Atypical combination of technologies in regional co-inventor networks

Abstract

We generate novel combinations of technologies from existing knowledge via collaborative work. Albeit inventors and their respective communities tend to be specialised, inventor collaborations across differently specialised peers have the potential to generate co-inventor networks that provide access to a diverse set of knowledge and facilitate the production of radical novelty. Previous research has demonstrated that short access in large co-inventor networks enables innovative outcomes in regional economies. However, how connections in the network across different technological knowledge domains matter and what impact they might generate is still unknown. The present investigation focuses on 'atypical' combinations of technologies as indicated in patent documents. In particular, the role of technological specialisations linked in co-inventor networks that result in radical innovation in European regions is analysed. It is confirmed that the share of atypical patents is growing in regions where bridging ties establish short access to and across cohesive co-inventor sub-networks. Furthermore, the evidence suggests that the strong specialisation of co-inventor communities in regions fosters atypical combinations because these communities manage to increase the scale and scope of novel combinations. Thus, bridges between communities that are specialised in different technologies favour atypical innovation outcomes. The work shows that not diversity per se, but links across variously specialised inventor communities can foster radical innovation.

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

1. Introduction

Innovation in regional economies mainly occurs in collaborative work that requires interpersonal relations in order to transfer and combine knowledge (Bettencourt et al., 2007; Burt, 2004; Wuchty et al., 2007). The 'Geography of Innovation' literature (Feldman and Kogler, 2010) highlights the relevance of co-inventor networks to proxy the knowledge transfer potential of social relations within and across spatial units. In this process, inventors are linked together according to whether they have collectively worked on a patent previously. The structure of these networks indicates the innovation capacity of regions because it can capture the potential of knowledge transfer and combination activities (Bergé et al., 2018; Breschi and Lenzi, 2016; Fleming et al., 2007a; Li et al., 2014; Lobo and Strumsky, 2008). For example, Fleming et al. (2007a) investigated whether regional innovation benefits from the small-world networks of co-inventor collaboration (Watts and Strogatz, 1998). This network structure can catalyse complex knowledge transfer processes in cohesive co-inventor communities while at the same time providing access to diverse knowledge through bridging ties across inventor communities (Tóth and Lengyel, 2021; Uzzi and Spiro, 2005).

Although previous research has investigated the relevance of network structure in regional innovation, a crucial element is still missing from the above discussion: the role of technological and knowledge domains along which co-inventor collaboration patterns shape. Little is known on whether the technological specialisation of closely-knit co-inventor communities or inter-connections among technologically distant communities favour regional innovation outcomes. In this paper, we propose an innovative approach to deal with this problem at the mesoscopic level of regional collaboration networks (the network communities) and subsequently investigate the creation of atypical inventions that require the combination of distinct knowledge to capture radical novelty in regions (Mewes, 2019).

Taking an evolutionary perspective, the argument is that the formation of new co-inventor collaborations is decisive for radically new combinations of knowledge because complex knowledge flows are restricted to short distances in networks (Sorenson et al., 2006). Yet, network formation in regions is a path-dependent process because creating new co-inventor ties heavily dependents on earlier relationships in the network (Glückler, 2007).

Moreover, similar knowledge is easier to combine (Boschma, 2005; Hidalgo, 2018), while triadic closure is also a trait of collaboration networks (Newman, 2001). Thus, most new collaborations remain within specialised co-inventor communities that can drive regional innovation towards potential lock-in (Boschma and Frenken, 2010; Giuliani, 2013). On the contrary, a path-breaking variation most likely occurs when new links bridge previously separated parts of the network where dissimilar technological expertise reside (Glückler, 2007; Juhász and Lengyel, 2018).

Our empirical approach rests on network communities: cohesive segments of networks that consist of densely connected nodes which are loosely connected to other communities (Girvan and Newman, 2002; Palla et al., 2005). Small-world networks can be decomposed to network communities such that inter-community ties form network bridges (Girvan and Newman, 2002; Watts and Strogatz, 1998). Since the detection of network communities relies on the structure of networks only (Fortunato, 2010), one can investigate the technological specialisation of detected communities and characterise bridges by the similarity or dissimilarity of the domains they link together. In this way, we can create new measures at the regional level that can capture novel aspects of regional knowledge diversity by quantifying access across different mesoscopic specialisations.

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 that groups structurally equivalent innovators into a single node to remedy biases caused by the automatic triadic closure when projecting bipartite collaboration networks (Lucena-Piquero and Vicente, 2019) and measure the degree of small-worldness in the networks of places transformed from co-inventor networks (Neal, 2017). Finally, we detect network communities over five-year time-windows of the networks of places (Blondel et al., 2008). The technological specialisation of communities, their interlinking, and the technological similarity of inter-linked communities are quantified on the regional level. This enables us to estimate the share of atypical patents in each region in the subsequent five-year time-window by means of these regional-level explanatory variables.

The results suggest that the share of atypical patents is growing in those regions where co-inventor collaboration resembles small-world networks. This finding supports the idea that short access in co-inventor networks matters for combining different technological knowledge domains. Furthermore, we find that technological specialisation of co-inventor communities correlates positively with the share of atypical patents. This correlation reveals that those regions where inventor communities specialise in certain knowledge domains can produce higher levels of radical innovation. There is also a more significant potential for combinations to occur between communities. Also, a growing share of bridging collaborations across communities with dissimilar technological portfolios further supports atypical patenting. This new evidence implies that not the diversity of various technologies per se, but instead, the presence of multiple, diversely specialised, and inter-linked inventor communities favour radical innovation outcomes in regional economies.

2. Prior Relevant Insights and Hypotheses

2.1. Co-inventor networks

Prior knowledge provides the necessary ingredients for innovation to occur (Nelson and Winter, 1982; Schumpeter, 1911), but radical novelty and technological breakthroughs require combinations that have rarely been made before or are entirely new. Such innovations are often referred to as atypical combinations[1] (Kim et al., 2016; Uzzi et al., 2013; Wang et al., 2017), blending distinct knowledge domains into new knowledge (Fontana et al., 2020; Wagner et al., 2019). Radical innovation created in collaboration (Inkpen, 1996; Uzzi et al., 2013; Wang, 2016) often forms spatially embedded networks (Bercovitz and Feldman, 2011; Cassi and Plunket, 2013; Tóth et al., 2021; Tubiana et al., 2021). Recent evidence suggests that due to the need for diverse knowledge, atypical innovation is concentrated more intensively in geographical space (Balland et al, 2020, Mewes, 2019) than innovation in general (Audretsch and Feldman, 1996; Bettencourt et al., 2007). Local collaborations facilitate atypical combinations because learning complex knowledge requires frequent interaction (Balland and Rigby, 2016; Sorenson et al., 2006; Wagner et al., 2019).

Co-inventor networks, defined by links between inventors who collaborate on at least one patent, can approximate the role of collaborations in regional innovation (Fleming et al., 2007a; Lobo and Strumsky, 2008). These networks are helpful for two reasons. First, co-invention offers the potential for new knowledge combinations by bringing together inventors (Cowan and Jonard, 2004; Kogut, 2000; Kogut and Zander, 1992; Owen-Smith and Powell, 2004). Most co-inventor collaboration is restricted to only a few patents, and new collaborations offer new combinations of knowledge (Fritsch and Kudic, 2021; Tóth et al., 2021). Second, collaboration creates social relationships that provide grounds for effective knowledge transfer processes, even after the patent is published (Breschi and Lissoni, 2009). Although co-inventor collaboration mostly happens within firm boundaries (Whittle et al., 2020), the created co-inventor ties can cross firm boundaries (Fleming et al., 2007a; Powell et

[1] In this paper, we use the terms ‘atypical combination’ and ‘novel combination’ interchangeably.

al., 1996); inventors can move from one firm to another. They, therefore, bring their social network with them (Kemeny et al., 2016; Tóth and Lengyel, 2021). These co-inventor ties help to characterise regional innovation via established networks within (Cantner and Graf, 2006; Fleming et al., 2007a) and across regions (Breschi and Lenzi, 2016; Le Gallo and Plunket, 2020; Tóth et al., 2021; Whittle et al., 2020).

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 in regions (Bergé et al., 2018). For example, Fleming et al. (2007a) demonstrate that the short average path length in local co-inventor networks correlates with the number of patents produced in the region. They suggest that knowledge combination is more straightforward in regions where networks can foster access to distinct knowledge. Breschi and Lenzi (2016) add that interregional collaboration also matters because it can increase the diversity of available knowledge.

This paper addresses two missing aspects that have not been dealt with in the previous relevant literature. First, we investigate how the mesoscopic structural properties (community level) of co-inventor networks influences atypical patenting activities in regions. Second, we explore how technological specialisation and the diversity in knowledge provided through the meso-level of collaborative networks affect regional innovative outcomes.

2.2. Small-world networks of regional co-innovation

-The small-world structure that is among the most reflected network characteristics in the regional innovation context provides one point of departure here (Fleming et al., 2007a, Bettencourt et al. 2007). Small-world networks consist of cohesive subnetworks, where the ratio of closed triangles is high, but few bridges between these cliques reduce the length of shortest paths in the entire network (Watts and Strogatz, 1998). This model reflects seminal works in the structuralist tradition of sociology that theorise information circulation in strongly knit cliques as a facilitator of specialised learning (Aral, 2016; Coleman, 1988). Bridging connections across cliques enables novel combinations by increasing access across diverse knowledge domains in the network (Granovetter, 1973; Burt, 2004). Studies on collaboration and co-inventor networks have found a non-linear, inverse U-shape relation between the small-worldness of the network and the quality of knowledge combination (measured by the reception and impact of new knowledge) (Uzzi and Spiro, 2005; Tóth and Lengyel, 2021). These studies suggest that an optimal structure for new knowledge production mixes the advantages of practical learning in cohesive cliques with access to diversity (Aral, 2016; Rocchetta et al., 2021).

Fleming et al. (2007a) found that small-worldness does not, but short average path length does, correlate with patent numbers in regions. Yet, we have reasons to think that the small-worldness of co-inventor networks matters for atypical combination of technologies to occur in regions for two reasons. First, the development of these patents requires access to more diverse knowledge rather than perhaps more simple incremental innovation activities. Small-world networks can facilitate the circulation of diverse knowledge pieces due to their short average path length. Second, atypical combinations demand a mutual understanding of distinct knowledge pieces. Strongly knit cliques in small-world networks can improve the processing of these distinct pieces of knowledge (Fleming et al., 2007b; Ter Wal et al., 2016; Tóth and Lengyel, 2021; Aral, 2016). Thus, small-world networks provide significant aspects needed for the development of atypical combinations of knowledge, i.e. diverse access in the full network as well as high absorptive capacity in the network communities (Uzzi and Spiro, 2005; Cohen and Levinthal, 1990).

Consequently, the medium-level of small-worldness in regional co-inventor networks could be optimal for atypical patenting. The theory suggests that networks possessing too low or too high values on this particular indicator can miss either absorptive capacity or the necessary diverse knowledge inputs that reside in the network. To test this non-linear relationship between the small-worldness of co-inventor networks and atypical innovations in regions, we quantify the small-worldness indicator and formulate the following Hypotheses 1a and 1b.

H1a: *The small-worldness of co-inventor networks is positively related to the proportion of atypical patents in the region.*

H1b: *The quadratic term of small-worldness of co-inventor networks is negatively related to the proportion of atypical patents in the region.*

2.3. Technological specialization and diversity in co-inventor networks

Although the spectrum of available technologies in a regional economy has a natural impact on the potential of knowledge combinations to occur, the technological dimension is still missing from the small-world approach. It is widely accepted that a diverse pool of knowledge in urban areas (Florida et al., 2017; Glaeser et al., 1992; Jacobs, 1961) allows for atypical combinations (Berkes and Gaetani, 2020). However, there is a growing body of literature arguing that specialisation can also facilitate innovation (Beaudry and Schiffauerova, 2009; Lobo and Strumsky, 2008; Ó Huallacháin and Lee, 2010) when critical masses of experts specialised in distinct pieces of knowledge (Castaldi et al., 2015) are connected through knowledge transfer mechanisms (Berkes and Gaetani, 2020). For example, the Boston biotechnology cluster has emerged from local skills accumulated in distinct local critical masses in engineering and biology (Cooke 2002). Later, they were connected by social interaction that facilitated their combinations (Powell et al. 1996). The variety of technologies available in a region conditions the structure of inventor collaboration (van der Wouden and Rigby, 2019) and determines the potential for radical new combinations in the region (Castaldi et al., 2015). However, whether the specialisation of co-inventor cliques and the short access across similar or dissimilar knowledge in small-world networks is beneficial for generating radical innovation remains unknown.

The present investigation argues that it is not a diverse pool of knowledge per se, but the presence of diverse specialisations and their interlinking that matter for radical innovation to occur within regions. Our approach is based on network communities and the bridges between them, which is a way to represent small-world networks, as will be discussed in further detail later. This approach allows for the measurement of technological specialisation in communities and the diversity across bridged communities. By utilizing these characteristics of communities and pairs of inter-linked communities, we construct region-level measures that can be compared with the role of the small-world network structure present in regions.

Most related work in economic geography and beyond seems to focus on network dynamics in regions as well as their evolutionary characteristics (Feldman and Kogler, 2010). Evidence on the role of technological similarity and triadic closure in increasing the likelihood of inventor collaboration implies that micro-mechanisms of collaboration drive regions toward technological specialisation (Abbasiharofteh and Broekel, 2020; Boschma and Frenken, 2010; Broekel and Boschma, 2012; Cantner and Graf, 2006; Cassi and Plunket, 2013; Giuliani, 2013; Grabher, 1993; Ter Wal, 2013). Such mechanisms threaten radical knowledge production, especially in regions characterised by specialisation where inventors tend to partner with co-inventors of similar technological profiles to a greater extent than inventors residing in technologically diverse cities (van der Wouden and Rigby, 2019).

However, Glückler (2007) theorises that the process of network retention[2] can be counter-balanced by network variation, when otherwise loosely knit network cliques bridged by few collaborations create momentum for radical combinations and regional diversity.

Systematic evidence on such balancing mechanisms between specialisation and diversity in collaboration networks to create novelty is somewhat limited. An exception is the work of Migliano et al. (2020) which describes drug discoveries with the dynamics of interaction networks of hunter-gatherer tribes. They demonstrate that the tribes must accumulate knowledge in experiments with plants separated by camps before combining these plants into a better drug development through the interactions across camps; an excellent example of the two mechanisms needed for novelty generation in small-world networks. In a first step there is the accumulation of specialised knowledge in cohesive network segments, which is then followed up by the combination of the newfound technical expertise with radical and novel bridges across the established network segments.

Co-inventor networks in regions are usually large but techniques of network science can be used to find patterns in these complex structures. Here, we take an approach of network communities that are dense and cohesive subnetworks loosely connected to each other (Girvan and Newman, 2002; Palla et al., 2005). This network phenomenon aligns with the small-world theory because the subnetworks constitute strongly knit cliques, but the loose connections across them make the average path length short. These communities in the co-inventor networks represent fields of technological specialisation due to micro-mechanisms of network retention. Finally, inventors of similar technological profiles create such communities in the network in the first place (Tóth et al. 2021).

The suggested network community approach can contribute to previous research on small-world networks along two lines. First, defining the borders of cohesive cliques is not a trivial task in small-world networks but can be done with community detection that relies only on network topology (Fortunato, 2010). That detection enables us to measure the technological specialisation of communities and the diversity across the inter-linked communities. Second, the communities can be re-identified over time. Therefore, two communities might merge if there are many bridges between them. This latter feature ensures that links across communities are indeed bridges.

[2] Network retention is the tendency for the structure of a network to be determined by pre-existing processes that formed the structure of the said network in the first place.

Based on the above argument, we formulate two hypotheses that reflect the simultaneous need for specialised knowledge production in cohesive co-inventor networks and their bridging to produce atypical knowledge combinations. The specialisation of co-inventor communities in specific technologies can facilitate the production of radical innovation because the depth of knowledge accumulated in the community increases the scale and scope of expertise in a specific domain (Kemeny and Storper, 2015; von Krogh et al., 2003; De Noni and Belussi, 2021).

Specialisation supports new knowledge combinations within the community when distinct knowledge from external sources is absorbed and processed in the cohesive sub-network (Ter Wal et al. 2016; Tóth and Lengyel, 2021) and can also provide sufficient input for knowledge combinations in collaboration with others (von Krogh et al., 2003; Uzzi et al., 2013). In this latter sense, there is a need for connections between specialised communities to enable combinations of distinct knowledge and establish channels of subsequent knowledge transfer (Powell et al. 1996, Glückler 2007). To avoid potential biases of extremely specialised communities, we take the median of community specialisations to characterise the technological knowledge expertise that resides in regional economies.

H2: *The median level of technological specialisation of co-inventor communities in the region is positively related to the proportion of atypical patents in the region.*

H3: *The proportion of inter-community ties of co-inventor networks is positively related to the proportion of atypical patents in the region.*

Finally, we aim to provide a better understanding of how bridging across co-inventor communities, in terms of their pairwise technological specialisation, supports the development of radical combinations the most. The growing literature on atypical combinations suggests that radically new knowledge can be generated by combining distinct knowledge pieces (Fontana et al. 2020, Uzzi et al. 2013, Wagner et al., 2019, Wang et al. 2017).

A central discussion in the relevant literature, i.e. in the field of Economic Geography, concerns how the availability of dissimilar knowledge in a region, termed 'related' and 'unrelated' variety, favours the creation of novel knowledge (Frenken et al., 2007). Some argue that unrelated variety in a region fosters radical novelty (Castaldi et al., 2015; Miguelez and Moreno, 2016). Others find that regions specialised in various related industries can produce more breakthrough innovations (De Noni and Belussi, 2021). Focusing on innovative output in general, a recent study by Rocchetta et al. (2021) finds that different technological diversification measures, e.g. coherence and entropy-variety, exert varying degrees of non-linear effects on regional productivity growth, and that higher productivity returns can be found in regions that have invested in their existing technological capabilities as well as in more distant knowledge domains at the same time.

Although collaborations within regions can facilitate the combination of diverse knowledge (De Noni et al., 2017), the role of technological relatedness across linked specialisations still requires a more detailed analysis. One study on industry growth in regions concludes that co-worker links across related industries are particularly beneficial for weakly specialised local industries (Eriksson and Lengyel, 2019). On the other hand, strongly specialised industries – and inventor communities – might be able to process unrelated knowledge because of greater absorptive capacity. They can do this more efficiently through collaborations (Ter Wal et al., 2016).

We expect that the likelihood of atypical patenting intensifies as the overlap of the technological profiles of connected communities decreases. Novel combinations are more likely when co-inventor communities accumulate knowledge in different domains, and then establish bridges to these dissimilar knowledge bases. These bridging collaboration links across communities increase the social proximity of otherwise loosely connected inventor groups. Thus, a greater degree of technological dissimilarity across these linked groups can maintain more diversity in the region (Boschma, 2005; Cassi and Plunket, 2014). We formalise this expectation in Hypothesis 4.

> ***H4:*** *Technological similarity across bridged inventor communities is negatively related to the proportion of atypical patents in the region.*

3. Empirical Approach

3.1. Data

Innovation scholars have employed patent databases extensively in order 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 literature has discussed the limitations of these types of data (Archibugi and Planta, 1996; Kogler, 2015), patent data indeed provide a valuable source of information to undertake empirical studies where the temporal dimension of inventive activities is under scrutiny.

We utilize the European Patent Office (EPO) PATSTAT database and the final dataset includes 1,489,954 inventions filed by 2,059,171 unique inventors between 1980 and 2014. We follow the common practice of aggregating collaborative ties in seven non-overlapping 5-year time-windows to mitigate the differences in patenting frequency between highly and moderately innovative regions (Abbasiharofteh and Broekel, 2020; Fleming et al., 2007a; Kogler et al., 2017; Menzel et al., 2017; Ter Wal, 2014).[3] The disambiguating of individuals' and entities' names to assign unique identifiers that can then be utilized in a meaningful network, or related, methods-driven analyses poses a challenging task. Several contributions in this context, for instance Li et al. (2014) and Pezzoni et al. (2014), amongst others, have tackled this problem and subsequently provided a systematic approach in this regard. We disambiguated inventor and assignee names in the data utilized according to an advanced Massacrator© algorithm as described in the Pezzoni et al. (2014) paper. The database also contains the region of the home location of inventors. The PATSTAT database provides some of the harmonised indicators, e.g., assignee names, but further processing was necessary to locate inventors' addresses and disambiguate inventors' names. Application Programming Interface (API) access via two independent service providers facilitated the geocoding of inventors' addresses. The geocodes of inventors' addresses correspond to the NUTS2 level as defined by EUROSTAT (2018).

Collaborative ties between inventors are distributed within and across 264 NUTS2 regions. We assign interregional collaborative ties to both NUTS2 regions involved in developing a patented invention to ensure that regional networks are not biased by the so-called modifiable areal unit problem (Scholl and Brenner, 2014). Also, and in the spirit of the Schumpeterian view on innovation (Schumpeter, 1911; Strumsky and Lobo, 2015; Weitzman, 1998), we utilise the information on technological knowledge domains listed in individual patent documents to identify what technology codes were combined for each invention (Lee et al., 2022). We use 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.[4]

[3] 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.

[4] 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

We can observe collaboration networks in patents by the co-presence of inventors in one or several joint patents (Broekel and Graf, 2012; Li et al., 2014; Menzel et al., 2017; Stefano and Zaccarin, 2013; Ter Wal, 2014). From a network perspective, inventors are nodes and ties between every two nodes illustrate that two inventors collaborated on developing at least one patent. One can optimally present and explore the co-inventorship relations using an inventor-by-patent matrix *G*. Each row represents an inventor, and each column corresponds to a specific invention. G_{ij} takes the value of one if the *ith* inventor participated in developing the *jth* invention. Otherwise, it takes the value of zero. Using linear algebra, one can project the inventor-by-patent matrix to a binary symmetric inventor-by-inventor matrix *A* (in which $A_{mn} = A_{nm}$). A_{mn} takes the value of one if the m^{th} and n^{th} inventors collaborated on at least one inventive project. Otherwise, it takes the value of zero.

While numerous empirical studies used this method in prior innovation studies to generate and analyse collaboration networks, there are concerns that this introduces a bias that affects the reliability of community detection algorithms (Newman, 2001; Zhou et al., 2007). The projection of inventor-by-patent networks (also known as bipartite networks) typically provides a high degree of network clustering in inventor-by-inventor matrices (also known as unipartite networks) potentially influencing the small-world indicators measured in networks (Uzzi and Spiro, 2005). This is especially problematic if these collaborations include more than three participants, which 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).

We rely on ‘structural equivalence’ to deal with the projection bias and in order to decrease the bias of automatic triadic closure. Structural equivalence is a social network concept developed by Lorrain and White (1971) and Burt (1987). They claim that nodes in a network are structurally equivalent if they are identical in terms of relationship and embeddedness patterns, which provide them with access to similar resources in the network (Gnyawali and Madhavan, 2001; Stuart and Podolny, 1996). In the present investigation we follow the method developed by Pizarro (2007). Thus, we created a new network (hereafter, the network of places) in which new nodes (hereafter referred to as 'places') replace a set of neighbouring nodes (nodes that are directly connected) that share identical structural properties (for a review, see Lucena-Piquero and Vicente, 2019). In other words, we group inventors into a single node if they are identical in their network properties. This technique helps us to reduce the impact of automatic triadic closure on our network indicators. The 'network of places' are simplified representations of the co-inventor networks in which nodes represent inventors, or structurally equivalent groups of inventors, and ties represent single co-inventor ties or a bunch of ties going from the group of identical inventors to their collaborators.

Figure 1 demonstrates how 'networks of places' are created from the co-inventor network. In case A, the collaboration of six inventors on a single patent is transformed into 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 connected by the bridging inventor. Case D is a complex composition in which one can find all the pairings mentioned above of inventors and projects. Some of the inventors are structurally equivalent, and some are different. It is worth noting that isolated places in the 'network of places' are either individual inventors or several inventors that are structurally equivalent. A higher share of isolated nodes in the network of places reveals that most inventors take part in one or a few projects rather than being involved in numerous collaborations.

Figure 1 about here

Furthermore, Figure 2 shows that while we controlled for the high degree of clustering in regional collaboration networks, the number of nodes and edges in each region scale linearly (in a log-log scale) with those of the 'networks of places.' Thus, the network of places transformation does not substantially change other structural properties of the original co-inventor networks.

Figure 2 about here

As outlined above, the places of a focal region may include multiple inventors from other regions that have created collaborative ties with inventors residing in the focal region. Indeed, the descriptive statistics show that places include inventors from 2 regions on average (mean: 2.1 and median: 2). Our approach to deal with this problem is explained in Section 3.3.2., below.

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. We can determine the choice of technologies in each invention via the information provided in patent documents. We can thus measure the degree of the 'atypicality' of patents by noting how often a pair of technology codes occur in the data[5], compared with the statistical expectation of random co-occurrence.[6] Uzzi et al. (2013) have used this method to define the extent to which scientific publications introduce atypical combinations of knowledge pieces. Mewes (2019) applied a similar 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 $\sigma_{i,j}$ denoting the standard deviation of the expected co-occurrence of two given technologies. Teece et al. (1994) argue that if the number of occurrences of two units (technology codes here) is relatively high, then presumably co-occurrence of these units is 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 numbers of technology codes i and j respectively, and N is the total number all technology codes. The square of standard deviation is defined as:

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

[5] Since we used 650 CPC codes at the 4-digit level, it gives 210925 (n (n-1)/2) technology pairs.
[6] This implies that we excluded patents which include only one CPC technology code at the 4-digit level.

Intuitively, a negative value of the z-score indicates that the number of random co-occurrences is higher than the number of observed ones. 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 (Kogler et al., 2022). In other words, each time-window includes patents from the preceding and current time-windows but not patents from the succeeding ones. A single patent might introduce a beneficial atypical combination of technologies, motivating other inventors to imitate the same pattern in the subsequent time-windows, making the combination more common (less atypical). Figure 3 shows the kernel density estimates for z-scores in the seven-time-windows. The results are consistent with Uzzi et al. (2013) and Mewes (2019), i.e. a relatively small share of all combinations is actually atypical. More interestingly, the percentage of atypical patents dropped from 30% to 25% between 1984 and 2014. Also, we used the Shannon entropy measure to estimate the entropy of z-score values for each time-window. We observed that the entropy indices increase across time-windows[7], thus suggesting that inventions move towards the two extremes of typicality and atypicality over time.

Figure 3 about here

Since z-scores are estimates for the combinations of technology codes and not patents per se, one needs another definition at the patent level. Notably, 49% of patents include only one technology code, which do not introduce a combination of technology codes. On the other hand, 30% of patents have two technology codes that provide one combination, and 21% of patents combine more than two technology codes. Thus, we defined atypical patents as those that include at least one combination of technologies with a negative z-score. The dependent variable (*ATYPICAL*) is the share of atypical patents in each NUTS2 region and time-window. Figures 4 and 5 show the distribution of the share and number of atypical patents across European regions and different technologies.

Figure 4 about here

Figure 5 about here

[7] 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.

3.3.2. Independent variables and controls

Independent and control variables take into consideration factors at community, regional, and network levels. The first network-level variable approximates the degree of small-worldness in regions' network of places. Although the notion of small-worldness is clearly defined by Watts and Strogatz (1998), measuring small-worldness of 'real-world' networks has been a challenging task (Fleming et al., 2007a; Humphries and Gurney, 2008; Neal, 2017). One of the main motivations to combine structurally equivalent inventors into places is to reduce the impact of automatic clustering of three or more inventors who collaborated in the development of a single patent. Next, we followed the more recently suggested method of a 'double-graph normalised index' to approximate the small-worldness of the networks of places (Neal, 2017). This method overcomes the limitations associated with small-world indices that are normalised only by random graphs. The double-graph normalised index also enables us to compare indices of networks of a distinct size. The small-worldness index is defined as:

$$\omega = \frac{L_r}{L} - \frac{C}{C_l} \tag{4}$$

where L denotes the mean path length of the observed networks of places and L_r the same index of random reference networks[8]. C and C_l denote the clustering coefficients of observed networks of places and reference lattice networks. ω ranges between minus one (lattice network) and one (random network), with values near zero representing a high degree of small-worldness. For the sake of concreteness, we transformed ω in a way that large values (near one) represent a high degree of small-worldness, and small values (near zero) correspond to other structural properties (random or lattice).

$$SMALLWORLDNESS = 1 - |\omega| \tag{5}$$

The random and lattice reference networks are simulated based on methods suggested by Erdős and Rényi (1960) and Watts and Strogatz (1998), respectively. It is important to note that we created specific reference networks for each network of places having the same number

[8] Contrary to the original model of small-worldness suggested by Watts and Strogatz (1998), 'real-world' networks normally consist of multiple components. To estimate the mean path length of the observed and simulated networks of places, the geodesic distance between nodes in different components corresponds to the number of nodes in the network minus one.

of nodes and density. Thus, *SMALLWORLDNESS* (network-level) captures the extent to which an observed network of places approaches the maximum level of small-worldness (i.e., *SMALLWORLDNESS* equals to one) (Neal, 2017).

Other variables of interest in this paper underline the mesoscopic properties of the networks of places, which capture the distribution of knowledge pieces regarding various technologies within a region. We identified a set of places that are more densely connected compared to the rest of places in the network of places. Intuitively, one can expect that places that are more densely connected include inventors with the same or similar expertise and underlying knowledge bases. Yet, few inventors might bridge cognitive gaps and connect two or several cognitively distant places. It is worth noting that all places of a region (e.g., Region A), and network communities, include inventors located in the same region (Region A) and may include also inventors from other regions (Region B and C) that collaborated with inventors from this focal region (Region A).

Empirically, we applied a community detection procedure to identify a set of densely connected places. While the theoretical argument is straightforward, the network science literature provides numerous community detection methods that do not necessarily provide comparable results. Their accuracy and efficiency mainly depend on networks' size and structural properties (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 sizes and structural properties. They used the Lancichinetti–Fortunato–Radicchi benchmark graph to test the accuracy of the community detection algorithms (i.e., fast greedy, info map, leading eigenvector, label propagation, multilevel, walk trap, spin glass, and edge betweenness). The results suggest that the multilevel algorithm (also called the Louvain algorithm) provides a greater accuracy when the number of nodes displays high variance and exceeds 1000, and μ (the mixing parameter[9]) is greater than 0.5. Also, 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 $O(E^2N)$. We opted for the Multilevel algorithm[10] (Blondel et al., 2008) because this algorithm offers reasonable levels of accuracy and efficiency given that networks of places vary considerably in size and density. It is important to note that the Multilevel algorithm counts

[9] 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.
[10] We used the igraph R package by Csardi and Nepusz (2006) to apply the multilevel algorithm.

isolated nodes (in our case isolated places) as single communities. Similar to the work done by Abbasiharofteh et al. (2021), we deliberately do not consider them as communities because such isolated places poorly contribute to the diffusion of knowledge.

On average, communities include 6.4 places (between 4.8 and 7.1 places across seven non-overlapping time-windows)[11]. The Île de France region surrounding Paris has the highest number of communities (aggregated across all time-windows), followed by two German regions (Ober Bayern and Stuttgart). The distribution of the community frequency is highly skewed, which implies that a few regions have a high number of communities, whereas many regions include a limited number of communities. Yet, the skewness of this distribution decreases over time. The number of communities strongly correlates with patent and inventor numbers of regions in the same time-window (the Pearson correlation coefficients: 0.95 and 0.96, respectively). However, the sheer community number correlates less strongly with the population of regions (the correlation coefficient: 0.26)[12]. Figure 6 illustrates the distribution of community frequency across regions and seven time-windows.

Figure 6 about here

To capture the degree of communities' specialisation for each region, we used the Hirschman-Herfindahl Index (Hall and Tideman, 1967), which measures the concentration of technologies in each community. *SPECIALIZATION* is a region-level variable, measured by the regional median of the Hirschman-Herfindahl Index of technological specialization of network communities in the region, and time-window. We deliberately used the Herfindahl-Hirschman Index because this measure is not strongly correlated with the size of communities (the Pearson correlation coefficients: -0.11). This index's median ensures that extremely specialised communities do not cause measurement biases at the regional level. We test other region-level aggregates (e.g., mean and standard deviation) that provide similar results (a further discussion on that follows below). It should be noted that the concentration of

[11] To ensure that the identified communities are robust, we have iteratively run the algorithm starting from different nodes in the network of places. Although each time the results slightly change, the outcomes are strongly correlated. Particularly, we ran the Louvain algorithm and detected communities in each network of places ten times and randomly set the resolution parameter following a uniform distribution. We used Cramer's V (a measure of association between two nominal variables) to estimate the association between the membership of nodes in detected communities. The averaged value of Cramer's V coefficients (0.99) suggests that the outcomes of community detection algorithm are not arbitrary, and that they do not dependent on the parameters of the algorithm.

[12] Note that the number of regions' communities normalised by the inventor number is even less strongly correlated with population (the correlation coefficient: 0.03).

technologies in each community approximates the technological portfolios of inventors embedded in the given community because inventors tend to utilise technologies like the ones they used in the past. In other words, although *SPECIALIZATION* approximates technological specialization of communities based on patents developed by inventors in such communities, this variable is correlated with the portfolios of corresponding inventors.

We needed to construct a variable that measures the inter-connectedness of communities in regions. Therefore, it is important to say that networks with different number of nodes typically show 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 of places 100 times while keeping their size and the degree sequence constant. In other words, we randomly assigned ties to places while we induced a degree distribution like the one of the observed networks of places. As a result, the number of ties each place (and, as a result, the overall number of ties) remains the same compared to the underlying network of places, whereas ties connect different sets of places in the rewired networks of places. Then, we normalised the number of inter-community relations by subtracting it from the average value of the number of inter-community ties observed in the rewired networks. Finally, we calculate *SICT* (community-level) which corresponds to the share of the inter-community links by dividing the normalised number of inter-community relations by the total number of ties in the given network of places corresponding to each NUTS2 region in each time-window.[13]

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. Thus, the increase in the number of communities does not necessarily correlate with the technological diversity of a given region. To substantiate this claim, we used the technology codes (CPC codes at the 4-digit level) utilised to develop patents filed in each region-time in conjunction with an entropy-based measure (ranges between zero and one) to approximate the technological diversity. Our observation suggests that while the size of a region (i.e., inventor number) correlates with the

[13] The *SICT* measure might be different on the network of places than on the network of inventors, because the transformation from inventors to places might eliminate more intra-community ties than inter-community ties. Therefore, we have calculated $SICT_{INV}$ by assigning inventors to the communities detected on the network of places and counting intra-, and inter-community co-inventor links instead of links across places. The Pearson correlation between *SICT* and $SICT_{INV}$ is 0.93 suggesting that the network of places transformation does not introduce a major bias to the *SICT* calculation.

number of communities in each region (the Pearson correlation coefficient: 0.95), these two variables seem not to be firmly related (0.23 and 0.27, respectively) with technological diversity.

Also, communities are not entirely 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 for each pair of communities (in each region-time) connected by at least one inter-community collaborative tie. The Spearman rank correlation (ranging between -1 and 1) is defined as:

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

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)[14]. Using the Spearman rank correlation coefficients, *SIMILARITY* is the median of the distribution of all pairwise similarity coefficients of connected communities for each NUTS2 region in each time-window. Regions with greater (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. Figure 8 illustrates the specialisation of co-inventor communities, the share of inter-community ties, and the technological similarity across communities.

Even though many network places include inventors from different regions, the regional aggregation of the community-level indicators helps us to avoid the problem of assigning inventions to the regions that were actually created extensively in other regions. The number of inventors and places are strongly correlated with the number of communities in the region (the Pearson correlation coefficients are 0.95 and 0.94, respectively) suggesting that the community-level measurement captures local innovation. On the contrary, the share of interregional ties (defined later) is not correlated with *SMALLWORLDNESS*,

[14] The Spearman rank correlation coefficients are 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).

SMALLWORLDNESS^2, *SPECIALIZATION*, *SICT*, and *SIMILARITY* (the Pearson correlation coefficients: -0.04, 0.06, -0.12, -0.07, and -0.11 respectively) also signalling that regions' engagement in inter-regional collaborations are independent from our measurements. Finally, we weight the values of specialization, the share of inter-communities, and similarities indices of places by the share of local inventors before aggregating at the regional levels for creating the main network variables (i.e., *SPECIALIZATION*, *SICT*, and *SIMILARITY*) and find a strong correlation between the original and the weighted measures (the Pearson correlation coefficients are 0.85, 0.96, and 0.96 respectively). These tests confirm that the network variables are not biased by inter-regional relations and can indeed capture the role of local co-inventor collaboration in atypical knowledge combinations.

Figure 7 about here

Figure 8 about here

In addition to the four main independent variables, we employed several control variables (regional-level 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). Nevertheless, it is still an open question whether related or unrelated variety contributes to atypical patenting (Castaldi et al, 2015; De Noni and Belussi, 2021, Miguelez and Moreno, 2016). Following the method developed by Hidalgo et al. (2007) we measured the related density of each technology code of regions, and subsequently employ the average related density (*RELATEDNESS*) for regions in each time-window (van der Wouden and Rigby, 2019). It is worth noting that this variable correlates with various variables capturing the size of regions, such as the number of patents, number of inventors, number of communities, and GDP. Thus, we refrained from including these latter variables in the regression models.

Also, we built on the method of reflection developed by Hidalgo and Hausmann (2009) to control for the effect of technologies that are not ubiquitous in all regions (i.e., complex technologies). These technologies might provide comparative advantages for some regions because inventors in such regions can combine spatially less ubiquitous technologies to introduce atypical patents. The variable *COMPLEXITY* corresponds to the median value of complexity indices of technology codes included in patents in each region and time-window. In other words, *COMPLEXITY* controls for the extent to which regions include complex technologies in each time-window.[15] Since technologies are dynamic and their spatial distribution may change over time, we iteratively calculated the complexity of technologies for each time-window. Thus, this variable is not biased by the changing number of technology classes over time.

Besides, we added a proxy for how inventors in regions tap into external knowledge pools by measuring the share of interregional ties. This variable corresponds to the normalised number of the interregional relations divided by the total number of ties in each NUTS2 region and time-window (*INTERREGIONAL*). Additionally, *POPULATION* is a size-related control variable that corresponds to the regions' population (log-transformed) in each time-window.

Moreover, we need to control for other structural properties of the networks of places to ensure that our new variables have a significant explanatory power. 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 density (*DENSITY*) and share of isolates[16] (*ISOLATE*). In addition, we normalised the number of regions' communities[17] by inventor numbers (*COMMUNITY*). As clarified earlier in this subsection, we used a rewiring method to normalise network indices. Also, we refrain from creating a variable capturing the centralisation of regional inventor networks because that network index correlates significantly with *SPECIALIZATION*. Van der Wouden and Rigby (2019) showed that specialised cities in the US have relatively denser co-inventor networks than diversified ones. A higher value of network density coupled with a tendency to preferentially establish new relations with inventors having a somewhat higher number of ties (Barabási and Albert, 1999) may account for a high correlation coefficient of *SPECIALIZATION* and regional network centralisation.

3.3.3. Model construction

We opted 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

[15] We used the EconGeo R-package developed by Balland (2017) for estimating the related density and complexity coefficients.
[16] *ISOLATE* (the share of isolated places) corresponds to the number of isolated places divided by the total number of places in each region and time-window.
[17] The number of communities is strongly correlated with the number of inventors and places in each region (the Pearson correlation coefficients: 0.95 and 0.94 respectively). On average, communities include 9 inventors (median: 7.4).

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

$$Y_{r,t} = \alpha + \beta_1 SMALLWORLDNESS_{r,t-1} + \beta_2 SPECIALIZATION_{r,t-1} + \beta_3 SICT_{r,t-1} + \beta_4 SIMILARITY_{r,t-1} + \beta_5 N_{r,t-1} + \beta_6 Z_{r,t-1} + \varphi_t + \mu_r + \varepsilon_{r,t} \tag{7}$$

The dependent variable *ATYPICAL* is the share of atypical patents in each region and time-window; *SMALLWORLDNESS* (and its quadratic form), *SPECIALIZATION*, *SICT*, and *SIMILARITY* denote the independent variables. $N_{r,t-1}$ stands for a set of network related variables, i.e., *ISOLATE, COMMUNITY,* and *DENSITY*. Similarly, $Z_{r,t-1}$ represents four control variables that capture the degree of relatedness (*RELATEDNESS*) , technological complexity (*COMPLEXITY*), population (*POPULATION*) in regions, and the share of interregional ties (*INTERREGIONAL)*. φ_t is a time-window fixed effect, μ_r is a region fixed effect, and $\varepsilon_{r,t}$ denotes regression residuals.

4. Results and discussion

We conducted a set of fixed effects panel regression models with control variables and added variables of interest stepwise. We tested for heteroscedasticity in the model. The distribution of residuals does not perfectly follow a normal distribution (kurtosis: 5.28). Therefore, we use the heteroskedasticity-consistent White estimation of robust standard errors (White, 1980). Table 1 reports the results of the regression models with robust standard errors.[18] The predictive power of models improves as we add new variables to the regression models. However, the predictive power slightly decreases after including variables that capture the effects of isolate and community numbers. Diagnostics for multicollinearity are estimated by variance inflation factors (VIF) for each predictor variable. 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 shows relatively high VIF values

[18] 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).

for *RELATEDNESS*, *ISOLATE, and COMMUNITY* (3.25, 5.39, and 5.55, respectively). Thus, we refrain from interpreting the reported coefficients of these three variables.

Considering the obtained results, these provide evidence of the positive relation between the small-world structural property of regions' network of places and the increase in the share of atypical patents in the next time-window. This finding is in line with the argument that increasing small-worldness triggers innovation because this structural property increases absorptive capacity in network communities through local clustering and facilitates a more effortless information transfer through decreased average path length (Cowan and Jonard, 2003; Schilling and Phelps, 2007; Uzzi and Spiro, 2005). Our result does not support the one by Fleming et al. (2007a), who argued that both larger connected components and short average path length (and not the combined effects of these two variables, i.e., small-world structure) are positively related to innovative regional capabilities. Also, contrary to Uzzi and Spiro's (2005) finding, the reported coefficient of the quadratic term for small-worldness does not provide evidence for an inverse U-shape relation between small-worldness and an increase in the share of atypical inventions.

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 between connected communities correlates negatively with the dependent variable. Because we created networks cumulatively (we do not eliminate old ties), the fixed effect regression captures the impact of changing technological similarity across communities that have been linked earlier or are linked by new ties more recently. It is important to note that we created an alternative variable for similarity based on the pair-wise technological proximity of all communities (and not exclusively based on connected ones). Consistent with our theoretical arguments, the new variable is not significantly correlated with the dependent variable. The *SICT* coefficient becomes significant after including *SIMILARITY* in Model 5 and remains consistent across all models with various specifications. This finding also aligns with our theoretical argument and suggests that inter-community ties contribute more to the share of atypical inventions in regions if they bridge technologically dissimilar communities. These results support four out of the five hypotheses formulated in this paper (H1a, H2, H3, H4, but not H1b).

Table 1 about here

The complexity of patents (*COMPLEXITY*) seems not statistically related to the extent to which regions generate atypical patents. At first glance, this result might come as a surprise. However, Strumsky and Lobo (2015) demonstrate empirically that recent patents are mainly developed by the 'reusing' and 'recombination' of existing technological capabilities. Although the authors do not provide specific evidence for atypical patents, this might explain why technological complexity does not impact the share of atypical patents. Of course, this calls for careful empirical research in the future. Similarly, the results suggest that the share of interregional relations and regions' population do not account for regions' ability to introduce atypical inventions.

The inclusion of a variable that captures the effect of the density of regions' networks of places supports the arguments of Vicente (2017) and Abbasiharofteh (2020) that dense network relations do not necessarily improve the diffusion of knowledge and support innovative performance. In a similar vein, our result suggests that network density does not correlate significantly with the relative number of atypical patents. Similar, and across the entire spectrum of invention, Lobo and Strumsky (2008) did not find positive correlations between the patenting rate and the density of connections across US metropolitan areas.

While we controlled for already identified critical factors at the micro-level (e.g., *ISOLATE*) and the macro-level (e.g., *RELATEDNESS*), our main contribution concerns those variables that capture the impact of the mesoscopic properties of regional collaboration networks (i.e., co-inventor communities). The same is true for their technological portfolio on the relative number of atypical inventions. We find that regions with inventors that are part of co-inventor communities with higher specialisation tend to introduce more atypical patents. 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 inventors 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, these findings corroborate the rationale behind the small-world theory that postulates the simultaneous need for efficient learning in locally cohesive networks and access to diverse knowledge through bridges (Aral, 2016; Uzzi and Spiro, 2005). Although this effect emerging from the meso-level (communities) of collaboration network has been a long-standing conjecture, most empirical works in innovation studies have focused only on the structural attributes of networks at the macro-

(networks) and micro-levels (individuals). They have left out the technological domains that shape these networks and determine the type of knowledge access in networks (Breschi and Lenzi, 2016; Fleming et al., 2007a; Lobo and Strumsky, 2008; van der Wouden and Rigby, 2019).

Interestingly, we observed that the small-world structural property correlates positively with the growth of atypical patents, but not with the one of all patents (see Table 2). Indeed, this finding resonates with Fleming et al. (2007a), who found that small-worldness is not associated with the increase in the total number of patents in regions. The comparison of the two models, i.e., Table 1 above and Table 2 below, is in line with our original argument. The small-world structural property and the connection of communities are critical 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. Having mentioned the main differences of the two models, the similarity between connected communities is nevertheless less significant, while specialisation correlates positively with the overall patent growth rate.

Table 2 about here

To ensure the robustness[19] of our models, we conducted several checks. First, we used the mean and standard deviation (instead of the median) of the distribution of the Hirschman-Herfindahl indices for technologies embedded in each community to create alternative variables to approximate the degree of regions' specialisation. As a result, the reported coefficients for alternative specialisation variables align with the original ones. At the same time, the new models support the positive and negative associations of the share of inter-community ties and the similarity of connected communities with the dependent variable.

Second, we added the dependent variable of each previous time-window (the share of atypical patents) as an independent variable in the models. This variable enables us to capture dynamics across each consequent time-window. The results suggest that while the growth rate of the share of atypical patents is significantly decreasing, the sign and significance of the variables of interest do not change.

Third, we ran a model with a new variable that captured the effect of assortativity (also known as assortative mixing) in the regions' network of places. This variable

[19] All robustness checks are available upon request.

(*ASSORTATIVITY*) is the Pearson correlation between places' degrees that are directly connected. The implication is that the variable increases if highly connected places are connected at the expense of places that occupy peripheral positions. The result does not provide evidence for the positive or negative relation between assortativity and the increase in the share of atypical inventions. This finding is contrary to the argument put forward by Vicente (2017) and Lucena-Piquero and Vicente (2019) who claim that assortative relations bring about an unfortunate network structure that hinders the optimal diffusion of knowledge between the core and periphery of networks.

Forth, we used the normalised median size of communities (*COMMUNITY_median*) instead of the normalised community number (*COMMUNITY*) in the models. As a result, the new and original variables correlate weakly (the Pearson correlation coefficients: 0.26). Although this specification led to a slightly better predictive power of the models, the sign and significance of the variables of interest are consistent with the ones of the original full model specification.

Fifth, although the panel fixed-effects models do not strongly violate the basic assumptions of linear models, one may argue that the dependent variable is a share (i.e., the share of atypical patents) and being bounded on two sides may decrease the efficiency of estimated models. To remedy this situation, Ferrari and Cribari-Neto (2004) proposed a beta regression model for cases in which dependent variables are rates, proportions, or concentration indices. To ensure the reliabilities of the results, we estimated a beta regression using betareg package in R (Cribari-Neto and Zeileis, 2010). The sign and the significance of the four variables of interest align with the ones of the panel fixed-effects model.

Finally, following the lines of arguments developed in the conceptual part of the paper, one might expect that regions could excel in introducing atypical inventions when the share of inter-community ties and dissimilarity of connected communities concurrently increase. In a similar vein, regions may benefit from the joint effects of the share of inter-community ties and the specialisation of communities. Thus, we specified regression models with two interaction terms (*SICT* × *SIMILARITY* and *SICT* × *SPECIALIZATION*). The models did not provide empirical evidence for such multiplicative effects, probably because we aggregate specialisation and co-inventor community measures to the regional level. Yet, these joint effects between community specialisation and interconnectedness might prevail on lower levels of aggregation that can be a matter of future research, as discussed in the next section.

Conclusion

A plethora of literature stresses the path-dependent nature of economic and technological progress and seeks to understand how path-breaking advances help to renew the capacity of local economies (Boschma et al., 2015; Carnabuci and Bruggeman, 2009; Dosi, 1982; Frenken et al., 2007; Glückler, 2007; Kuhn, 1962). The ongoing specialisation versus diversity debate is very much at the core of this line of inquiry and most recent efforts investigate how specialised individuals, firms, or industries can establish and benefit from diversity in local ecosystems (Balland et al., 2022, De Noni and Belussi, 2021, Eriksson and Lengyel, 2019, Kim et al., 2022). Our results speak to these debates by emphasising the role of collaboration networks that can capture path-dependent and path-breaking dynamics at the meso-level via practical tools that link micro-level specialisation tendencies with the benefits of macro-level diversity.

We find new evidence that small-world networks of co-inventor collaboration favour atypical combinations of technological knowledge domains more extensively in those regions where communities of inventors are specialised in different technologies bridged by collaborations. By distinguishing between typical and atypical technological knowledge, we provide empirical evidence that both types of knowledge benefit from specialisation and being connected to technologically dissimilar ones. However, a small-world structural property along with a higher relative number of inter-community relations certainly favours the creation of atypical technological knowledge.

These results suggest that it is neither specialisation nor diversity at the regional level per se that favours innovation, which resonates with recent findings by Rocchetta et al. (2022). Instead, the presence of multiple specialisations at the community level and their connections can help knowledge combinations in regions. We argue that meso-level network mechanisms of collaborations are decisive for regional innovation, and that they can generate benefits that derive from the advantages of being specialised and diverse at the same time. Endogenous network formulation, driven through technological similarity and triadic closure, helps to accumulate specialised knowledge in cohesive regional subnetworks leading to an increase in the scale and scope of potential combinations. At the same time, bridging ties that connect divergent specialisations in separated parts of the network can provide the necessary access to diverse knowledge.

This evidence provides new insights for regional innovation policy on how the generation of radical inventive outcomes can be fostered via the support of a particular constellation of collaboration patterns. In particular, the recommendation is to encourage and to enable specialised collaborations and bridging collaborations in tandem. Regions that manage such a setting are more likely to create more considerable proportions of atypical inventions that have distinct specialisations of knowledge bases. Thus, supporting the endogenous network formation in diversely specialised, incremental knowledge production is beneficial for enabling and increasing the potential of future, novel knowledge re-combination processes. It is specialised communities and local strongholds that are needed in the first place to generate something radically new in the long run. Nevertheless, the connections across diverse sets of specialisations are also crucial. Bridging collaborations among actors and entities of dissimilar knowledge might require policy support because community bridging demands extra motivation in the first place.

In this regard, the present investigation has direct implications for place-based innovation policies. In the European context, Smart Specialisation has been one of the central place-based innovation policies. Aiming at regional economic growth by building on existing competencies, Smart Specialisation supports diversification into related economic activities, entrepreneurial discovery processes, and local institutions (Balland et al., 2018; Kogler, et al., 2017; Foray et al., 2011, Rigby et al., 2022). In this ongoing discussion, finding the right balance between specialisation and diversity is a significant challenge for avoiding the lock-in of related development and mitigating the high risks of diversification in unrelated activities. Our results suggest that specialising into several technologies and promoting inter-community bridges between such specialised islands could be a better strategy for Smart Specialisation.

The results are relevant in the context of mission-oriented policies as well. An increasing discussion claims that solutions to tackle grand societal challenges require inter-disciplinary collaborations (Mazzucato, 2018). However, such collaborations do not necessarily occur due to the path-dependent nature of creating collaborative ties and the demand for institutional and financial support. Since atypical inventions are associated with interdisciplinary collaborations (Fontana et al., 2020), the results of this paper on the role of bridging collaborations across different knowledge domains can be used as a point of departure for further research to understand the way institutional and interaction failures can be minimised in the context of mission-oriented and sectoral policy objectives (Wanzenböck and Frenken, 2020; Janssen and Abbasiharofteh, 2022; Simensen and Abbasiharofteh, 2022; Kabirigi et al., 2022).

We acknowledge several limitations of this study. First, we analysed the co-occurrence of technology codes on patent documents to approximate atypical technology combinations and identify atypical patents: 49% of filed patents include only one technology code (at the 4-digit level). We did not investigate such patents as they do not provide any combination of technology codes. Future studies can build on newly developed Natural Language Processing (NLP) methods to alternatively identify atypical patents by analysing the text of patent documents.

Second, it is of critical importance to distinguish between atypical inventions and breakthroughs. While one can single out breakthroughs by the atypical combination of existing and new technologies, they usually receive a higher forward citation and a longer lifecycle. We acknowledge that the focus of this study was exclusively on exploring factors that may trigger atypical inventions. Indeed, a larger share of inventions with atypical technology combinations are doomed to fail, whilst successful atypical inventions have higher payoffs (Fleming, 2001). Thus, we encourage future empirical studies to determine the key factors that account for the development of atypical inventions with exceptional impact on future technologies and the commercial success of underlying products and services.

Third, 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 firms' boundaries and which links have linked more firms due to inventor mobility. These decisions have limited us in analysing how strategy, alliances, and competition of firms influence atypical innovation in regions. Future research, similar to Wanzenböck et al. (2022) who provide already some insights into the relationship between a regions' organisations' network structure and its ability to enter new specialisations, should shed light on these mechanisms by generating co-inventor networks differently and focusing more on inter-firm links.

Fourth, alternative approaches should be developed in future research to tackle methodological challenges of investigating knowledge domains in small-world collaboration networks and especially how automatic clustering can be dealt with. For example, the inter-community and inter-regional links might be overrepresented in the network of places approach in case the transformation eliminates intra-community and intra-regional ties disproportionally. Therefore, the network of places method might be problematic to sort out bridging collaborations in studies that aim to understand knowledge combination in collaboration networks on a lower level of aggregation.

Last but related to the previous point, we do not find multiplicative effects of community specialisation, the proportion of inter-community ties, and the similarity of inter-linked specialisations on the regional level. Taking the median levels of these community-level indicators to characterize regions might be a reason for the missing multiplicative effects. Nevertheless, significant joint effects can be expected on a lower level, based on previous results (Eriksson and Lengyel, 2019). Therefore, we urge future research to investigate how specialisation and access to diversity in small-world collaboration networks influence knowledge combinations on the level of individuals, firms, and industries.

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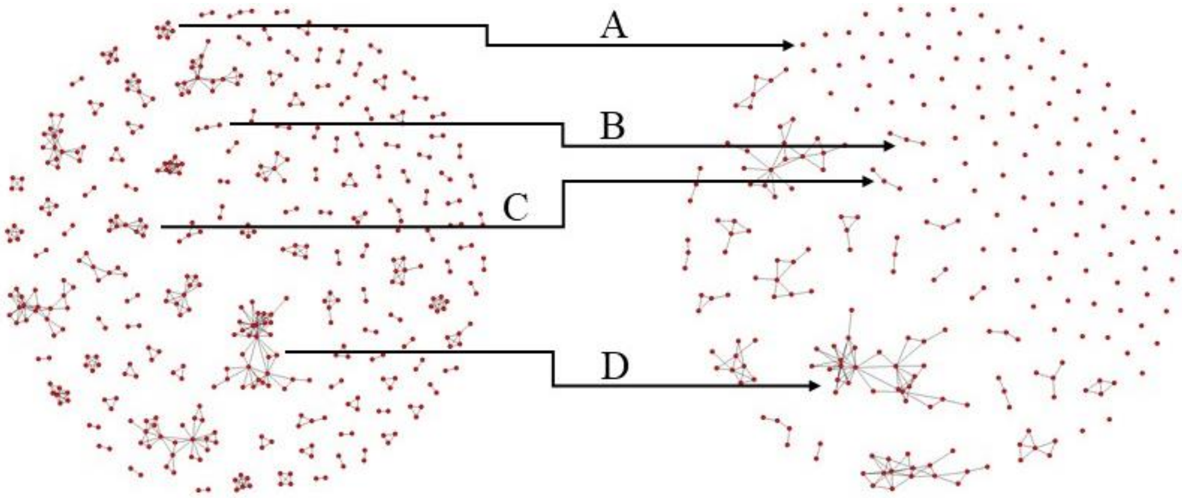

Figure 1. The projected co-inventor network (left) and the co-inventor network of places (right).

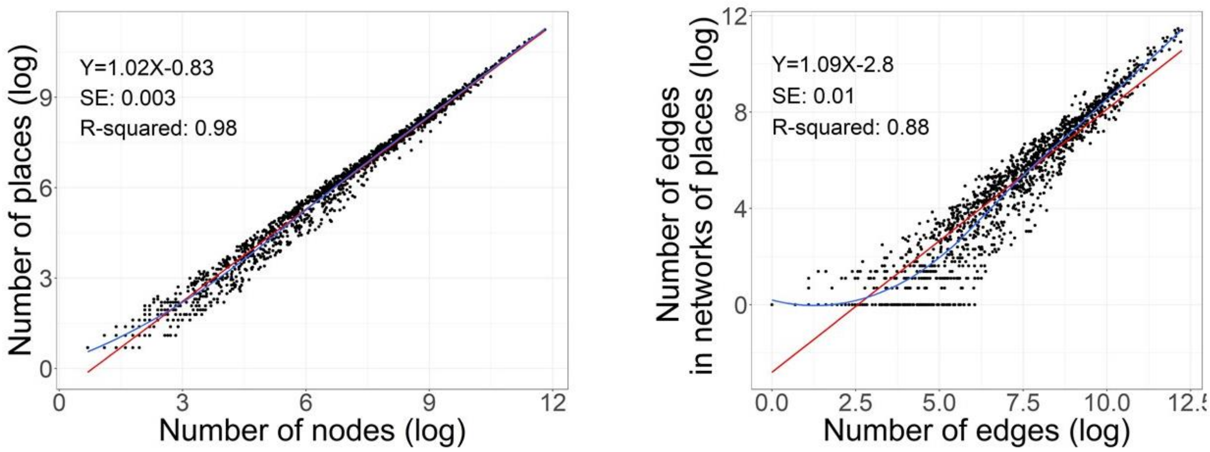

Figure 2. The projected co-inventor network (left) and the co-inventor network of places (right).

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

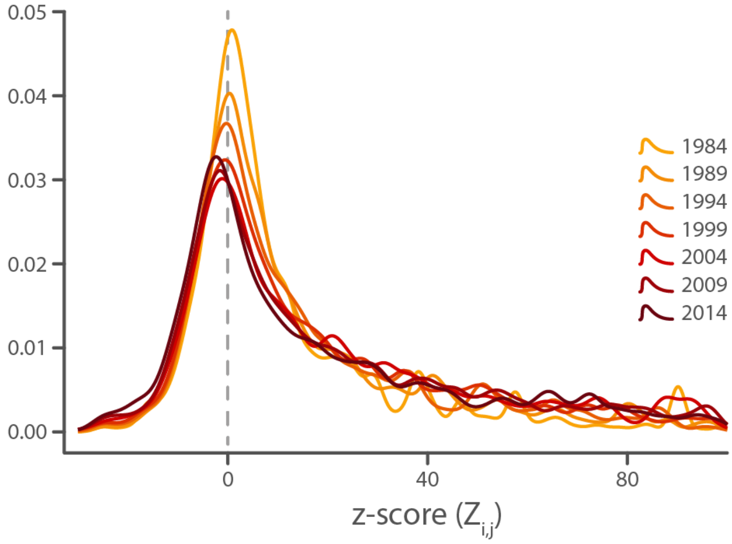

Figure 3. The kernel density of z-scores for the combination of each technology pair.

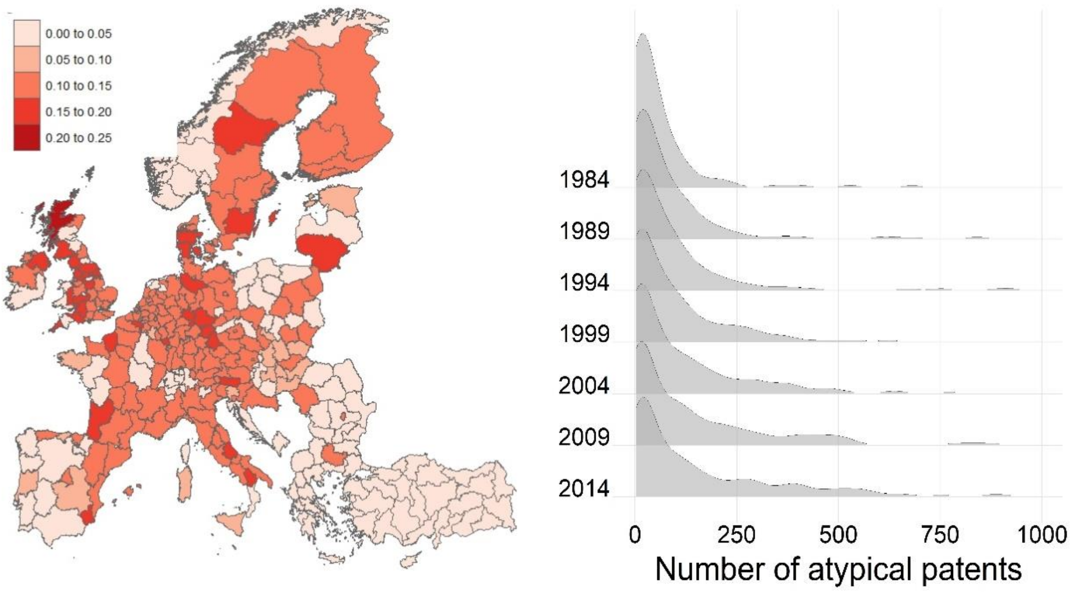

Figure 4. The share of atypical patents between 1984 and 2014 (left) and the distribution of the number of atypical patents across seven time-windows (right).

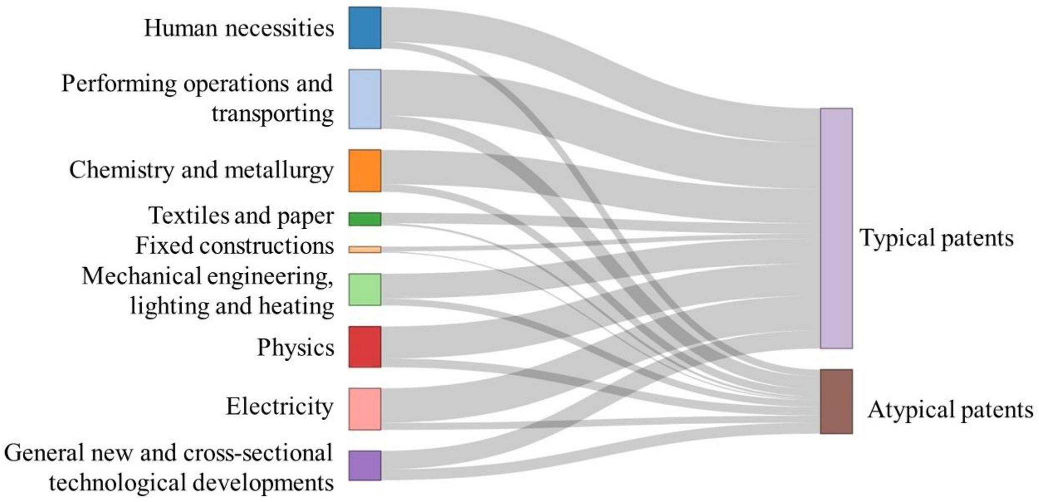

Figure 5. The distribution of typical and atypical patents (1980-2014) across Cooperative Patent Classifications (CPC) schemes.

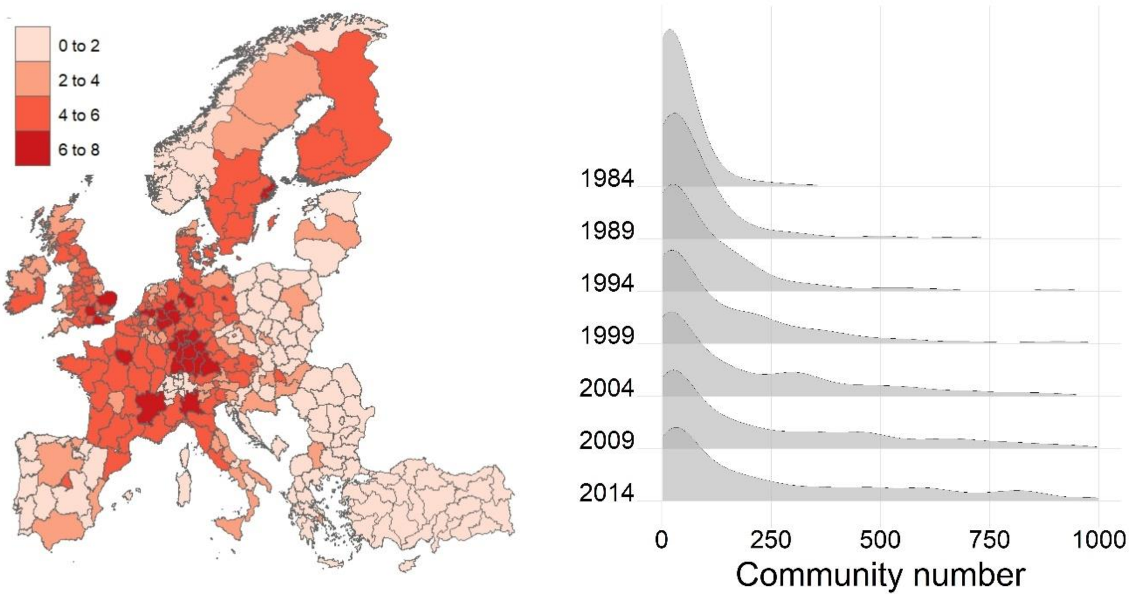

Figure 6. The number of detected communities in log (left) and the distribution of community numbers across seven time-windows.

Note: The number corresponds to the median value of community numbers across seven time-windows between 1980-2014. The legend is in logarithmic scale.

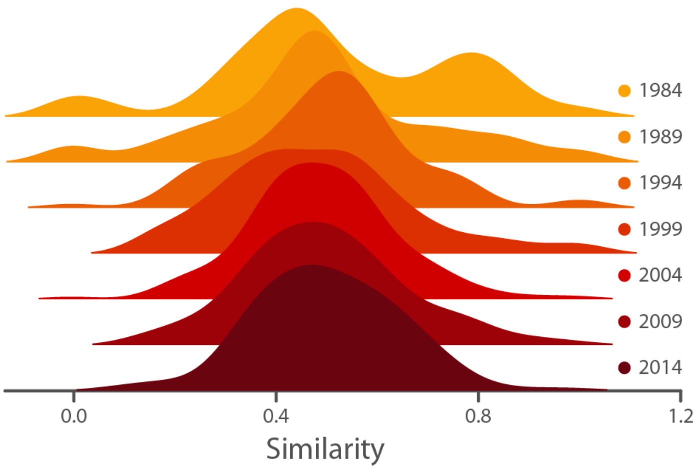

Figure 7. An approximation of the density of the variable *SIMILARITY* (kernel density estimation) over time.

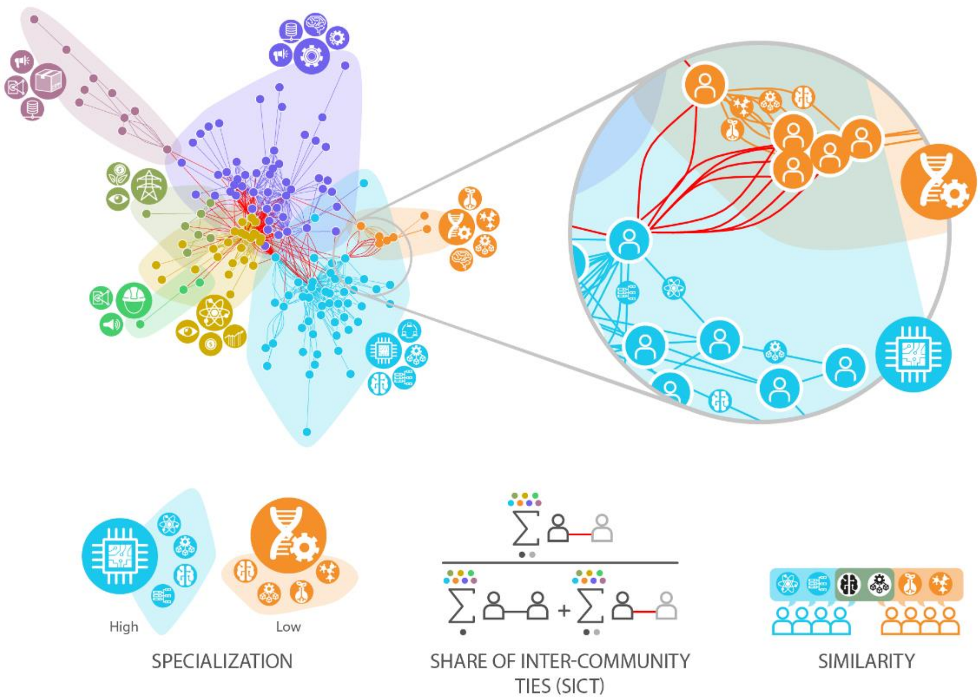

Figure 8. Visual representations of detected communities, inter-community ties, and three variables of interests.

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

	Dependent variable: share of atypical patents								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
SMALLWORLDNESS		0.0148***	0.0131***	0.0131***	0.0115***	0.0116***	0.0136***	0.0114***	0.0115**
		(0.0040)	(0.0039)	(0.0039)	(0.0039)	(0.0039)	(0.0042)	(0.0039)	(0.0052)
SMALLWORLDNESS^2		0.0037	0.0045	0.0048	0.0030	0.0010	0.0022	0.0029	0.0007
		(0.0043)	(0.0042)	(0.0043)	(0.0042)	(0.0042)	(0.0043)	(0.0043)	(0.0042)
SPECIALIZATION			0.0458**	0.0451**	0.0405**	0.0576***	0.0608***	0.0437**	0.0558**
			(0.0185)	(0.0186)	(0.0188)	(0.0189)	(0.0223)	(0.0195)	(0.0220)
SICT				0.0331	0.1041**	0.1103**	0.1124**	0.1091**	0.1039**
				(0.0465)	(0.0523)	(0.0530)	(0.0534)	(0.0524)	(0.0493)
SIMILARITY					-0.0342***	-0.0248**	-0.0317***	-0.0336***	-0.0231**
					(0.0105)	(0.0102)	(0.0106)	(0.0105)	(0.0094)
RELATEDNESS	-0.0007	-0.0017**	-0.0018**	-0.0017**	-0.0017**	-0.0015**	-0.0016**	-0.0017**	-0.0014*
	(0.0007)	(0.0007)	(0.0007)	(0.0007)	(0.0007)	(0.0007)	(0.0007)	(0.0007)	(0.0007)
COMPLEXITY	-0.0003	-0.0003	-0.0003	-0.0003	-0.0003	-0.0002	-0.0003	-0.0003	-0.0002
	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)
INTERREGIONAL	-0.0507	-0.0488	-0.0509	-0.0505	-0.0499	-0.0559	-0.0524	-0.0501	-0.0572*
	(0.0362)	(0.0356)	(0.0348)	(0.0348)	(0.0346)	(0.0348)	(0.0349)	(0.0348)	(0.0346)
POPULATION	-0.0001	0.0001	0.0002	0.0002	0.0001	-0.0001	0.00002	0.0001	-0.0001
	(0.0029)	(0.0029)	(0.0028)	(0.0028)	(0.0028)	(0.0029)	(0.0029)	(0.0029)	(0.0029)
ISOLATE						0.1030**			0.1336*
						(0.0455)			(0.0792)
COMMUNITY							-0.2746		0.0313
							(0.1958)		(0.3192)
DENSITY								-0.1339	0.1943
								(0.2458)	(0.2298)
Region FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Time FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	1,526	1,526	1,526	1,526	1,526	1,526	1,526	1,526	1,526
R^2	0.3967	0.4048	0.4091	0.4093	0.4118	0.4166	0.4144	0.4122	0.4172
Adjusted R^2	0.2657	0.2745	0.2792	0.2788	0.2813	0.2866	0.2839	0.2812	0.2862
Residual Std. Error	0.0859 (df = 1253)	0.0853 (df = 1251)	0.0851 (df = 1250)	0.0851 (df = 1249)	0.0849 (df = 1248)	0.0846 (df = 1247)	0.0848 (df = 1247)	0.0850 (df = 1247)	0.0847 (df = 1245)
Note:									*p<0.1; **p<0.05; ***p<0.01

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

	Dependent variable:	
	Share of atypical patents	Total patent growth rate
SMALLWORLDNESS	0.0115**	0.0336
	(0.0052)	(0.0796)
SMALLWORLDNESS^2	0.0007	-0.0360
	(0.0042)	(0.0915)
SPECIALIZATION	0.0558**	1.6982***
	(0.0220)	(0.4397)
SICT	0.1039**	0.5302
	(0.0493)	(0.7598)
SIMILARITY	-0.0231**	-0.3266*
	(0.0094)	(0.1709)
RELATEDNESS	-0.0014*	-0.0181
	(0.0007)	(0.0124)
COMPLEXITY	-0.0002	0.0119***
	(0.0004)	(0.0036)
INTERREGIONAL	-0.0572*	0.1680
	(0.0346)	(0.5276)
POPULATION	-0.0001	-0.0467
	(0.0029)	(0.0433)
ISOLATE	0.1336*	1.5586
	(0.0792)	(1.7011)
COMMUNITY	0.0313	5.7878
	(0.3192)	(4.7590)
DENSITY	0.1943	1.9777
	(0.2298)	(3.4265)
Region FE	YES	YES
Time FE	YES	YES
Observations	1,526	1,526
R^2	0.4172	0.3684
Adjusted R^2	0.2862	0.2263
Residual Std. Error (df = 1245)	0.0847	1.4252
Note:		*p<0.1; **p<0.05; ***p<0.01

Table 2. Results of regression models with the original (share of atypical patents) and alternative dependent (Total patent growth rate) variables.