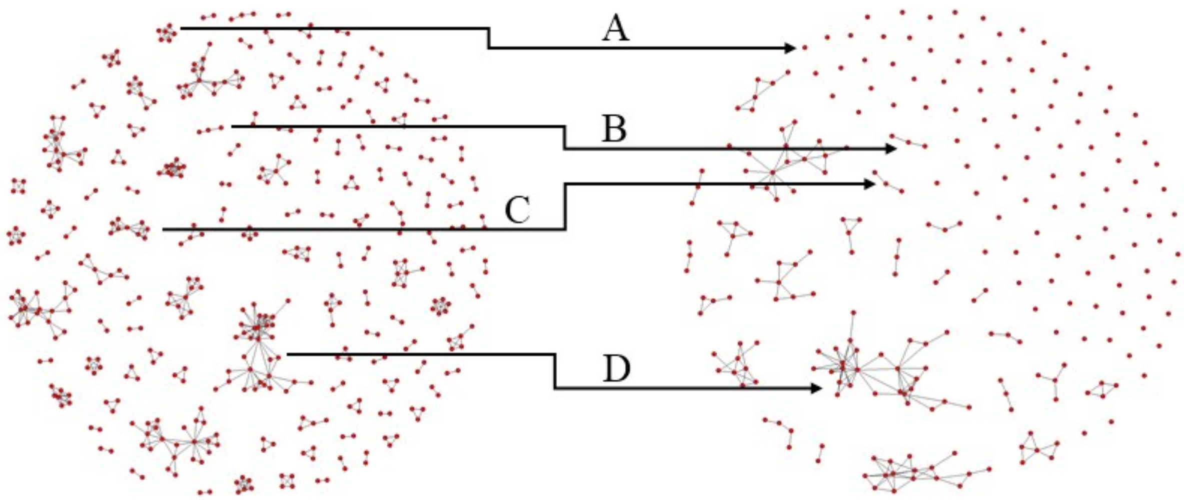

Figure 1. The projected co-inventor network (left) and the co-inventor network of places (right).

Figure 2 shows that while we control for the high degree of clustering in regional collaboration networks, the number of nodes and edges in each region scale almost linearly (in a log-log scale) with the ones of the networks of places, and thus we preserve other structural properties of original networks.

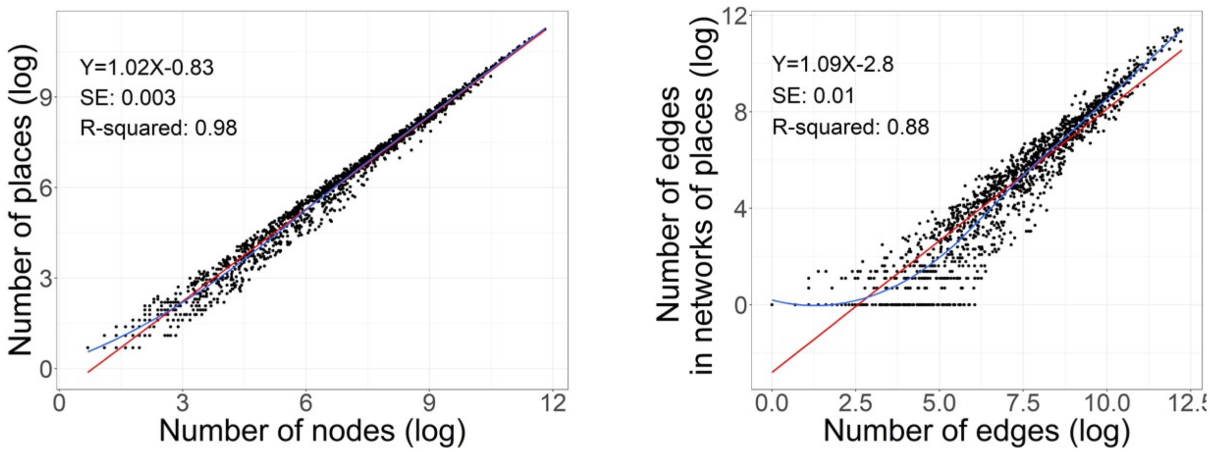

Figure 2. The projected co-inventor network (left) and the co-inventor network of places (right).

Note: Each dot represents the structural properties of a NUTS2 region in one of the seven defined time-windows.

3.3. Measures

3.3.1. Dependent variable

In line with the theoretical argumentation, we seek to identify patents that introduce atypical technological knowledge combinations. Patent data provide a possibility to probe what technology codes were combined in each patent application. Therefore, we can measure the degree of the 'atypicality' of patents by comparing how often the pair of technology codes co-occur in the data, [4] with the statistical expectation of random co-occurrence.[5] Uzzi et al. (2013) have used this method to define the extent to which scientific publications introduce atypical combinations of knowledge pieces. Similarly, Mewes (2019) applied the same method to identify atypical patents in the US. In doing so, we follow Teece et al. (1994) and estimate the z-score to capture the atypicality of each technology combination. Specifically, the z-score is defined as follows:

$$Z_{i,j} = \frac{O_{i,j} - E_{i,j}}{\sigma_{i,j}} \tag{1}$$

where $O_{i,j}$ is the number of the co-occurrence of two technology codes i and j. $E_{i,j}$ is the statistical expectation of technologies i and j co-occurring randomly, and $\sigma i, j$ denotes the standard deviation. Teece et al. (1994) argue that if the number of occurrence of two units (technology codes here) is relatively high, the co-occurrence of these units is presumably high driven by random effects. Thus, the expected co-occurrence ($E_{i,j}$) is given by:

$$E_{i,j} = \frac{n_i n_j}{N} \tag{2}$$

where n_i and n_j are the overall number of technology codes i and j respectively, and N is the number all technology codes. The standard deviation is defined as:

$$\sigma^2{}_{i,j} = E_{i,j}\left(1 - \frac{n_i}{N}\right)\left(\frac{N - n_j}{N - 1}\right) \tag{3}$$

Intuitively, the negative value of the z-score indicates that the number of random co-occurrence is higher than the number of observed ones, and therefore a negative value reflects an atypical combination of two technology codes. It is important to note that we iteratively estimated z-scores for each time window to control for technological dynamics. This is relevant because a single patent might already introduce a beneficial atypical combination of technologies motivating other inventors to imitate the same pattern in the subsequent time windows that makes the combination more common (less atypical) over time. Figure 3 shows the kernel

[4] Since we use 650 CPC codes at the 4-digit level, it gives 210925 (n (n-1)/2) technology pairs.

[5] This implies that we exclude patents which include only one CPC technology code at the 4-digit level.

density estimates for z-scores in the seven time-windows. The results are consistent with the findings of Uzzi et al. (2013) and Mewes (2019) because a relatively small share of combinations are identified as atypical. More interestingly, the share of atypical patents drops from 0.3 to 0.25 between 1984 and 2014. Also, we used the Shannon entropy measure to estimate the entropy of z-score values for each time-window.[6] We observed that the entropy indices increase across time-windows, thus suggesting that inventions move towards the two extremes of typicality and atypicality over time.

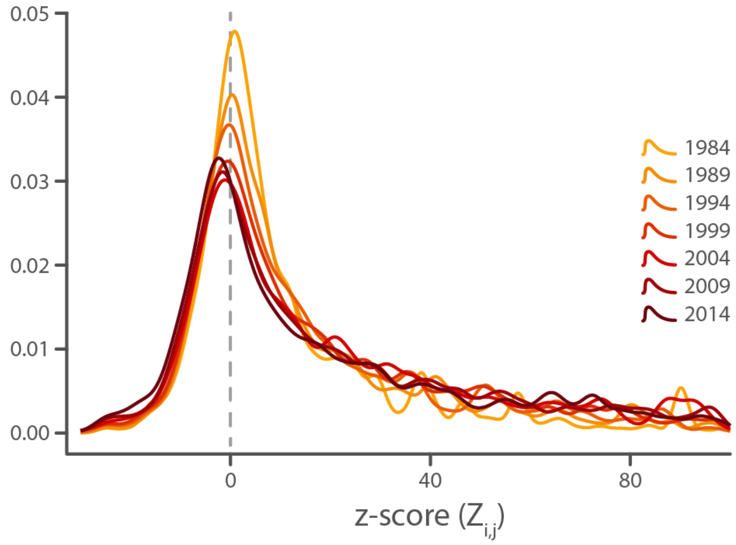

Figure 3. The kernel density of z-scores for the combination of each technology pair.
Note: For the sake of simplicity, we label each time window with the corresponding latest year.

Since z-scores are estimated for the combinations of technology codes and not patents per se, one needs another definition at the patent level. We define atypical patents as those that include at least one combination of technologies with a negative z-score. We assign patents to regions in which inventors resided at the time of invention. The dependent variable (*ATYPICAL*) is the share of atypical patents in each NUTS2 region and time-window. Figure 4 and 5 show the distribution of atypical patents across European regions and across different technologies, respectively.

[6] The Shannon entropy index for each time-window corresponds to 1984: 15.35, 1989: 15.93, 1994: 16.15, 1999: 16.66, 2004: 17, 2009: 17.18, and 2014: 17.18.

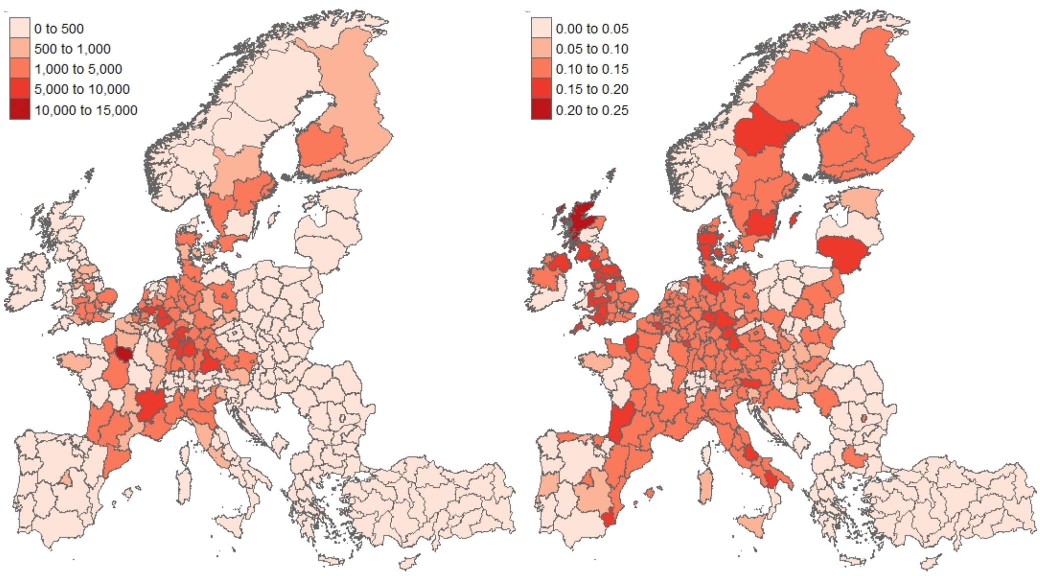

Figure 4. The number (left) and share (right) of atypical patents 1980-2014 in European regions.

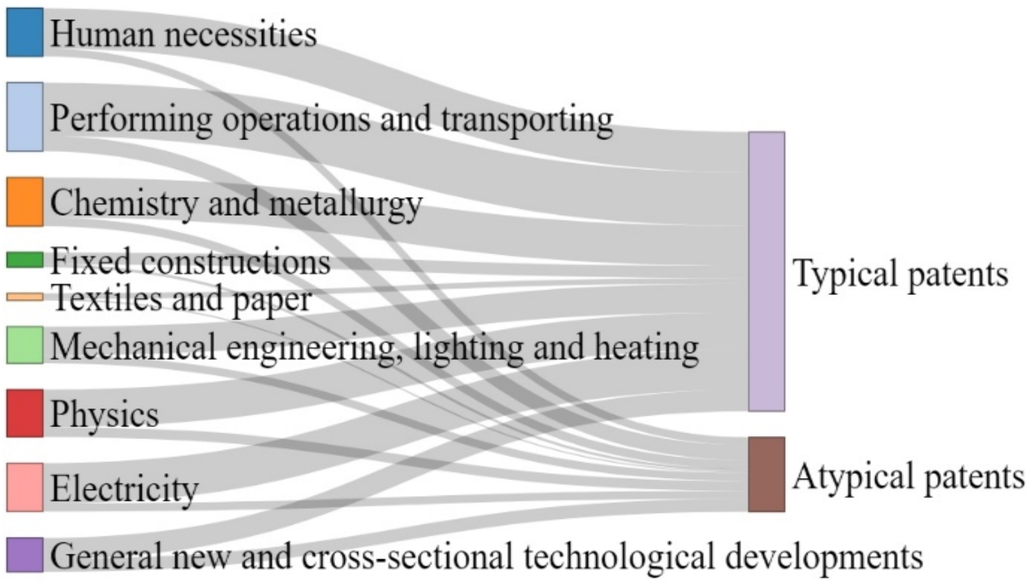

Figure 5. The distribution of typical and atypical patents (1980-2014) across Cooperative Patent Classifications (CPC) schemes.

3.3.2. Independent variables and controllers

The main variables of interest in this paper underline the mesoscopic properties of the networks of places, which capture how knowledge pieces regarding various technologies are distributed within a region. In doing so, we detected communities in which places are more densely connected compared to the rest of places in the network. Intuitively, one can expect that inventors cluster in groups based on their field of expertise and the underlying knowledge bases. Yet, a relatively low number of inventors might bridge cognitive gaps and connect two or several cognitively distant communities.

While the theoretical argument is straightforward, there are numerous community detection algorithms which do not necessarily provide comparable results, and their accuracy and efficiency mostly depends on the size and structural properties of networks (Clauset et al., 2004). Yang et al. (2016) conducted an empirical analysis and compared the accuracy and efficiency of eight major community detection algorithms using various networks of different size and structural properties. Following their findings, we opt for the Multilevel algorithm,[7] (Blondel et al., 2008) because this one offers reasonable levels of accuracy[8] and efficiency,[9] given the fact that regional networks of places vary considerably in network size.

Figure 6 illustrates our three independent variables: specialization of co-inventor communities, the share of inter-community ties, and the technological similarity across communities.

The first variable of interest is the extent to which the inventor communities of regions are specialized. To capture this attribute of regions, we use the Herfindahl Index (Hall and Tideman, 1967) to estimate the concentration of technologies in each community. We use the median of the distribution of the Herfindahl indices for each region and time-window, as a proxy for the specialization of the communities of regions (SPECIALIZATION).

To construct the second variable that measures the inter-connectedness of communities in regions, it is important to note that networks with different number of nodes normally demonstrate different structural properties, and we cannot directly compare size-dependent network indices. Thus, we followed the method suggested by Cimini et al. (2019) and rewired each network 100 times while we kept their size and the degree sequence constant. Then, we normalized the number of inter-community ties by subtracting it from the average value of the number of inter-community ties observed in the rewired networks. We calculate the share of

[7] We used the igraph R package by Csardi and Nepusz (2006) to apply the multilevel algorithm.

[8] Yang et al. (2016) use the Lancichinetti–Fortunato–Radicchi benchmark graph to test the accuracy of widely used communication detection algorithms (i.e. fastgreedy, infomap, leading eigenvector, label propagation, multilevel, walktrap, spinglass, and edge betweenness). The results suggest that the multilevel algorithm provides a greater accuracy when the number of nodes is over 1000 and μ (the mixing parameter) is greater than 0.5. The mixing parameter is the sum of the number of edges connecting to other communities divided by the sum of nodes' degree in the given community.

[9] Based on Yang et al. (2016) the time complexity of the multilevel algorithm is $O(N\ logN)$ which is considerably faster than most well-known algorithms. For instance, the computational complexity of the edge betweenness algorithm is $O(E^2N)$.

inter-community ties (SICT), which is the normalized number of inter-community ties divided by the total number of ties corresponding to each NUTS2 region in each time-window.

While we have an intuitive idea that communities are a hub of cognitively close inventors separated from other cognitively distant communities. In large regions with numerous communities, there might be several communities with similar technological portfolios, separated by other socio-economic forces that are invisible to us. The descriptive statistics (see Appendix B) suggest that while the size of a region (i.e. inventor number) is correlated with the number of communities in each region (the Pearson correlation coefficient: 0.95), these two variables seem not to be strongly related with technological diversity (0.23 and 0.27 respectively).

Also, communities are not completely similar or dissimilar, and we expect to see a varying degree of overlaps between technological portfolios among connected communities. Therefore, we calculated the Spearman rank correlation coefficients (ranging between -1 and 1) for each inter-community ties defined by:

$$\rho = 1 - \frac{6 \sum d^2}{p(p^2 - 1)} \tag{4}$$

where d and p are the difference in the paired rank of technology codes in two connected communities, and the number of technology codes, respectively. The Spearman rank correlation is the preferred specification because monotonic relationship between the number of technology codes in two communities is not a strict assumption of this measure compared to the one of the Pearson correlation (Broekel and Brenner, 2007; Fornahl and Brenner, 2009). [10] The third independent variable (*SIMILARITY*) is the median of the distribution of the Spearman rank correlation coefficients for each NUTS2 region in each time-window. Regions with larger (smaller) values of this variable show a relatively higher (lower) degree of technological overlaps among their connected communities. Figure 7 illustrates the distribution of the variable *SIMILARITY* across European regions over time.

[10] The Spearman rank correlation coefficients found to be positively correlated with the cosine similarity measure (the Pearson correlation coefficient: 0.55), and highly correlated with the Jaccard similarity index (the Pearson correlation coefficient: 0.96).

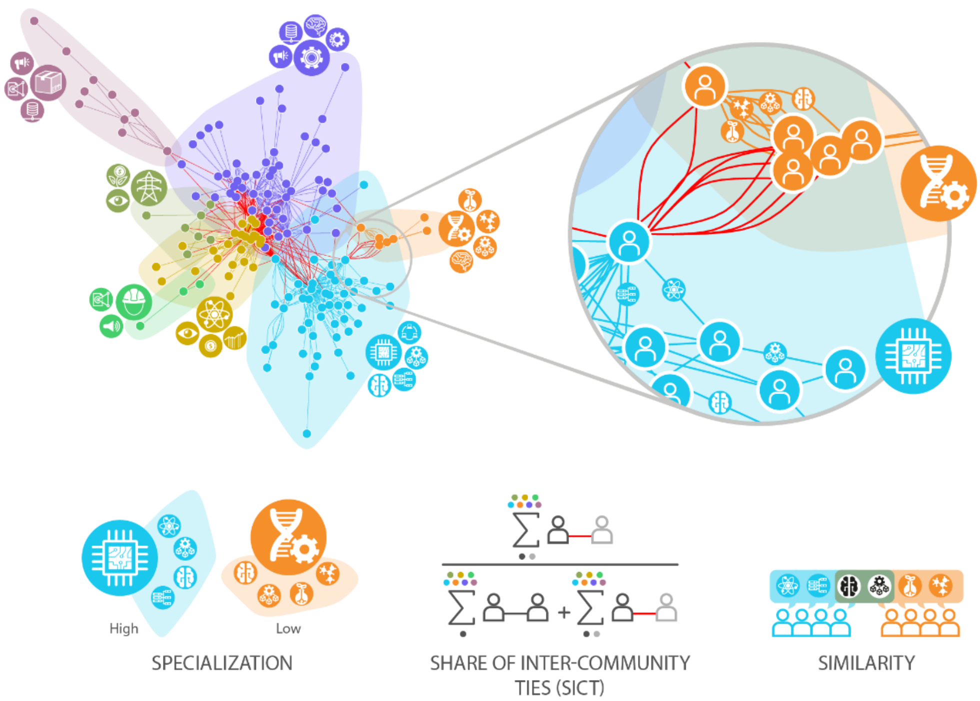

Figure 6. Visual representations of detected communities, inter-community ties, and three variables of interests.

Note: Regions' networks of places normally include various components. For the sake of illustration, only one large component is shown in this visualization.

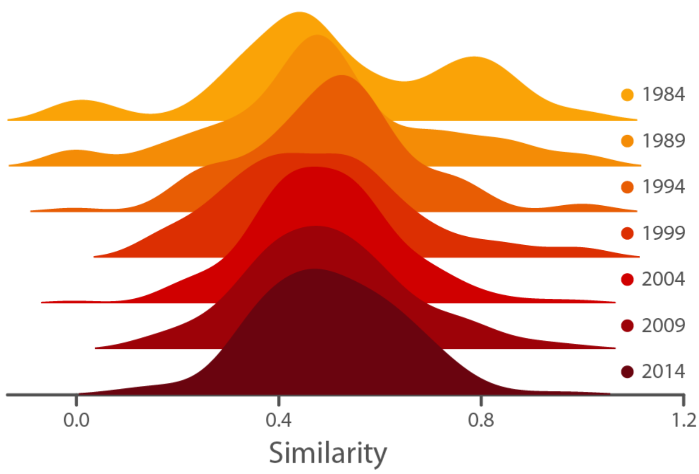

Figure 7. An approximation of the density of the variable *SIMILARITY* (kernel density estimation) over time.

In addition to the three main independent variables, we employ several control variables. Firstly, the related variety literature has provided empirical evidence that regions are more inclined to diversify into related products and activities (Balland et al., 2018; Boschma et al., 2015; Boschma, 2016; Hidalgo et al., 2007). One can argue that large cities and agglomerations are home to more diverse knowledge communities, and thus inventors are more likely to introduce patents with new technological combinations. Following the method developed by Hidalgo et al. (2007), we measure the related density of each technology code of regions. Then, we use the average relatedness (*RELATEDNESS*) as a proxy for the degree of specialization for regions in each time-window (van der Wouden and Rigby, 2019). It is worth noting that this variable is highly correlated with various variables capturing the size of regions such as: patent number, inventor number, community number, and GDP (see Appendix C). Thus, we refrain from including these variables in models. *POPULATION* is an additional size-related control variable that corresponds to the population (log-transformed) of regions in each time-window.

Also, we build on the method of reflection developed by Hidalgo and Hausmann's (2009) to control for the effect of complex technologies that are not ubiquitous in all regions. These technologies might provide comparative advantages for some regions because inventors in such regions have the possibility to combine complex (less ubiquitous) technologies to introduce atypical patents. The variable *COMPLEXITY* controls for the extent to which regions include complex technologies in each time-window.[11]

Moreover, we need to control for a range of effects that emerges from the structural properties of the networks of places, to ensure that the results are not driven by other network related effects. Following similar empirical works in innovation studies that investigate the structure of co-inventor networks (Bergé et al., 2018; Breschi and Lenzi, 2016; Lobo and Strumsky, 2008; Lucena-Piquero and Vicente, 2019; van der Wouden and Rigby, 2019), we created variables for assortativity (*ASSORTATIVITY*), density (*DENSITY*) and share of isolates (*ISOLATE*).[12] Besides, we added a proxy for the extent to which inventors in regions tap into external knowledge pools by measuring the share of inter-regional ties (*INTERREGIONAL*). Descriptive statistics of all variables are presented in Appendix D.

3.3.3. Model construction

We opt for a fixed effects panel regression model with two-way fixed effects on regions and time-windows that controls for all types of unobservable regional- and time-variant

[11] We used the EconGeo R-package developed by Balland (2017) for estimating the related density and complexity coefficients.
[12] As clarified earlier in this subsection, we used a rewiring method to normalize network indices. Also, we refrain from creating a variable capturing the centralization of regional inventor networks because this network index is highly correlated with *SPECIALIZATION*.

heterogeneities. To avoid endogeneity problems, independent variables are lagged by one time-window.

$$Y_{r,t} = \alpha + \beta_1 SPECIALIZATION_{r,t-1} + \beta_2 SICT_{r,t-1} + \beta_3\, SIMILARITY_{r,t-1} + \beta_4 N_{r,t-1} + \beta_5 Z_{r,t-1} + \varphi_{t-1} + \mu_r + \varepsilon_{r,t-1} \quad (5)$$

The dependent variable is the share of atypical patents in each region and time-window (*ATYPICAL*), *SPECIALIZATION, SICT,* and *SIMILARITY* denote the independent variables. $N_{r,t-1}$ stands for a set of network related variables, i.e. *ASSORTATIVITY*, *DENSITY*, *ISOLATE* and *INTERREGIONAL*. Similarly, $Z_{r,t-1}$ denotes three control variables that capture the degree of specialization (*RELATEDNESS*), technological complexity (*COMPLEXITY*), and population (*POPULATION*) in regions. φ_{t-1} is time-window fixed effect, μ_r is a region fixed effect, and $\varepsilon_{r,t-1}$ denotes a regression residual.

4. Results and discussion

Diagnostics for the multicollinearity are estimated by variance inflation factors (VIF) for each predictor variable (see Appendix E). Although there is controversy about what value should serve as a threshold value for multicollinearity, there is strong evidence of multicollinearity if the value of VIF for a given variable exceeds 10 (Chatterjee and Price, 1995). However, a more conservative view defines a threshold value between 3 and 5 (Kock and Lynn, 2012). The multicollinearity test of the full model demonstrates relatively high VIF values (3) for *RELATEDNESS*. We present the results of the regression models in a stepwise manner. It is also important to note that the coefficient of *RELATEDNESS* in the full model should be interpreted with care. Moreover, we have tested for heteroscedasticity in the model. The distribution of residuals does not follow a normal distribution (kurtosis: 5.28). To control for this, we use the heteroskedasticity-consistent White estimation of robust standard errors (White, 1980). Table 1 as well as regression tables in appendices show the results of the regression models and robust standard errors.[13]

Model 1 includes the explanatory variables. The reported coefficient of the variable associated with *SPECIALIZATION* is positive and statistically significant. The share of inter-community ties *SICT* has a significantly positive impact on the share of atypical patents. The negative and significant coefficient of *SIMILARITY* suggests that technological proximity

[13] To run the models, estimating VIFs and robust standard errors we used the following R-packages: plm by Croissant and Millo (2008), sandwich by Zeileis (2004), and lmtest by Zeileis and Hothorn (2002).

between connected communities is negatively correlated with the dependent variable. The sign and significance of coefficients regarding these three variables remain robust across various specifications in all models. This result confirms the three hypotheses outlined above.

Table 1. Results of two-way fixed effects linear regressions with robust standard errors.

	Dependent variable: share of atypical patents						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
SPECIALIZATION	0.0430**	0.0455**	0.0466**	0.0447**	0.0498**	0.0636***	0.0619***
	(0.0194)	(0.0194)	(0.0193)	(0.0216)	(0.0199)	(0.0192)	(0.0214)
SICT	0.1325**	0.1301**	0.1248**	0.1247**	0.1301**	0.1319**	0.1268**
	(0.0527)	(0.0516)	(0.0510)	(0.0509)	(0.0512)	(0.0517)	(0.0497)
SIMILARITY	-0.0441***	-0.0434***	-0.0430***	-0.0432***	-0.0424***	-0.0336***	-0.0325***
	(0.0106)	(0.0108)	(0.0108)	(0.0109)	(0.0109)	(0.0109)	(0.0107)
RELATEDNESS		-0.0008	-0.0009	-0.0009	-0.0010	-0.0007	-0.0006
		(0.0006)	(0.0007)	(0.0007)	(0.0007)	(0.0007)	(0.0007)
COMPLEXITY		-0.0002	-0.0003	-0.0003	-0.0003	-0.0003	-0.0003
		(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)
INTERREGIONAL			-0.0514	-0.0521	-0.0516	-0.0575	-0.0590*
			(0.0348)	(0.0352)	(0.0350)	(0.0351)	(0.0353)
POPULATION			-0.0001	-0.0001	-0.0001	-0.0003	-0.0003
			(0.0028)	(0.0028)	(0.0029)	(0.0029)	(0.0029)
ASSORTATIVITY				-0.0031			-0.0019
				(0.0118)			(0.0117)
DENSITY					-0.1400		0.1732
					(0.2497)		(0.2441)
ISOLATE						0.0992**	0.1201**
						(0.0464)	(0.0516)
Region FE	YES	YES	YES	YES	YES	YES	YES
Time FE	YES	YES	YES	YES	YES	YES	YES
Observations	1,526	1,526	1,526	1,526	1,526	1,526	1,526
R^2	0.4030	0.4046	0.4072	0.4073	0.4077	0.4118	0.4122
Adjusted R^2	0.2740	0.2747	0.2768	0.2763	0.2768	0.2818	0.2812
Residual Std. Error	0.0854 (df = 1254)	0.0853 (df = 1252)	0.0852 (df = 1250)	0.0852 (df = 1249)	0.0852 (df = 1249)	0.0849 (df = 1249)	0.0850 (df = 1247)
Note:							$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

In addition to the three variables of interest, Model 2 includes a summary of two control variables. Interestingly, it seems that the degree of specialization and complexity of patents (*RELATEDNESS* and *COMPLEXITY*) do not play a significant role in explaining the extent to which regions provide atypical patents. At the first glance, this result might come as a surprise. However, specialization triggers diversification into related activities, whereas our aim is to understand what factors contribute to the atypical combination of technology codes. This finding corroborates the ones by Barbieri et al. (2020) and Castaldi et al. (2015) who show that the degree of specialization correlates with the share of incremental inventions. Strumsky and Lobo (2015) empirically show that recent patents are mostly developed by the 'reusing' and 'recombination' of existing technological capabilities, and although the authors do not provide evidence for atypical patents specifically, this might account for why technological complexity does not have an impact on the share of atypical patents. Of course, this calls for careful empirical research in future. Similarly, Model 3 suggests that the share of interregional relations and population do not account for the ability of regions to introduce atypical patents.

Model 4 suggests that assortativity has a negative but insignificant association with the share of atypical inventions; this effect is also reported insignificant in the full model. This does not corroborates the argument of Vicente (2017) and Lucena-Piquero and Vicente (2019) who claim that assortative relations bring about an unfortunate network structure which hinders the optimal diffusion of knowledge between the core and periphery of networks.

More interestingly, in contrast with the dominant view of policy makers, Vicente (2017) and Abbasiharofteh (2020) argue that dense network relations do not necessarily improve the diffusion of knowledge and better innovative performance. In a similar vein, Model 5 suggests that network density is negatively but not significantly correlated with the relative number of atypical patents. Lobo and Strumsky (2008) found significant negative correlations between patenting rate and the density of connections in the US metropolitan areas.

Our results are in line with the ones of Lobo and Strumsky (2008) regarding the positive impact of isolated inventors in the network on the growth of atypical invention in regions. This is important to note that isolate nodes in our empirical setting are not necessarily individuals because we have clustered all inventors with similar structural properties. Thus, the results suggest that not only isolated inventors, but also isolated teams contribute to the ability of regions to introduce atypical inventions.

Our main variables of interest are the ones that capture the impact of the mesoscopic properties of regional collaboration networks on the relative number of atypical inventions (Model 1 to 7). We find that specialized co-inventor communities help the creation of atypical inventions. New connections that bridge segregated communities have a strong positive impact on atypical patenting suggesting that these links enable the combination of distinct knowledge domains. Such combinations are even more likely if the inter-community links bridge technologically differently oriented communities.

There is evidence that people partly create collaborative ties with the ones with whom they are cognitively proximate (Boschma, 2005; Nooteboom, 2000). Over time however, the high degree of cognitive proximity might lead to redundancy and the exhaustion of radically new ideas. Therefore, this finding corroborates the rationale behind the structural-hole argument by Burt (1992) who argues that bridging structural holes provides brokers (and arguably connected communities) with novel ideas and inputs for radical inventions. Although this effect emerging from the meso-level (communities) of collaboration network has been a long-standing conjecture, most empirical works in innovation studies focus only on the attributes of networks at the macro- (networks) and micro-levels (individuals) (Breschi and Lenzi, 2016; Eriksson and Lengyel, 2019; Lobo and Strumsky, 2008; van der Wouden and Rigby, 2019).

To ensure the robustness of our models, we added the dependent variable of each previous time-window (the share of atypical patents) as an independent variable in models. This enables us to capture dynamics across each consequent time-windows. The results (see Appendix F) suggest that while the growth rate of the share of atypical patents is significantly decreasing, the sign and significance of the three variables of interest do not change. Alternatively, we regress the total patent growth on the constructed variables to test whether the same effects are given for all patents (and not only atypical patents). Interestingly, the similarity between connected communities are found to be negatively correlated (nevertheless less significant) with the overall patent growth rate. Similarly, specialization is positively associated with the growth of all patents. However, the share of inter-community ties (*SICT*) loses significance in this model. The comparison of the two models (see Appendix G) is in line with our original argument. That is, the connection of specialized and technologically distant communities is of critical importance for introducing atypical patents perhaps because this type of invention requires the combinations of different knowledge pieces, which is not necessarily the case for all patents most of which are identified as typical (see Figure 5, above).

5. Conclusion

In the present investigation, we find evidence that atypical combinations of technological knowledge domains are more extensively generated in those regions where technologically dissimilar communities of inventors are bridged by collaboration. Community bridging demands extra effort that breaks the endogenous formulation of innovative collaboration that is mostly driven by similarities in inventors' technological expertise and triadic closure. Therefore, our results provide new insights for regional innovation policy on how the generation of radical inventive outcomes can be fostered by supporting bridges of innovative collaboration.

We argue that diversity and specialization should be fostered in tandem. Only those regions can create atypical inventions that possess distinct knowledge bases. Specialized knowledge production must take place in regions insofar that endogenous network formulation can develop separated communities with divergent knowledge trajectories. It is these mechanisms that establish the conditions that in turn enable the bridging of strongly divergent specialized communities in the first place and then the subsequent outcome that these local strongholds will also be able to create something radically new.

Most inventor collaboration happens within the boundaries of firms that our exercise could not consider. Since we have kept past co-inventor ties and grew their networks cumulatively for the sake of the fixed-effect regression specification, we were not able to identify what co-inventor links remained within firm boundaries and which links have linked more firms due to inventor mobility. These decisions have limited us to analyse how strategy, alliances, and competition of firms influence atypical innovation in regions. Future research shall shed light on these mechanisms by generating co-inventor networks differently and focusing more on inter-firm links of collaborators.

That said, this study has implications for place-based and mission-oriented innovation policies as well. In the European context, smart specialization has been one of the main place-based innovation policies, which aims to trigger economic growth in regions by building on existing competencies and moving to related economic activities, supporting entrepreneurial discovery processes, and supporting local institutions (Balland et al., 2018; Kogler et al., 2017; Foray et al., 2011). This is an ongoing scholarly debate that specializing based on related competences might lead to the lock-in situation in the future, whereas diversification into unrelated activities is constrained by a high risk. Our results suggest that perhaps specializing in several technologies and promoting intercommunity bridges between such specialized islands could be an optimal strategy. Similarly, the results can be discussed in the context of mission-oriented policies. Scholars discuss that providing solutions to encounter grand societal challenges requires inter-disciplinary collaborations (Mazzucato, 2018) which do not necessarily occur due to the path-dependent nature of creating collaborative ties (i.e. the retention mechanism). Since atypical inventions are associated with interdisciplinary collaborations (Fontana et al., 2020), the results of this paper can be used as a point of departure for further research efforts that aim at studying how to minimize institutional and interaction failures (Wanzenböck and Frenken, 2020) in the context of mission-oriented policy.

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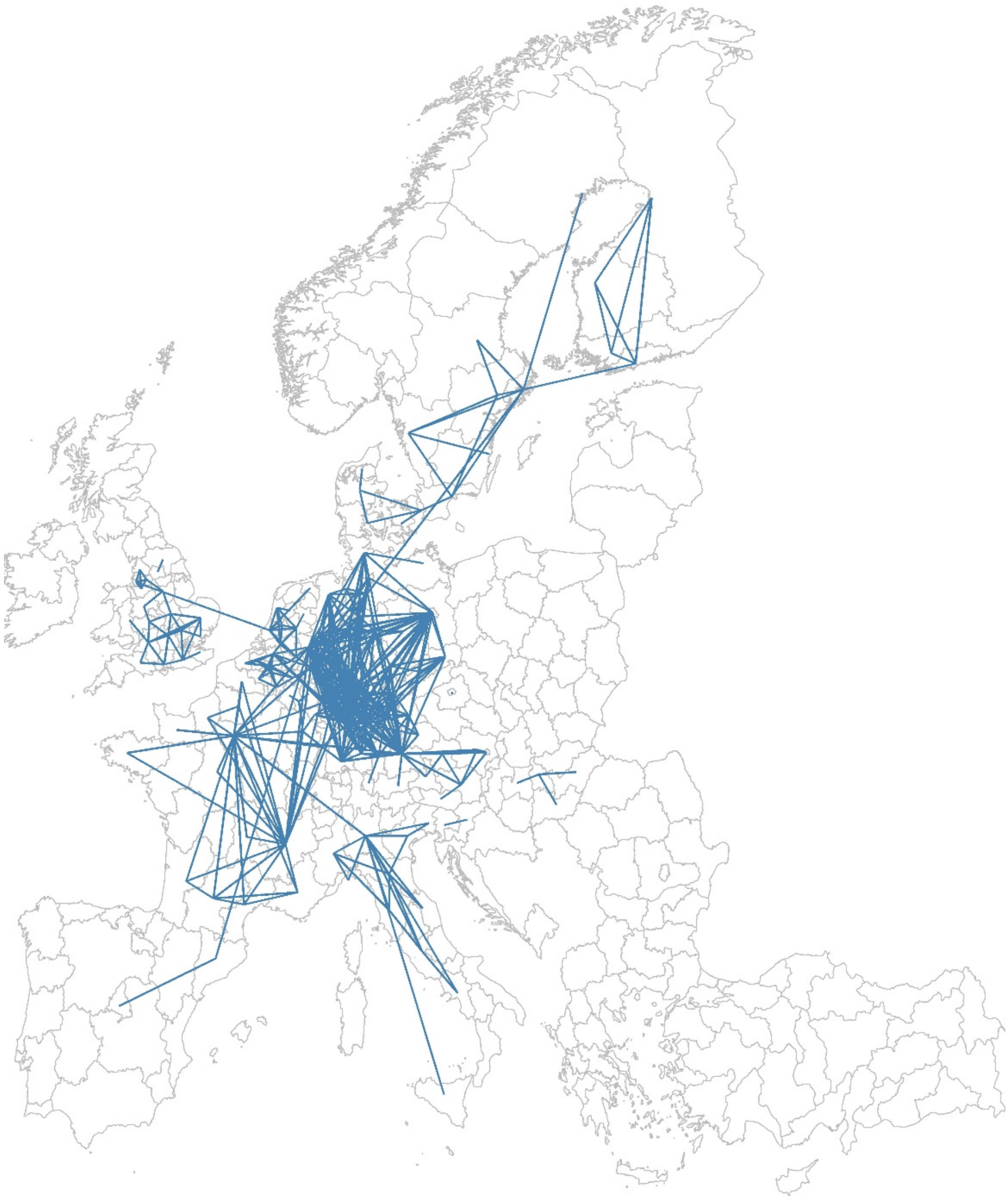
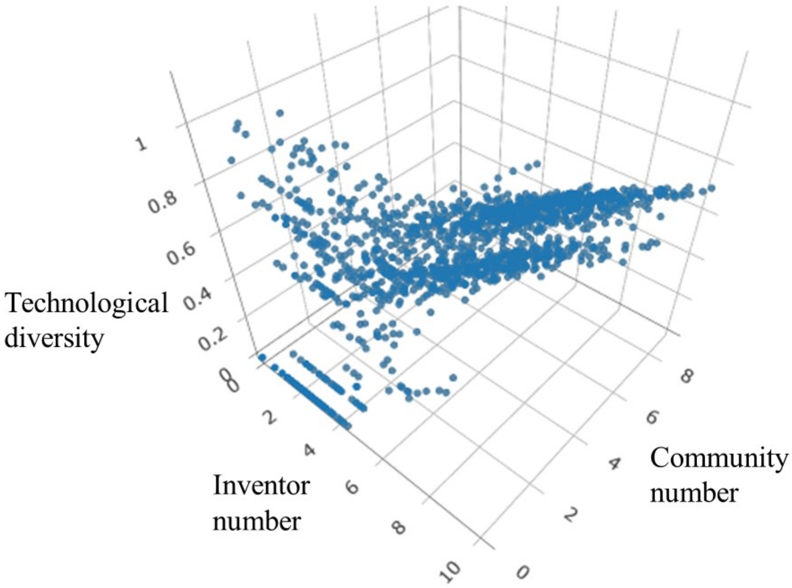
Supplemental material
Appendix A



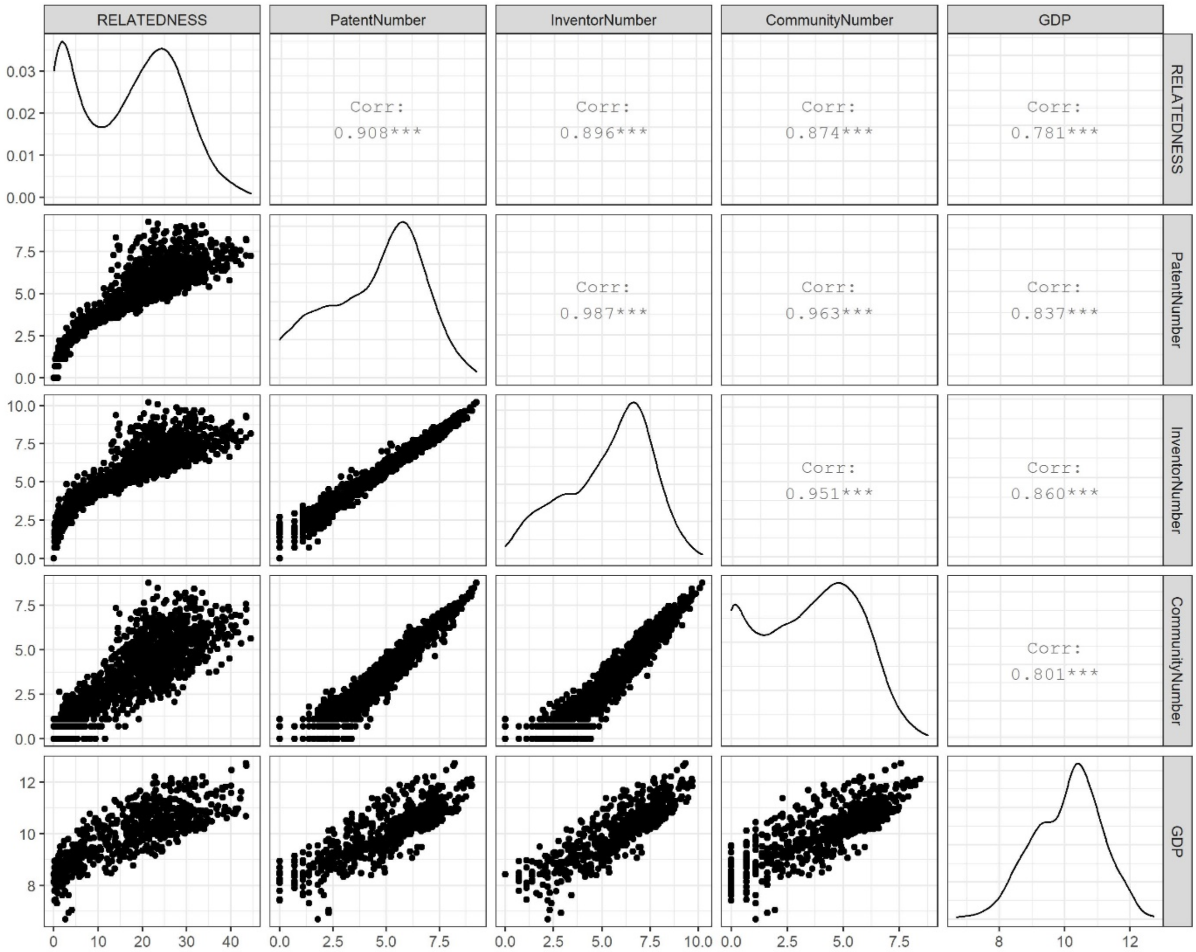
Note: only intense inter-regional collaborative ties (>the 95th percentile) at the aggregate level (1980-2014) are shown.

Appendix B



Note: the values on the x and y axes are log-transformed. Technological diversity corresponds to the median of the distribution of the Shannon entropy coefficients for all communities in each region.

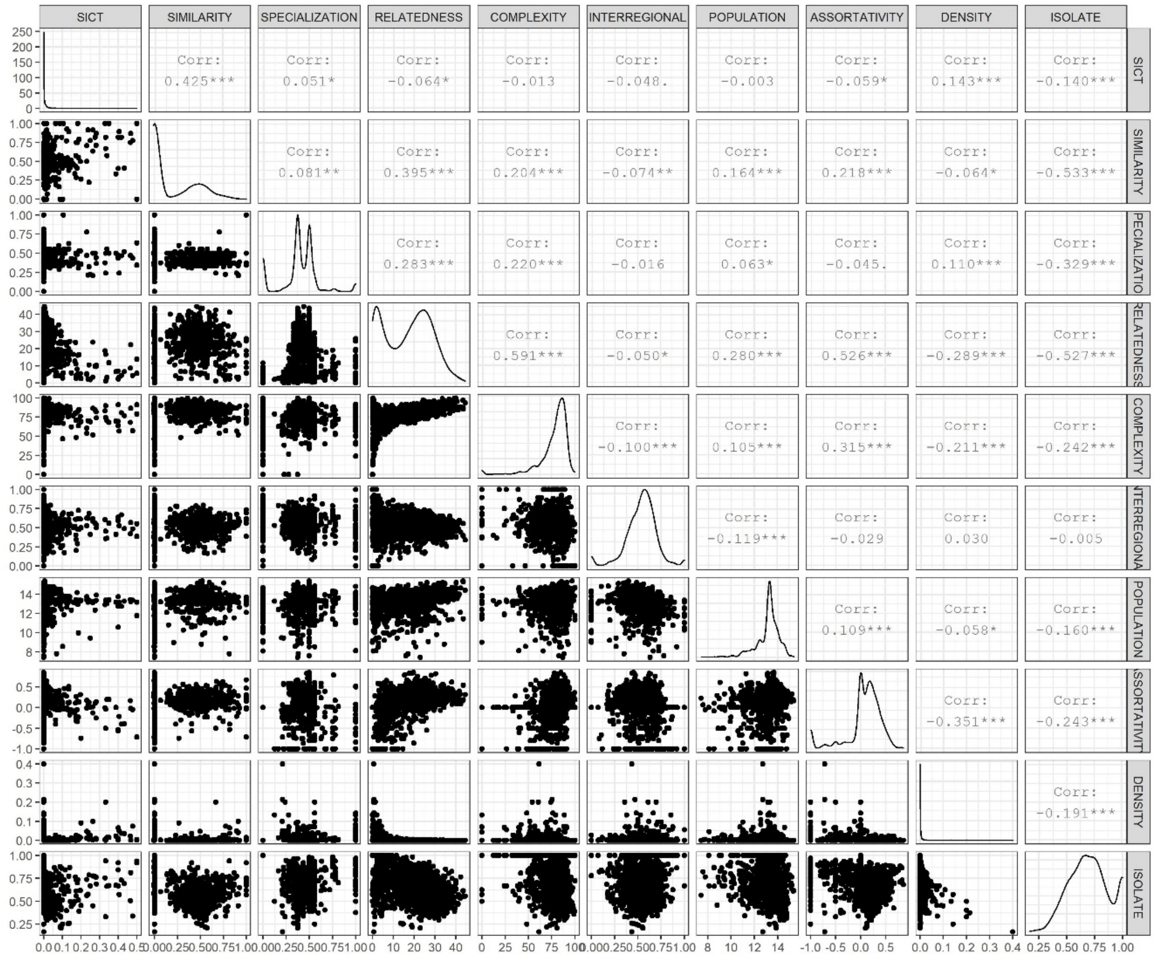
Appendix C



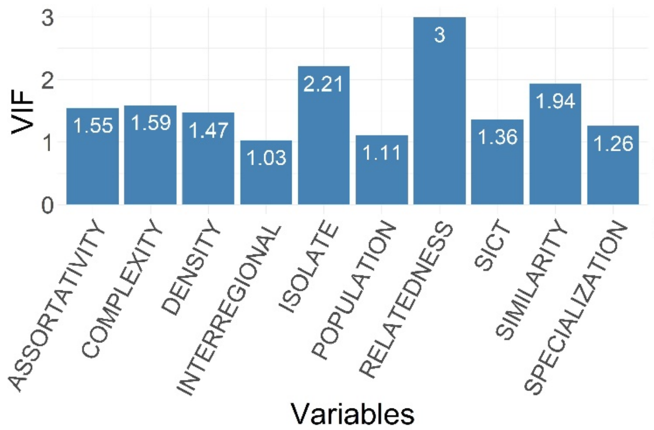
RELATEDNESS
PatentNumber
InventorNumber
CommunityNumber
GDP
Corr:
0.908***
Corr:
0.896***
Corr:
0.874***
Corr:
0.781***
Corr:
0.987***
Corr:
0.963***
Corr:
0.837***
Corr:
0.951***
Corr:
0.860***
Corr:
0.801***

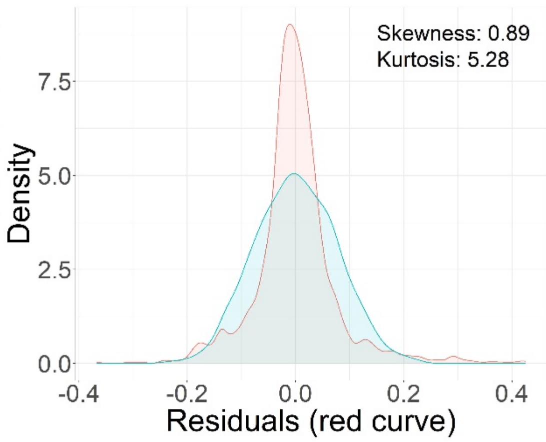
Appendix D

Statistic	N	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
SICT	1,526	0.01	0.05	0	0	0.01	0.5
SIMILARITY	1,526	0.19	0.26	0	0	0.4	1
SPECIALIZATION	1,526	0.39	0.20	0.00	0.36	0.50	1.00
RELATEDNESS	1,526	16.74	11.24	0.00	5.32	25.76	44.55
COMPLEXITY	1,526	78.16	14.88	0.00	73.95	87.38	100.00
INTERREGIONAL	1,526	0.54	0.16	0.00	0.45	0.63	1.00
POPULATION	1,526	13.13	1.03	7.42	12.83	13.70	15.38
ASSORTATIVITY	1,526	0.07	0.36	-1.00	0.00	0.29	0.85
DENSITY	1,526	0.01	0.02	0.00	0.0002	0.002	0.40
ISOLATE	1,526	0.71	0.18	0.17	0.57	0.82	1.00



Appendix E


VIF
3
2
1
0
1.55
1.59
1.47
1.03
2.21
1.11
3
1.36
1.94
1.26
ASSORTATIVITY
COMPLEXITY
DENSITY
INTERREGIONAL
ISOLATE
POPULATION
RELATEDNESS
SICT
SIMILARITY
SPECIALIZATION
Variables


Skewness: 0.89
Kurtosis: 5.28
Density
7.5
5.0
2.5
0.0
-0.4
-0.2
0.0
0.2
0.4
Residuals (red curve)

Appendix F

	Dependent variable: share of atypical patents	
	(1)	(2)
SICT	0.1268**	0.1378**
	(0.0497)	(0.0539)
SIMILARITY	-0.0325***	-0.0356***
	(0.0107)	(0.0110)
SPECIALIZATION	0.0619***	0.0686***
	(0.0214)	(0.0218)
RELATEDNESS	-0.0006	-0.0004
	(0.0007)	(0.0008)
COMPLEXITY	-0.0003	-0.0002
	(0.0004)	(0.0004)
INTERREGIONAL	-0.0590*	-0.0588*
	(0.0353)	(0.0354)
POPULATION	-0.0003	-0.0007
	(0.0029)	(0.0029)
ASSORTATIVITY	-0.0019	-0.0036
	(0.0117)	(0.0119)
DENSITY	0.1732	0.1010
	(0.2441)	(0.2391)
ISOLATE	0.1201**	0.1037*
	(0.0516)	(0.0536)
ATYPICAL_t0		-0.1182***
		(0.0350)
Region FE	YES	YES
Time FE	YES	YES
Observations	1,526	1,526
R^2	0.4122	0.4206
Adjusted R^2	0.2812	0.2908
Residual Std. Error	0.0850 (df = 1247)	0.0844 (df = 1246)
Note:		*p<0.1; **p<0.05; ***p<0.01

Appendix G

	Dependent variable	
	Share of atypical patents	Total patent growth rate
	(1)	(2)
SICT	0.1268**	0.7577
	(0.0497)	(0.7812)
SIMILARITY	-0.0325***	-0.4538***
	(0.0107)	(0.1659)
SPECIALIZATION	0.0619***	1.7746***
	(0.0214)	(0.4259)
RELATEDNESS	-0.0006	-0.0081
	(0.0007)	(0.0112)
COMPLEXITY	-0.0003	0.0114***
	(0.0004)	(0.0036)
INTERREGIONAL	-0.0590*	0.1110
	(0.0353)	(0.5097)
POPULATION	-0.0003	-0.0447
	(0.0029)	(0.0420)
ASSORTATIVITY	-0.0019	-0.3008
	(0.0117)	(0.2631)
DENSITY	0.1732	2.3273
	(0.2441)	(3.9049)
ISOLATE	0.1201**	0.2655
	(0.0516)	(1.1932)
Region FE	YES	YES
Time FE	YES	YES
Observations	1,526	1,526
R^2	0.4122	0.3677
Adjusted R^2	0.2812	0.2268
Residual Std. Error (df = 1247)	0.0850	1.4247
Note:		*p<0.1; **p<0.05; ***p<0.01