Abbasiharofteh, Milad; Kogler, Dieter F.; Lengyel, Balázs

Atypical combinations of technologies in regional co-inventor networks

Research Policy

Provided in Cooperation with:
Leibniz Institute of Agricultural Development in Transition Economies (IAMO), Halle (Saale)

Suggested Citation: Abbasiharofteh, Milad; Kogler, Dieter F.; Lengyel, Balázs (2023) : Atypical combinations of technologies in regional co-inventor networks, Research Policy, ISSN 1873-7625, Elsevier, Amsterdam, Vol. 52, Iss. 10, pp. --, https://doi.org/10.1016/j.respol.2023.104886 , https://www.sciencedirect.com/science/article/pii/S0048733323001701

Research Policy 52 (2023) 104886

Contents lists available at ScienceDirect

Research Policy

journal homepage: www.elsevier.com/locate/respol

Atypical combinations of technologies in regional co-inventor networks

Milad Abbasiharofteh [a,b,c,*], Dieter F. Kogler [d,e,f], Balázs Lengyel [g,h,i]

[a] Department of Economic Geography, Faculty of Spatial Sciences, University of Groningen, 9747 AD Groningen, the Netherlands
[b] Department of Human Geography and Spatial Planning, Utrecht University, 3584 CB Utrecht, the Netherlands
[c] Department of Structural Change, Leibniz Institute of Agricultural Development in Transition Economies, 06120 Halle, Germany
[d] Spatial Dynamics Lab, University College Dublin, D04 V1W8 Dublin, Ireland
[e] Insight Centre for Data Analytics, University College Dublin, D04 V1W8 Dublin, Ireland
[f] School of Architecture, Planning & Environmental Policy, University College Dublin, D04 V1W8 Dublin, Ireland
[g] Agglomeration and Social Networks Lendület Research Group, Centre for Economic- and Regional Studies, Eötvös Loránd Research Network, 1097 Budapest, Hungary
[h] Laboratory for Networks, Technology and Innovation, Corvinus Institute for Advanced Studies, Corvinus University of Budapest, 1093 Budapest, Hungary
[i] Institute of Data Analytics and Information Systems, Corvinus University of Budapest, 1093 Budapest, Hungary

ARTICLE INFO

Keywords:
Novelty
Invention
Collaboration networks
Small-world networks
Network communities
Technological similarity
Network of places
Patent analysis
Regional economies

ABSTRACT

Novel combinations of technologies are usually the result of collaborative work that builds on existing knowledge. Albeit inventors and their respective communities tend to be specialized, inventor collaborations across differently specialized 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 specializations linked in co-inventor networks that result in radical innovation in European regions is analyzed. Our results confirm that the share of atypical patents is growing in regions where bridging ties establish short access to and across cohesive co-inventor subnetworks. Furthermore, the evidence suggests that the strong specialization 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 specialized in different technologies favor atypical innovation outcomes. The work shows that not diversity per se, but links across variously specialized inventor communities can foster radical innovation.

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 patented invention 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 catalyze 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 prior research efforts have been directed toward investigating the relevance of network structures in regional innovation activities, a crucial element is still missing from the above discussion: the role of technological and knowledge domains along which co-inventor collaboration is shaped and how this might impact the inventive potential of regional economies. Little is known about whether the technological specialization of closely-knit co-inventor communities or

* Corresponding author at: Department of Economic Geography, Faculty of Spatial Sciences, University of Groningen, 9747 AD Groningen, the Netherlands.
E-mail addresses: m.abbasiharofteh@rug.nl (M. Abbasiharofteh), dieter.kogler@ucd.ie (D.F. Kogler), lengyel.balazs@krtk.hu (B. Lengyel).

https://doi.org/10.1016/j.respol.2023.104886
Received 19 November 2020; Received in revised form 30 August 2023; Accepted 30 August 2023
Available online 5 September 2023

inter-connections among technologically distant communities favor 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 on regional economic development (Kogler, 2015a; Kogler et al., 2023a), 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 depends 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 specialized co-inventor communities that can drive regional innovation toward 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).

The pursued 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 into 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 specialization of detected communities and characterize bridges by the similarity or dissimilarity of the domains they link together. In this way, it is possible to create new measures at the regional level that can capture novel aspects of regional knowledge diversity by quantifying access across different mesoscopic specializations.

Following Uzzi et al. (2013), we measure radical innovation by identifying atypical combinations of technologies in patents using the European Patent Office (EPO) PATSTAT database over more than three decades (1980–2014). The co-inventor network is constructed for NUTS2 regions 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 specialization of communities, their interlinking, and the technological similarity of interlinked communities are quantified at the regional level. This approach 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 specialization of co-inventor communities correlates positively with the share of atypical patents. This correlation reveals that those regions where inventor communities specialize 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. The new evidence implies that not the diversity of various technologies per se, but the presence of multiple, diversely specialized, and interlinked inventor communities favor 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 (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 patented invention, 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 collaborations are 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 (Kogler et al., 2023b; Shin et al., 2023), the created co-inventor ties can cross firm boundaries (Fleming et al., 2007a; Powell et 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 characterize 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; Kogler et al., 2023b).

Contradicting earlier approaches that argue for the importance of isolated inventors (Lobo and Strumsky, 2008), a few 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 inter-regional collaboration also matters because it can increase the diversity of available knowledge.

This present study addresses two missing aspects that have not been dealt with in the previous relevant literature. First, we investigate how

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

the mesoscopic structural properties (community level) of co-inventor networks influence atypical patenting activities in regions. Second, we explore how technological specialization and the diversity in knowledge provided through the meso-level of collaborative networks is affecting 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 theorize information circulation in strongly knit cliques as a facilitator of specialized 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 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 knowledge pieces (Fleming et al., 2007b; Ter Wal et al., 2016; Tóth and Lengyel, 2021; Aral, 2016). Thus, small-world networks facilitate the development of atypical combinations of knowledge through 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 theoretically 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 the linear and non-linear relationship between the small-worldness of co-inventor networks and atypical innovations in regions, we quantify the small-worldness indicator and formulate 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 also a body of literature that argues that specialization might facilitate innovation as well (Beaudry and Schiffauerova, 2009; Lobo and Strumsky, 2008; Ó Huallacháin and Lee, 2010) when critical masses of experts specialized in distinct knowledge pieces (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 specialization 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 specializations 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 specialization in communities and the diversity across bridged communities. By utilizing these characteristics of communities and pairs of interlinked 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 specialization (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 characterized by specialization 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) theorizes 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 specialization 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 the first step, there is the accumulation of specialized knowledge in cohesive network segments, followed 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 define network communities as dense and cohesive subnetworks that are loosely connected (Girvan and Newman, 2002; Palla et al., 2005). This network phenomenon aligns with the small-world

[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.

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 specialization 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). Then, one can measure the technological specialization of communities and the diversity across the interlinked 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.

Based on the above argument, we formulate two hypotheses that reflect the simultaneous need for specialized knowledge production in cohesive co-inventor networks and their bridging to produce atypical knowledge combinations. The specialization 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).

Specialization 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 specialized 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 specialized communities, we take the median of community specializations to characterize the technological knowledge expertise that resides in regional economies.

H2. The median level of technological specialization 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 specialization, 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 Economic Geography, concerns how the availability of dissimilar knowledge in a region, termed ‘related’ and ‘unrelated’ variety, favors 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 specialized 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 specializations 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 specialized local industries (Eriksson and Lengyel, 2019). On the other hand, strongly specialized 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 formalize this expectation in Hypothesis 4.

H4. The median level of 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, 2015b), 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 disambiguation of individuals' and entities' names to assign unique identifiers that can then be utilized in a meaningful network or related, methods-driven analyzes poses a challenging task. Several contributions in this context, for instance, Li et al. (2014) and Pezzoni et al. (2014), among others, have tackled this problem and subsequently provided a systematic approach. We disambiguated inventor and assignee names in the data utilized using an advanced Massacrator© algorithm 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 harmonized 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).

[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.

Collaborative ties between inventors are distributed within and across 264 NUTS2 regions (see Appendix A). We assign interregional collaborative ties to all NUTS2 regions involved in the development of a particular 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 utilize 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 each patent introduces, which we return to and explain later in this section.[4]

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 i^{th} inventor participated in developing the j^{th} 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 analyze collaboration networks, there are concerns that this projection 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 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 neighboring nodes (nodes that are directly connected) that are connected to an identical set of nodes (for a review, see Lucena-Piquero and Vicente, 2019). In other words, we group inventors into a single node if the structures of their networks are identical. 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 several ties going from the group of identical inventors to their collaborators.

Fig. 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.

Furthermore, Fig. 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.

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 outlined earlier, 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. The z-score is defined as follows:

$$Z_{i,j} = \frac{O_{i,j} - E_{i,j}}{\sigma_{i,j}} \quad (1)$$

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 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 the co-occurrence of these units is driven by random effects. Thus, the expected co-occurrence ($E_{i,j}$) is given by:

$$E_{i,j} = \frac{n_i n_j}{N}, \quad (2)$$

[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.

[5] Since we used 650 CPC codes at the 4-digit level, it results in potentially max. 210,925 (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.

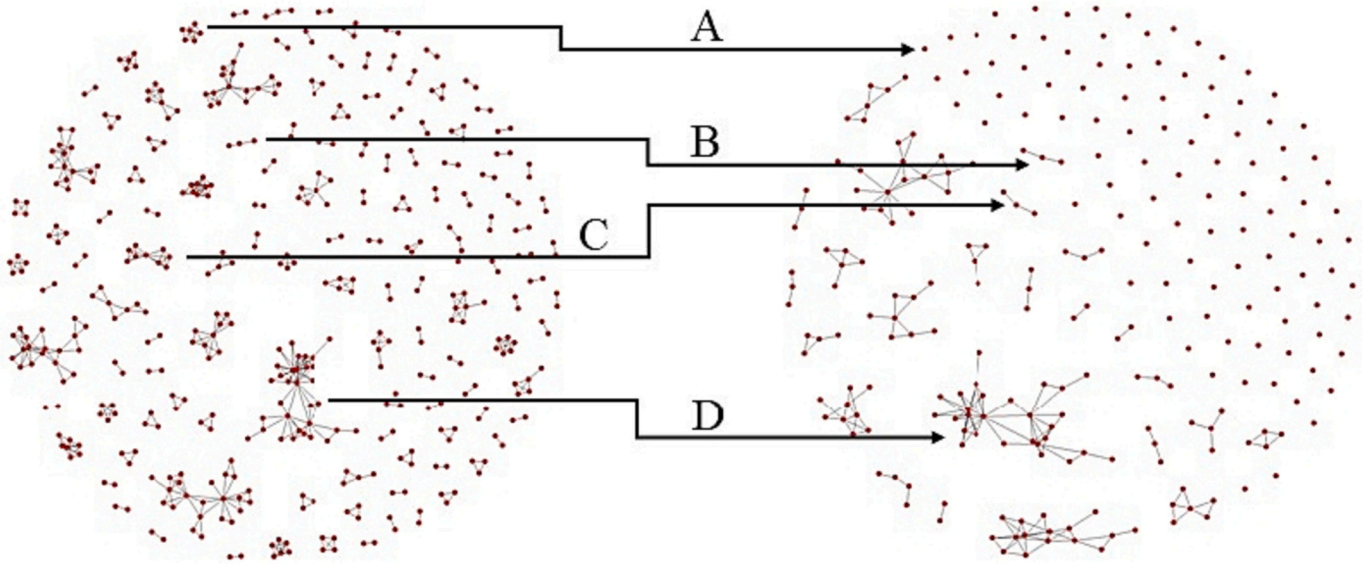

Fig. 1. The projected co-inventor network (left) and the co-inventor network of places (right).

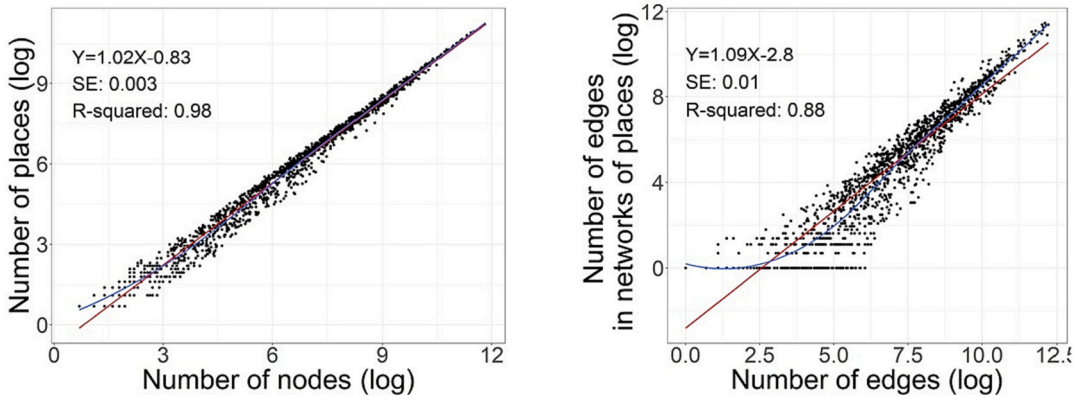

Fig. 2. The number of nodes (left) and the number of edges (right) in the projected co-inventor network versus the network of places.
Note: Each dot represents the structural properties of a NUTS2 region in one of the seven defined time-windows.

where n_i and n_j are the numbers of patents with technology codes i and j, respectively, and N is the total number of patents. The square of standard deviation is defined as:

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

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). Fig. 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., only a relatively small share of all combinations is atypical. More interestingly, the percentage of

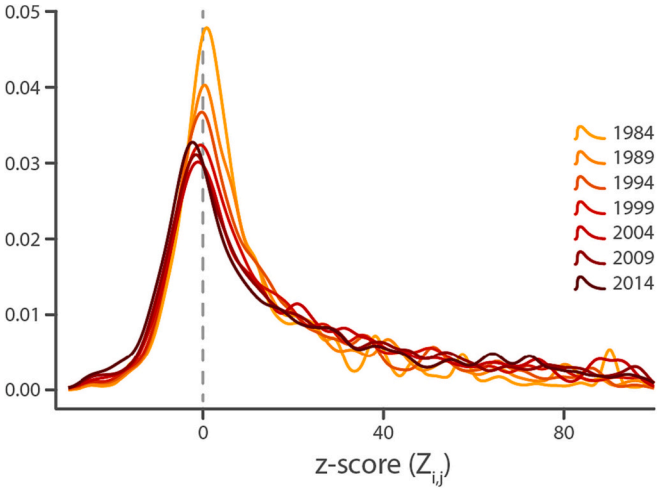

Fig. 3. The kernel density of z-scores for the combination of each technology pair.

atypical patents dropped from 30 % to 25 % between 1984 and 2014. We observed that the Shannon entropy of the z-score indices increases across time-windows,[7] suggesting that inventions move toward the two extremes of typicality and atypicality over time (Fig. 2).

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. Figs. 4 and 5 show the distribution of the share and number of atypical patents across European regions and different technologies.

3.3.2. Independent variables and controls

The first explanatory 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 for combining structurally equivalent inventors into places is to reduce the impact of the automatic clustering of three or more inventors who collaborated to develop a single patent. Next, we followed the more recently suggested method of a 'double-graph normalized 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 normalized only by random graphs. The double-graph normalized index also enables us to compare indices of networks of distinct sizes. 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 Erdös 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 of nodes and density. Thus, *SMALLWORLDNESS* 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).

The following two variables of interest 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 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 inventors from other regions too (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 greater accuracy when the number of nodes displays high variance and exceeds 1000, and μ (the mixing parameter[9]) is >0.5. Also, the time complexity of the Multilevel algorithm is $\mathcal{O}(N\,logN)$ which is considerably faster than most well-known algorithms. For instance, the computational complexity of the edge betweenness algorithm is $\mathcal{O}(E^2N)$. 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 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 contribute poorly 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

[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.

[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.

[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.

[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, detected communities in all networks of places across seven time-windows 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 newly detected communities and the one used for variable creation. The average value of Cramer's V coefficients (0.99) suggests that the outcomes of community detection algorithm are not arbitrary, and that they do not depend on the parameters of the algorithm. Furthermore, we used another community detection algorithm to ensure that identified communities in networks of places are not dependent on the Louvain community detection algorithm. Using the Infomap algorithm (Rosvall and Bergstrom, 2008) on 500 randomly selected networks of places suggests that the community membership of places is very similar (mean of Cramer's V coefficients: 0.99).

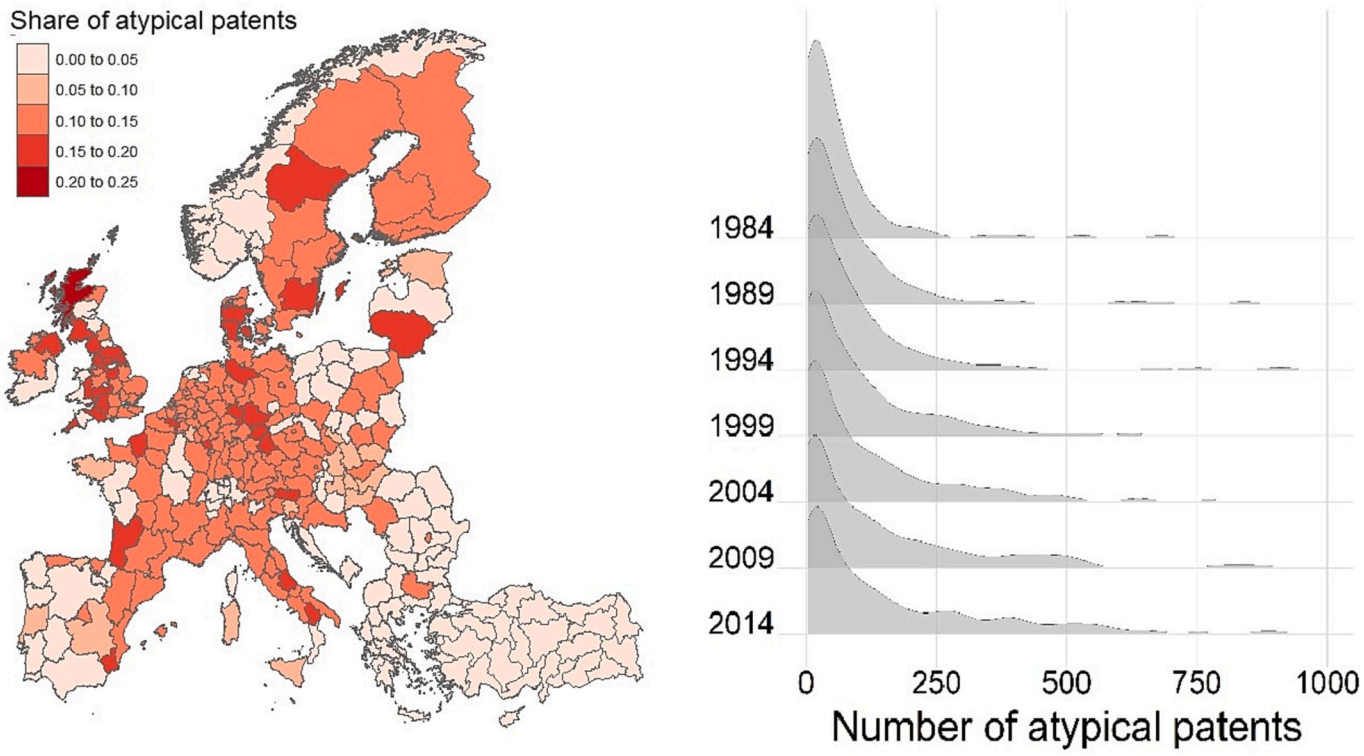

Fig. 4. The share of atypical patents between 1984 and 2014 (left) and the distribution of the number of atypical patents in regions across seven time-windows (right).

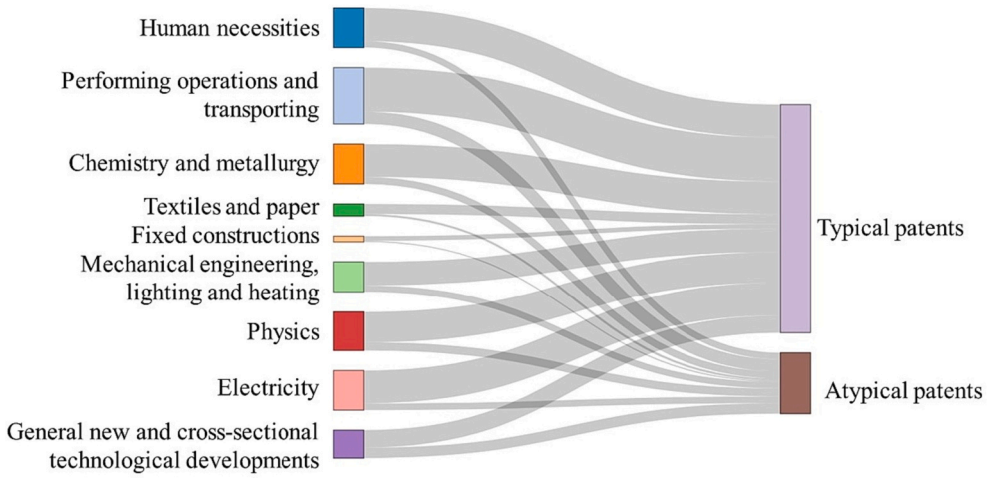

Fig. 5. The distribution of typical and atypical patents (1980–2014) across Cooperative Patent Classifications (CPC) schemes.

time. The number of communities strongly correlates with patent and inventor numbers of regions at 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] Fig. 6 illustrates the distribution of community frequency across regions and seven time-windows.

To capture the degree of communities' specialization 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 specialized 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 technologies in each community approximates the technological portfolios of inventors embedded in the given community because inventors tend to utilize technologies like the ones they used in the past. In other words, although *SPECIALIZATION* approximates the technological

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

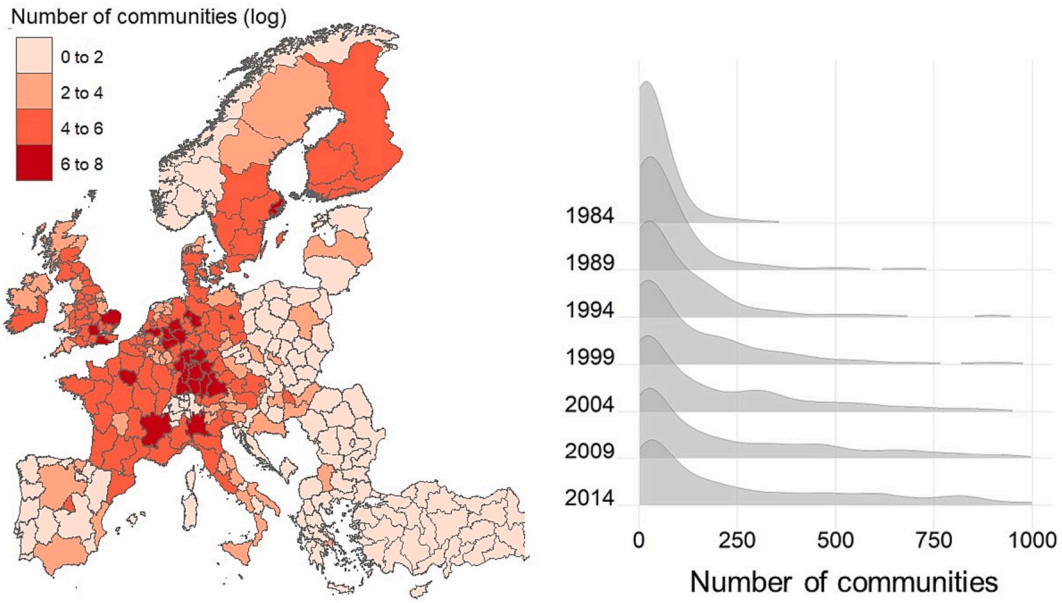

Fig. 6. The number of detected communities in log (left) and the distribution of the number of communities in regions across seven time-windows.
Note: The number corresponds to the median value of community numbers across seven time-windows between 1980 and 2014. The legend is in logarithmic scale.

specialization of communities based on patents developed by inventors in such communities, this variable is correlated with the portfolios of corresponding inventors (see Appendix B).

We needed to construct a variable that measures the interconnectedness of communities in regions. Therefore, it is important to say that networks with different numbers 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 of 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 normalized 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*, which corresponds to the share of the inter-community ties by dividing the normalized 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, large regions might host several communities that have similar technological portfolios but are 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) utilized 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 number of communities in each region (the Pearson correlation coefficient: 0.95), these two variables seem not to be firmly related to technological diversity (0.23 and 0.27, respectively; see the three-dimensional scatter plot in Appendix C).

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 the 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. Fig. 7 illustrates the distribution of the variable *SIMILARITY* across European regions over time. Fig. 8 shows the specialization 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

[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.

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

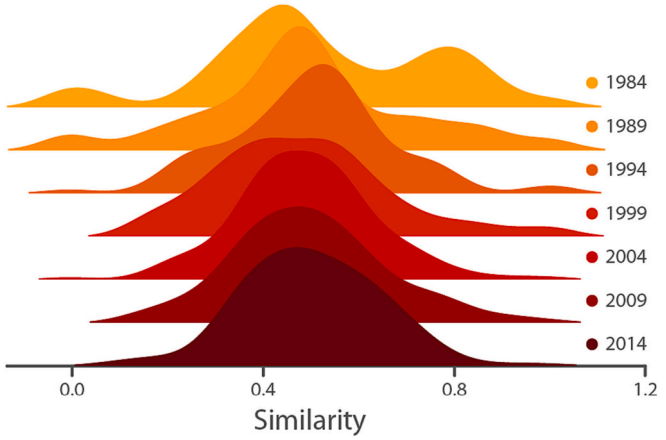

Fig. 7. An approximation of the density of the variable *SIMILARITY* (kernel density estimation) over time.

helps us to avoid the problem that inventions created extensively in other regions are assigned to the region in focus. The number of inventors and places strongly correlates with the number of communities in the region (the Pearson correlation coefficients are 0.95 and 0.94, respectively), suggesting that the measurement captures local innovation. On the contrary, the share of interregional ties (defined later) is not correlated with *SMALLWORLDNESS*, *SMALLWORLDNESS^2*, *SPECIALIZATION*, *SICT*, and *SIMILARITY* (the Pearson correlation coefficients: −0.04, 0.06, −0.12, −0.07, and −0.11 respectively) also signaling that regions' engagement in inter-regional collaborations is independent of our measurements. Finally, we weight the values of specialization, the share of inter-community ties, and similarity 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 variables are not biased by inter-regional relations and can capture local co-inventor collaboration's role in atypical knowledge combinations.

In addition to the main independent variables, we employed 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). 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 employed 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 normalized 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 normalized the number of regions' communities[17] by inventor numbers (*COMMUNITY*). As clarified earlier in this subsection, we used a rewiring method to normalize network indices. Also, we refrained from creating a variable capturing the centralization of regional inventor networks because that network index correlates significantly with *SPECIALIZATION*. van der Wouden and Rigby (2019) showed that specialized 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 centralization. Descriptive statistics of all variables and their pairwise correlation coefficients are presented in Appendix D.

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

$$\begin{aligned} Y_{r,t} = {} & \alpha + \beta_1 \mathrm{SMALLWORLDNESS}_{r,t-1} + \beta_2 \mathrm{SMALLWORLDNESS}^2_{r,t-1} \\ & + \beta_3 SPECIALIZATION_{r,t-1} + \beta_4 SICT_{r,t-1} + \beta_5 SIMILARITY_{r,t-1} \\ & + \beta_6 N_{r,t-1} + \beta_7 Z_{r,t-1} + \varphi_t + \mu_r + \varepsilon_{r,t} \end{aligned} \quad (7)$$

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 explanatory 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.

[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).

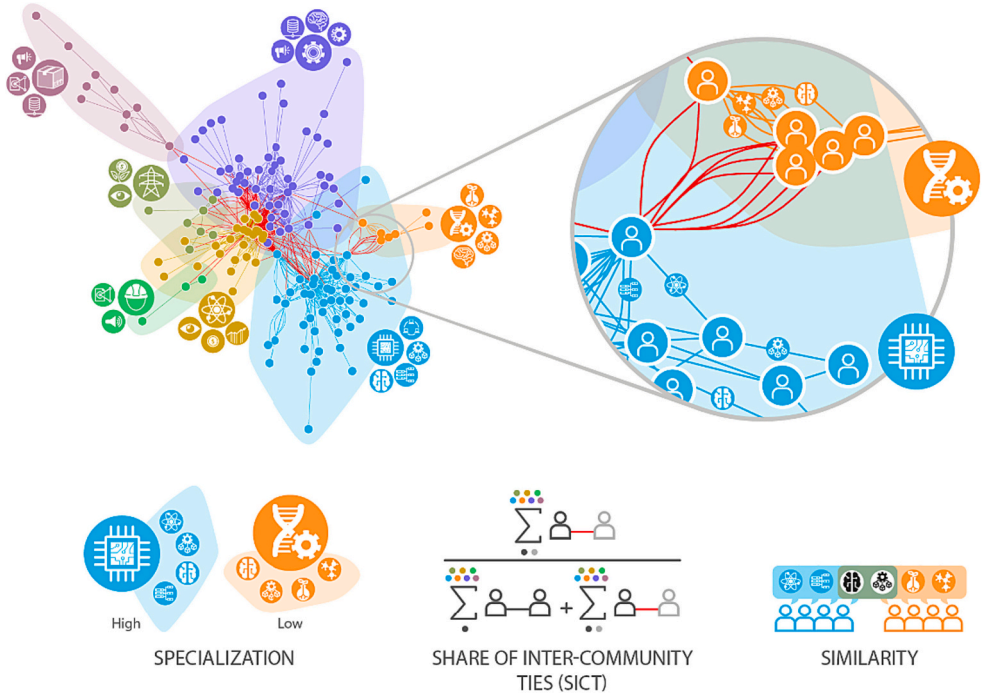

Fig. 8. Visual representations of detected communities, inter-community ties, and three variables of interests.
Note: Regions' networks of places normally include various components. For the sake of illustration, only one large component is shown in this visualization.

4. Results and discussion

We conducted a set of fixed effects panel regression models with control variables and added variables of interest in a stepwise manner. We tested for heteroscedasticity in the model. The distribution of residuals (Appendix E) 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 (see Appendix F). 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 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.

We find evidence for 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 fosters absorptive capacity in network communities through local clustering and facilitates a more effective 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 *SMALLWORLDNESS* does not provide evidence for an inverse U-shape relation between *SMALLWORLDNESS* and 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 relationship with 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 role 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).

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 correlate with the share of atypical patents. Of course, this calls for

[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).

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)	(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	1526	1526	1526	1526	1526	1526	1526	1526	1526
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)

* $p < 0.1$.
** $p < 0.05$.
*** $p < 0.01$.

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.

Including 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. Our result suggests that network density does not correlate significantly with the relative number of atypical patents. Similarly, 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 applies to 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 specialization tend to introduce more atypical patents. Connections that bridge segregated communities strongly impact 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 different communities. There is evidence that inventors partly create collaborative ties with the ones they are cognitively proximate with (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 networks 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 *SMALLWORLDNESS* 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 between the two models, the *SIMILARITY* between connected communities is less significant, while *SPECIALIZATION* correlates positively with the overall patent growth rate.

To ensure the robustness 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 their specialization. As a result, the reported coefficients for alternative specialization variables align with the original ones. At the same time, the new models support the positive

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

	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	1526	1526
R^2	0.4172	0.3684
Adjusted R^2	0.2862	0.2263
Residual Std. Error (df = 1245)	0.0847	1.4252

* $p < 0.1$.
** $p < 0.05$.
*** $p < 0.01$.

and negative associations of the *SICT* and the *SIMILARITY* of connected communities with the dependent variable (Appendix G).

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 sign and significance of the variables of interest do not change (Appendix H).

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 (*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 those occupying 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 (see Appendix I).

Fourth, we used the normalized median size of communities (*COMMUNITY_median*) instead of the normalized community number (*COMMUNITY*) that correlates 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 (see Appendix J).

Fifth, although the panel fixed-effects models do not strongly violate the basic assumptions of linear models, one may argue that the dependent variable (i.e., the share of atypical patents) 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 reliability of the results, we estimated a beta regression using the 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 (see Appendix K).

Finally, following the line of argument 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. Similarly, regions may benefit from the joint effect of the share of inter-community ties and the specialization of communities. Thus, we estimated regression models with two additional interaction terms (*SICT* × *SIMILARITY* and *SICT* × *SPECIALIZATION*). The models did not provide empirical evidence for such multiplicative effects, probably because we aggregate specialization and co-inventor community measures to the regional level. Yet, the joint effect between community specialization and interconnectedness might prevail on lower aggregation levels, which can be a matter of future research, as discussed in the next section.

5. Concluding remarks

A plethora of literature stresses the path-dependent nature of economic and technological progress along evolutionary trajectories (Kogler, 2015a; Kogler et al., 2023a), 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 specialization versus diversity debate is very much at the core of this line of inquiry and most recent efforts investigate how specialized 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 emphasizing 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 specialization tendencies with the benefits of macro-level diversity.

Grouping co-inventor collaborations into network communities, we quantify the level of specialization on the community level and technological difference on the pairwise community level. The median of these measures enables us to infer region-level innovation capacities by capturing the tendency that inventor groups are specialized in certain technologies and linked to other groups that are specialized in other technologies. We find new evidence that small-world networks of co-inventor collaboration favor atypical combinations of technological knowledge domains more extensively in those regions where communities of inventors specialized in different technologies are bridged by collaborations. By distinguishing between typical and atypical technological knowledge, we provide empirical evidence that both types of knowledge benefit from specialization and being connected to technologically dissimilar ones. However, a small-world structural property, along with a higher relative number of inter-community relations only favors the creation of atypical technological knowledge.

These results suggest that it is neither specialization nor diversity at the regional level per se that favors innovation, which resonates with recent findings by Rocchetta et al. (2021). Instead, the presence of multiple specializations at the community level and their connections can help knowledge combinations in regions. We argue that meso-level network mechanisms in collaborations are decisive for regional innovation and can generate benefits that derive from the advantages of being specialized and diverse simultaneously. Endogenous network formation, driven through technological similarity and triadic closure, helps to accumulate specialized knowledge in cohesive regional sub-networks, increasing the scale and scope of potential combinations. At

the same time, bridging ties that connect divergent specializations 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 specialized collaborations and bridging collaborations in tandem. Regional economies that manage such a setting are more likely to create more considerable proportions of atypical inventions that have distinct specializations of knowledge bases. Thus, supporting the endogenous network formation in diversely specialized, incremental knowledge production is beneficial for enabling and increasing the potential of future, novel knowledge re-combination processes. It is specialized 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 specializations are also crucial. Bridging collaborations among actors and entities of dissimilar knowledge might require policy support because community bridging demands extra motivation.

In this regard, the present investigation directly impacts place-based innovation policies. In the European context, e.g., Smart Specialization has been a central contemporary place-based innovation policy. Aiming at regional economic growth by building on existing competencies, Smart Specialization 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 specialization 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 specializing in several technologies and promoting inter-community bridges between such specialized islands could be a better and more successful strategic approach for Smart Specialization.

The results are relevant in the context of mission-oriented policies as well. An increasing discussion claims that solutions to grand societal challenges require interdisciplinary 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 minimized 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 analyzed 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 analyzing the text of patent documents (Abbasiharofteh et al., 2023).

Second, detecting communities of real-world networks is an 'ill-defined' problem and is subject to lively scholarly debate (Fortunato and Hric, 2016). Although we selected the Louvain algorithm based on empirical findings and suggestions in network science literature, we acknowledge the limitations of this method. For instance, the Louvain algorithm may split network communities to maximize the modularity of detected communities, or it does not allow detected communities to overlap. One may employ inferential community detection techniques (e.g., a stochastic block model) to remedy this situation. However, applying inferential techniques to large networks leads to NP-hard problems and unreliable results within a reasonable time (Peixoto, 2022). Nevertheless, future research on co-inventor network communities must ensure that the partitioning is stable, which we did by cross-checking our community structure with the Infomap algorithm.

Third, 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 higher forward citation counts and exhibit a longer lifecycle. We acknowledge that this study focused exclusively on exploring factors that may trigger atypical inventions. Indeed, a larger share of inventions with atypical technology combinations are doomed to fail, while 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 (Abbasiharofteh et al., 2022).

Fourth, 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 analyzing how strategy, alliances, and competition of firms influence atypical innovation in regions. Wanzenböck et al. (2022) provide some insights into the relationship between the network structure of organizations in regions and their ability to enter new specializations. Future research should shed light on these mechanisms by generating co-inventor networks differently and focusing more on inter-firm links.

Fifth, 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 in sorting out bridging collaborations in studies that aim to understand knowledge combinations in collaboration networks on a lower level of aggregation.

Last but related to the previous point, we do not find multiplicative effects of community specialization, the proportion of inter-community ties, and the similarity of interlinked specializations 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. In fact, inferring city-level behavior from the median of community-level specialization and pairwise technological similarity of connected communities is probably only the first step in understanding how technological knowledge combination leads to radical innovation outcomes in regions. Nevertheless, based on previous results, significant joint effects can be expected on a lower level (Eriksson and Lengyel, 2019). Therefore, we urge future research to investigate how specialization and access to diversity in small-world collaboration networks influence knowledge combinations on the level of individuals, firms, and industries.

CRediT authorship contribution statement

All authors designed the study and reviewed the manuscript. Milad Abbasiharofteh and Balázs Lengyel manipulated and analyzed the data, prepared the figures, and developed the manuscript.

Declaration of competing interest

The authors declare no conflicts of interest regarding the research,

authorship, and publication of this article.

Data availability

Data will be made available on request.

Acknowledgement

Milad Abbasiharofteh acknowledges the support of the BMBF junior research group TRAFOBIT (031B0020). Dieter F. Kogler acknowledges funding from the European Research Council under the European Union's Horizon 2020 Research and Innovation Programme [grant agreement number 715631, ERC TechEvo], and from the Science Foundation Ireland (SFI) under the SFI Science Policy Research Programme [grant agreement number 17/SPR/5324, SciTechSpace]. Balázs Lengyel acknowledges financial help received from the Hungarian Scientific Research Fund (OTKA K-129207). We acknowledge the help of our illustrator, Szabolcs Tóth-Zs.

Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.respol.2023.104886.

References

Abbasiharofteh, M., 2020. Endogenous effects and cluster transition: a conceptual framework for cluster policy. Eur. Plan. Stud. 30, 1–24. https://doi.org/10.1080/09654313.2020.1724266.

Abbasiharofteh, M., Broekel, T., 2020. Still in the shadow of the wall? The case of the Berlin biotechnology cluster. Environ. Plan. A: Econ. Space 46, 3. https://doi.org/10.1177/0308518X20933904.

Abbasiharofteh, M., Kinne, J., Krüger, M., 2021. The Strength of Weak and Strong Ties in Bridging Geographic and Cognitive Distances. ZEW Discussion Paper No. 21-049, Mannheim.

Abbasiharofteh, M., Castaldi, C., Petralia, S.G., 2022. From Patents to Trademarks: Towards a Concordance Map (Final report).. European Patent Office (EPO).

Abbasiharofteh, M., Krüger, M., Kinne, J., Lenz, D., Resch, B., 2023. The digital layer: alternative data for regional and innovation studies. Spat. Econ. Anal. 1–23. https://doi.org/10.1080/17421772.2023.2193222.

Aral, S., 2016. The future of weak ties. Am. J. Sociol. 121 (6), 1931–1939. https://doi.org/10.1086/686293.

Archibugi, D., Planta, M., 1996. Measuring technological change through patents and innovation surveys. Technovation 16 (9), 451–519. https://doi.org/10.1016/0166-4972(96)00031-4.

Audretsch, D., Feldman, M.P., 1996. R&D spillovers and the geography of innovation and production. Am. Econ. Rev. 86, 630–640.

Balland, P.-A., 2017. Economic Geography in R: Introduction to the EconGeo package. Papers in Evolutionary Economic Geography (PEEG), 1709. Department of Human Geography and Spatial Planning, Group Economic Geography, Utrecht University.

Balland, P.-A., Rigby, D., 2016. The geography of complex knowledge. Econ. Geogr. 93 (1), 1–23. https://doi.org/10.1080/00130095.2016.1205947.

Balland, P.-A., Boschma, R., Crespo, J., Rigby, D.L., 2018. Smart specialization policy in the European Union: relatedness, knowledge complexity and regional diversification. Reg. Stud. 35 (4), 1–17. https://doi.org/10.1080/00343404.2018.1437900.

Balland, P.-A., Jara-Figueroa, C., Petralia, S.G., Steijn, M.P.A., Rigby, D.L., Hidalgo, C.A., 2020. Complex economic activities concentrate in large cities. Nat. Hum. Behav. https://doi.org/10.1038/s41562-019-0803-3.

Balland, P.-A., Broekel, T., Diodato, D., Giuliani, E., Hausmann, R., O'Clery, N., Rigby, D., 2022. The new paradigm of economic complexity. Res. Policy 51 (3), 104450. https://doi.org/10.1016/j.respol.2021.104450.

Barabási, A.-L., Albert, R., 1999. Emergence of scaling in random networks. Science 286, 509–512. https://doi.org/10.1126/science.286.5439.509.

Beaudry, C., Schiffauerova, A., 2009. Who's right, Marshall or Jacobs?: the localization versus urbanization debate. Res. Policy 38 (2), 318–337. https://doi.org/10.1016/j.respol.2008.11.010.

Bercovitz, J., Feldman, M., 2011. The mechanisms of collaboration in inventive teams: composition, social networks, and geography. Res. Policy 40 (1), 81–93. https://doi.org/10.1016/j.respol.2010.09.008.

Bergé, L., Carayol, N., Roux, P., 2018. How do inventor networks affect urban invention? Reg. Sci. Urban Econ. 71, 137–162. https://doi.org/10.1016/j.regsciurbeco.2018.05.002.

Berkes, E., Gaetani, R., 2020. The geography of unconventional innovation. Econ. J. https://doi.org/10.1093/ej/ueaa111.

Bettencourt, L.M.A., Lobo, J., Strumsky, D., 2007. Invention in the city: increasing returns to patenting as a scaling function of metropolitan size. Res. Policy 36 (1), 107–120. https://doi.org/10.1016/j.respol.2006.09.026.

Blondel, V.D., Guillaume, J.-L., Lambiotte, R., Lefebvre, E., 2008. Fast unfolding of communities in large networks. J. Stat. Mech: Theory Exp. 2008 (10), P10008. https://doi.org/10.1088/1742-5468/2008/10/P10008.

Boschma, R., 2005. Proximity and innovation: a critical assessment. Reg. Stud. 39 (1), 61–74. https://doi.org/10.1080/0034340052000320887.

Boschma, R., 2016. Relatedness as driver of regional diversification: a research agenda. Reg. Stud. 51 (3), 351–364. https://doi.org/10.1080/00343404.2016.1254767.

Boschma, R., Frenken, K., 2010. The spatial evolution of innovation networks. A proximity perspective. In: Boschma, R., Martin, R. (Eds.), The Handbook of Evolutionary Economic Geography. Cheltenham, U.K, Edward Elgar Pub, pp. 120–135.

Boschma, R., Balland, P.-A., Kogler, D.F., 2015. Relatedness and technological change in cities: the rise and fall of technological knowledge in US metropolitan areas from 1981 to 2010. Ind. Corp. Chang. 24 (1), 223–250. https://doi.org/10.1093/icc/dtu012.

Breschi, S., Lenzi, C., 2016. Co-invention networks and inventive productivity in US cities. J. Urban Econ. 92, 66–75. https://doi.org/10.1016/j.jue.2015.12.003.

Breschi, S., Lissoni, F., 2009. Mobility of skilled workers and co-invention networks: an anatomy of localized knowledge flows. J. Econ. Geogr. 9 (4), 439–468. https://doi.org/10.1093/jeg/lbp008.

Broekel, T., 2019. Using structural diversity to measure the complexity of technologies. PLoS One 14 (5), e0216856. https://doi.org/10.1371/journal.pone.0216856.

Broekel, T., Boschma, R., 2012. Knowledge networks in the Dutch aviation industry: the proximity paradox. J. Econ. Geogr. 12 (2), 409–433. https://doi.org/10.1093/jeg/lbr010.

Broekel, T., Brenner, T., 2007. Measuring Regional Innovativeness. A Methodological Discussion and an Application to One German Industry. Max Planck Institute of Economics, Jena, Germany.

Broekel, T., Graf, H., 2012. Public research intensity and the structure of German R&D networks: a comparison of 10 technologies. Econ. Innov. New Technol. 21 (4), 345–372. https://doi.org/10.1080/10438599.2011.582704.

Burt, R.S., 1987. Social contagion and innovation: cohesion versus structural equivalence. Am. J. Sociol. 92 (6), 1287–1335. https://doi.org/10.1086/228667.

Burt, R.S., 2004. Structural holes and good ideas. Am. J. Sociol. 110 (2), 349–399. https://doi.org/10.1086/421787.

Cantner, U., Graf, H., 2006. The network of innovators in Jena: an application of social network analysis. Res. Policy 35 (4), 463–480. https://doi.org/10.1016/j.respol.2006.01.002.

Carnabuci, G., Bruggeman, J., 2009. Knowledge specialization, knowledge brokerage and the uneven growth of technology domains. Soc. Forces 88 (2), 607–641. https://doi.org/10.1353/sof.0.0257.

Cassi, L., Plunket, A., 2013. Research collaboration in co-inventor networks: combining closure, bridging and proximities. Reg. Stud. 49 (6), 936–954. https://doi.org/10.1080/00343404.2013.816412.

Cassi, L., Plunket, A., 2014. Proximity, network formation and inventive performance: in search of the proximity paradox. Ann. Reg. Sci. 53 (2), 395–422. https://doi.org/10.1007/s00168-014-0612-6.

Castaldi, C., Frenken, K., Los, B., 2015. Related variety, unrelated variety and technological breakthroughs: an analysis of US state-level patenting. Reg. Stud. 49 (5), 767–781. https://doi.org/10.1080/00343404.2014.940305.

Chatterjee, S., Price, B., 1995. Praxis der Regressionsanalyse. Oldenbourg Verlag, München.

Cimini, G., Squartini, T., Saracco, F., Garlaschelli, D., Gabrielli, A., Caldarelli, G., 2019. The statistical physics of real-world networks. Nat. Rev. Phys. 1 (1), 58–71. https://doi.org/10.1038/s42254-018-0002-6.

Clauset, A., Newman, M.E.J., Moore, C., 2004. Finding community structure in very large networks. Phys. Rev. https://doi.org/10.1103/PhysRevE.70.066111. E, Statistical, nonlinear, and soft matter physics 70 (6 Pt 2), 66111.

Cohen, W.M., Levinthal, D.A., 1990. Absorptive capacity: a new perspective on learning and innovation. Adm. Sci. Q. 35 (1), 128. https://doi.org/10.2307/2393553.

Coleman, J.S., 1988. Social capital in the creation of human capital. Am. J. Sociol. 94, 95–120.

Cooke, P., 2002. Regional science policy and the growth of knowledge megacentres in bioscience clusters. In: ERSA Conference Papers Ersa02p503. European Regional Science Association.

Cowan, R., Jonard, N., 2003. The dynamics of collective invention. J. Econ. Behav. Organ. 52 (4), 513–532. https://doi.org/10.1016/S0167-2681(03)00091-X.

Cowan, R., Jonard, N., 2004. Network structure and the diffusion of knowledge. J. Econ. Dyn. Control. 28 (8), 1557–1575. https://doi.org/10.1016/j.jedc.2003.04.002.

Cribari-Neto, F., Zeileis, A., 2010. Beta regression in R. J. Stat. Softw. 34 (2) https://doi.org/10.18637/jss.v034.i02.

Croissant, Y., Millo, G., 2008. Panel data econometrics in R: the plm package. J. Stat. Softw. 27 (2) https://doi.org/10.18637/jss.v027.i02.

Csardi, G., Nepusz, T., 2006. The igraph software package for complex network research. Int. J. Complex Syst. 1695 (http://igraph.org).

Dosi, G., 1982. Technological paradigms and technological trajectories. Res. Policy 11 (3), 147–162. https://doi.org/10.1016/0048-7333(82)90016-6.

Erdös, P., Rényi, A., 1960. On the evolution of random graphs. Publ. Math. Inst. Hung. Acad. Sci. 5, 17–61.

Eriksson, R.H., Lengyel, B., 2019. Co-worker networks and agglomeration externalities. Econ. Geogr. 95 (1), 65–89. https://doi.org/10.1080/00130095.2018.1498741.

Feldman, M.P., Kogler, D.F., 2010. Stylized facts in the geography of innovation. In: Hall, B., Rosenberg, N. (Eds.), Handbook of the Economics of Innovation. Elsevier, pp. 381–410.

Ferrari, S., Cribari-Neto, F., 2004. Beta regression for modelling rates and proportions. J. Appl. Stat. 31 (7), 799–815. https://doi.org/10.1080/0266476042000214501.

Fleming, L., 2001. Recombinant uncertainty in technological search. Manag. Sci. 47 (1), 117–132. https://doi.org/10.1287/mnsc.47.1.117.10671.
Fleming, L., King, C., Juda, A.I., 2007a. Small worlds and regional innovation. Organ. Sci. 18 (6), 938–954. https://doi.org/10.1287/orsc.1070.0289.
Fleming, L., Mingo, S., Chen, D., 2007b. Collaborative brokerage, generative creativity, and creative success. Adm. Sci. Q. 52 (3), 443–475. https://doi.org/10.2189/asqu.52.3.443.
Florida, R., Adler, P., Mellander, C., 2017. The city as innovation machine. Reg. Stud. 51 (1), 86–96. https://doi.org/10.1080/00343404.2016.1255324.
Fontana, M., Iori, M., Montobbio, F., Sinatra, R., 2020. New and atypical combinations: an assessment of novelty and interdisciplinarity. Res. Policy 49 (7), 104063. https://doi.org/10.1016/j.respol.2020.104063.
Foray, D., David, P.A., Hall, B.H., 2011. Smart specialization. In: From Academic Idea to Political Instrument, The Surprising Career of a Concept and the Difficulties Involved in Its Implementation (MTEI-working paper, Lausanne).
Fornahl, D., Brenner, T., 2009. Geographic concentration of innovative activities in Germany. Struct. Chang. Econ. Dyn. 20 (3), 163–182. https://doi.org/10.1016/j.strueco.2009.05.001.
Fortunato, S., 2010. Community detection in graphs. Phys. Rep. 486 (3–5), 75–174. https://doi.org/10.1016/j.physrep.2009.11.002.
Fortunato, S., Hric, D., 2016. Community detection in networks: a user guide. Phys. Rep. 659 (12), 1–44. https://doi.org/10.1016/j.physrep.2016.09.002.
Frenken, K., van Oort, F., Verburg, T., 2007. Related variety, unrelated variety and regional economic growth. Reg. Stud. 41 (5), 685–697. https://doi.org/10.1080/00343400601120296.
Fritsch, M., Kudic, M., 2021. Micro dynamics and macro stability in inventor networks. J. Technol. Transf. 45 (3), 425. https://doi.org/10.1007/s10961-021-09851-8.
Girvan, M., Newman, M.E.J., 2002. Community structure in social and biological networks. Proc. Natl. Acad. Sci. U. S. A. 99 (12), 7821–7826. https://doi.org/10.1073/pnas.122653799.
Giuliani, E., 2013. Network dynamics in regional clusters: evidence from Chile. Res. Policy 42 (8), 1406–1419. https://doi.org/10.1016/j.respol.2013.04.002.
Glaeser, E.L., Kallal, H.D., Scheinkman, J.A., Shleifer, A., 1992. Growth in cities. J. Polit. Econ. 100 (6), 1126–1152. https://doi.org/10.1086/261856.
Glückler, J., 2007. Economic geography and the evolution of networks Johannes. J. Econ. Geogr. 7 (5), 619–634.
Gnyawali, D.R., Madhavan, R., 2001. Cooperative networks and competitive dynamics: a structural embeddedness perspective. Acad. Manag. Rev. 26 (3), 431. https://doi.org/10.2307/259186.
Grabher, G., 1993. The weakness of strong ties: the lock-in of regional development in the Ruhr area. In: Grabner, G. (Ed.), The Embedded Firm. On the Socioeconomics of Industrial Networks. Routledge, London, pp. 255–277.
Granovetter, M., 1973. The strength of weak ties. Am. J. Sociol. 78, 1360–1380.
Hall, M., Tideman, N., 1967. Measures of concentration. J. Am. Stat. Assoc. 62 (317), 162–168.
Hidalgo, C.A., 2018. The principle of relatedness. In: Morales, A.J., Gershenson, C., Braha, D., Minai, A.A., Bar-Yam, Y. (Eds.), Unifying Themes in Complex Systems IX. Proceedings of the Ninth International Conference on Complex Systems. Springer International Publishing, Cham, pp. 451–457.
Hidalgo, C.A., Hausmann, R., 2009. The building blocks of economic complexity. Proc. Natl. Acad. Sci. U. S. A. 106 (26), 10570–10575. https://doi.org/10.1073/pnas.0900943106.
Hidalgo, C.A., Klinger, B., Barabási, A.-L., Hausmann, R., 2007. The product space conditions the development of nations. Science (New York, N.Y.) 317 (5837), 482–487. https://doi.org/10.1126/science.1144581.
Humphries, M.D., Gurney, K., 2008. Network 'small-world-ness': a quantitative method for determining canonical network equivalence. PLoS One 3 (4), e0002051. https://doi.org/10.1371/journal.pone.0002051.
Inkpen, A.C., 1996. Creating knowledge through collaboration. Calif. Manag. Rev. 39 (1), 123–140. https://doi.org/10.2307/41165879.
Jacobs, J., 1961. The Death and Life of Great American Cities. Random House, New York.
Jaffe, A.B., 1986. Technological opportunity and spillovers of R&D: evidence from firms' patents, profits, and market value. Am. Econ. Rev. 76 (5), 984–1001.
Jaffe, A.M.T.H.R., 1993. Geographic localization of knowledge spillovers as evidenced by patent citations. Q. J. Econ. 108 (3), 577–598.
Janssen, M.J., Abbasiharofteh, M., 2022. Boundary spanning R&D collaboration: key enabling technologies and missions as alleviators of proximity effects? Technol. Forecast. Soc. Chang. 180 (6460), 121689 https://doi.org/10.1016/j.techfore.2022.121689.
Juhász, S., Lengyel, B., 2018. Creation and persistence of ties in cluster knowledge networks. J. Econ. Geogr. 121, 1203–1226.
Kabirigi, M., Abbasiharofteh, M., Sun, Z., Hermans, F., 2022. The importance of proximity dimensions in agricultural knowledge and innovation systems: the case of banana disease management in Rwanda. Agric. Syst. 202 (3), 103465 https://doi.org/10.1016/j.agsy.2022.103465.
Kemeny, T., Storper, M., 2015. Is specialization good for regional economic development? Reg. Stud. 49 (6), 1003–1018. https://doi.org/10.1080/00343404.2014.899691.
Kemeny, T., Feldman, M., Ethridge, F., Zoller, T., 2016. The economic value of local social networks. J. Econ. Geogr. 16 (5), 1101–1122. https://doi.org/10.1093/jeg/lbv043.
Kim, D., Cerigo, D.B., Jeong, H., Youn, H., 2016. Technological novelty profile and invention's future impact. EPJ Data Sci. 5 (1), 721. https://doi.org/10.1140/epjds/s13688-016-0069-1.
Kim, K., Kogler, D.F., Lee, C., Kang, T., 2022. Changes in regional knowledge bases and its effect on local labour markets in the midst of transition: evidence from France over 1985–2015. Appl. Spat. Anal. Policy. https://doi.org/10.1007/s12061-022-09444-4.
Kock, N., Lynn, G., 2012. Lateral collinearity and misleading results in variance-based SEM: an illustration and recommendations. J. Assoc. Inf. Syst. 13 (7), 546–580. https://doi.org/10.17705/1jais.00302.
Kogler, D.F., 2015a. Editorial: evolutionary economic geography - theoretical and empirical Progress. Reg. Stud. 49 (5), 705–711.
Kogler, D.F., 2015b. Intellectual property and patents: knowledge creation and diffusion. In: Bryson, J., Clark, J., Vanchan, V. (Eds.), Handbook of Manufacturing Industries in the World Economy. Edward Elgar Publishing, pp. 163–188.
Kogler, D.F., Rigby, D.L., Tucker, I., 2013. Mapping knowledge space and technological relatedness in US cities. Eur. Plan. Stud. 21 (9), 1374–1391. https://doi.org/10.1080/09654313.2012.755832.
Kogler, D.F., Essletzbichler, J., Rigby, D.L., 2017. The evolution of specialization in the EU15 knowledge space. J. Econ. Geogr. 17 (2), 345–373. https://doi.org/10.1093/jeg/lbw024.
Kogler, D.F., Davies, R.B., Lee, C., 2022. Regional knowledge spaces: the interplay of entry-relatedness and entry-potential for technological change and growth. J. Technol. Transfer. https://doi.org/10.1007/s10961-022-09924-2.
Kogler, D.F., Evenhuis, E., Giuliani, E., Martin, R., Uyarre, E., Boschma, R.A., 2023a. Re-imagining evolutionary economic geography. Camb. J. Reg. Econ. Soc. https://doi.org/10.1093/cjres/rsad029.
Kogler, D.F., Kim, K., Whittle, A., Lengyel, B., 2023b. Understanding regional branching: Knowledge diversification via inventor and firm collaboration networks. Econ. Geogr. Forthcoming https://www.tandfonline.com/journals/recg20.
Kogut, B., 2000. The network as knowledge: generative rules and the emergence of structure. Strateg. Manag. J. 21 (3), 405–425. https://doi.org/10.1002/(SICI)1097-0266(200003)21:3<405:AID-SMJ103>3.0.CO;2-5.
Kogut, B., Zander, U., 1992. Knowledge of the firm, combinative capabilities, and the replication of technology. Organ. Sci. 3 (3), 383–397. https://doi.org/10.1287/orsc.3.3.383.
Krogh, G. von, Spaeth, S., Lakhani, K.R., 2003. Community, joining, and specialization in open source software innovation: a case study. Res. Policy 32 (7), 1217–1241. https://doi.org/10.1016/S0048-7333(03)00050-7.
Kuhn, T., 1962. The Structure of Scientific Revolutions. University of Chicago Press, Chicago.
Le Gallo, J., Plunket, A., 2020. Regional gatekeepers, inventor networks and inventive performance: spatial and organizational channels. Res. Policy 49 (5), 103981. https://doi.org/10.1016/j.respol.2020.103981.
Lee, C., Shin, H., Kim, K., Kogler, D.F., 2022. The effects of regional capacity in knowledge recombination on production efficiency. Technol. Forecast. Soc. Chang. 180 https://doi.org/10.1016/j.techfore.2022.121669.
Li, G.-C., Lai, R., D'Amour, A., Doolin, D.M., Sun, Y., Torvik, V.I., Yu, A.Z., Fleming, L., 2014. Disambiguation and co-authorship networks of the U.S. patent inventor database (1975–2010). Res. Policy 43 (6), 941–955. https://doi.org/10.1016/j.respol.2014.01.012.
Lobo, J., Strumsky, D., 2008. Metropolitan patenting, inventor agglomeration and social networks: a tale of two effects. J. Urban Econ. 63 (3), 871–884. https://doi.org/10.1016/j.jue.2007.07.005.
Lorrain, F., White, H.C., 1971. Structural equivalence of individuals in social networks. J. Math. Sociol. 1 (1), 49–80. https://doi.org/10.1080/0022250X.1971.9989788.
Lucena-Piquero, D., Vicente, J., 2019. The visible hand of cluster policy makers: an analysis of Aerospace Valley (2006–2015) using a place-based network methodology. Res. Policy 48 (3), 830–842. https://doi.org/10.1016/j.respol.2019.01.001.
Mazzucato, M., 2018. Mission-oriented innovation policies: challenges and opportunities. Ind. Corp. Chang. 27 (5), 803–815. https://doi.org/10.1093/icc/dty034.
Menzel, M.-P., Feldman, M.P., Broekel, T., 2017. Institutional change and network evolution: explorative and exploitative tie formations of co-inventors during the dot-com bubble in the Research Triangle region. Reg. Stud. 51 (8), 1179–1191. https://doi.org/10.1080/00343404.2016.1278300.
Mewes, L., 2019. Scaling of atypical knowledge combinations in American metropolitan areas from 1836 to 2010. Econ. Geogr. 95 (4), 341–361. https://doi.org/10.1080/00130095.2019.1567261.
Migliano, A.B., Battiston, F., Viguier, S., Page, A.E., Dyble, M., Schlaepfer, R., Smith, D., Astete, L., Ngales, M., Gomez-Gardenes, J., Latora, V., Vinicius, L., 2020. Hunter-gatherer multilevel sociality accelerates cumulative cultural evolution. Sci. Adv. 6 (9), eaax5913. https://doi.org/10.1126/sciadv.aax5913.
Miguelez, E., Moreno, R., 2016. Relatedness, external linkages and regional innovation in Europe. Reg. Stud. 52 (5), 688–701. https://doi.org/10.1080/00343404.2017.1360478.
Neal, Z., 2017. How small is it?: comparing indices of small worldliness. Netw. Sci. 5 (1), 30–44. https://doi.org/10.1017/nws.2017.5.
Nelson, R.R., Winter, S., 1982. An Evolutionary Theory of Economic Change. Harvard University Press, Cambridge, MA.
Newman, M.E., 2001. Scientific collaboration networks. II. Shortest paths, weighted networks, and centrality. Phys. Rev. E Stat. Nonlinear Soft Matter Phys. 64 (1 Pt 2), 16132. https://doi.org/10.1103/PhysRevE.64.016132.
de Noni, I., Belussi, F., 2021. Breakthrough invention performance of multispecialized clustered regions in Europe. Econ. Geogr. 97 (2), 164–186. https://doi.org/10.1080/00130095.2021.1894924.
de Noni, I., Ganzaroli, A., Orsi, L., 2017. The impact of intra- and inter-regional knowledge collaboration and technological variety on the knowledge productivity of European regions. Technol. Forecast. Soc. Chang. 117, 108–118. https://doi.org/10.1016/j.techfore.2017.01.003.

Nooteboom, B., 2000. Learning by interaction: absorptive capacity, cognitive distance and governance. J. Manag. Gov. 4 (1/2), 69–92. https://doi.org/10.1023/A:1009941416749.
Ó Huallacháin, B., Lee, D.-S., 2010. Technological specialization and variety in urban invention. Reg. Stud. 45 (1), 67–88. https://doi.org/10.1080/00343404.2010.486783.
Owen-Smith, J., Powell, W.W., 2004. Knowledge networks as channels and conduits: the effects of spillovers in the Boston biotechnology community. Organ. Sci. 15 (1), 5–21. https://doi.org/10.1287/orsc.1030.0054.
Palla, G., Derényi, I., Farkas, I., Vicsek, T., 2005. Uncovering the overlapping community structure of complex networks in nature and society. Nature 435 (7043), 814–818. https://doi.org/10.1038/nature03607.
Peixoto, T.P., 2022. Descriptive vs. inferential community detection in networks: pitfalls, myths, and half-truths (arXiv:2112.00183).
Pezzoni, M., Lissoni, F., Tarasconi, G., 2014. How to kill inventors: testing the Massacrator© algorithm for inventor disambiguation. Scientometrics 101 (1), 477–504. https://doi.org/10.1007/s11192-014-1375-7.
Pizarro, N., 2007. Structural identity and equivalence of individuals in social networks: beyond duality. Int. Sociol. 22 (6), 767–792. https://doi.org/10.1177/0268580907082260.
Powell, W.W., Koput, K.W., Smith-Doerr, L., 1996. Interorganizational collaboration and the locus of innovation: networks of learning in biotechnology. Adm. Sci. Q. 41 (1), 116–145. https://doi.org/10.2307/2393988.
Rigby, D.L., Roesler, C., Kogler, D.F., Boschma, R., Balland, P.-A., 2022. Do EU regions benefit from Smart Specialisation principles? Reg. Stud. https://doi.org/10.1080/00343404.2022.2032628.
Rocchetta, S., Ortega-Argilés, R., Kogler, D.F., 2021. The nonlinear effect of technological diversification on regional productivity: implications for growth and Smart Specialisation Strategies. Reg. Stud. https://doi.org/10.1080/00343404.2021.1939292.
Rosvall, M., Bergstrom, C.T., 2008. Maps of random walks on complex networks reveal community structure. Proc. Natl. Acad. Sci. U. S. A. 105 (4), 1118–1123. https://doi.org/10.1073/pnas.0706851105.
Schilling, M.A., Phelps, C.C., 2007. Interfirm collaboration networks: the impact of large-scale network structure on firm innovation. Manag. Sci. 53 (7), 1113–1126. https://doi.org/10.1287/mnsc.1060.0624.
Scholl, T., Brenner, T., 2014. Detecting spatial clustering using a firm-level cluster index. Reg. Stud. 50 (6), 1054–1068. https://doi.org/10.1080/00343404.2014.958456.
Schumpeter, J.A., 1911. Theorie der wirtschaftlichen Entwicklung (Theory of Economic Development). Duncker und Humblot, Berlin.
Shin, H., Kim, K., Lee, J., Kogler, D.F., 2023. Inventors, firms & localities: insights into the nexus that forms and alters the potential evolution of regional knowledge spaces. Camb. J. Reg. Econ. Soc. 16 (3) https://doi.org/10.1093/cjres/rsad019.
Simensen, E.O., Abbasiharofteh, M., 2022. Sectoral patterns of collaborative tie formation: investigating geographic, cognitive, and technological dimensions. Ind. Corp. Chang. 00, 1–36. https://doi.org/10.1093/icc/dtac021.
Sorenson, O., Rivkin, J.W., Fleming, L., 2006. Complexity, networks and knowledge flow. Res. Policy 35 (7), 994–1017. https://doi.org/10.1016/j.respol.2006.05.002.
Stefano, D. de, Zaccarin, S., 2013. Modelling multiple interactions in science and technology networks. Ind. Innov. 20 (3), 221–240. https://doi.org/10.1080/13662716.2013.791130.
Strumsky, D., Lobo, J., 2015. Identifying the sources of technological novelty in the process of invention. Res. Policy 44 (8), 1445–1461. https://doi.org/10.1016/j.respol.2015.05.008.
Stuart, T.E., Podolny, J.M., 1996. Local search and the evolution of technological capabilities. Strateg. Manag. J. 17 (S1), 21–38. https://doi.org/10.1002/smj.4250171004.
Teece, D.J., Rumelt, R., Dosi, G., Winter, S., 1994. Understanding corporate coherence. J. Econ. Behav. Organ. 23 (1), 1–30. https://doi.org/10.1016/0167-2681(94)90094-9.
Ter Wal, A., 2014. The dynamics of the inventor network in German biotechnology: geographic proximity versus triadic closure. J. Econ. Geogr. 14 (3), 589–620. https://doi.org/10.1093/jeg/lbs063.
Ter Wal, A.L.J., 2013. Cluster emergence and network evolution: a longitudinal analysis of the inventor network in Sophia-Antipolis. Reg. Stud. 47 (5), 651–668. https://doi.org/10.1080/00343401003614258.
Ter Wal, A.L.J., Alexy, O., Block, J., Sandner, P.G., 2016. The best of both worlds: the benefits of open-specialized and closed-diverse syndication networks for new ventures' success. Adm. Sci. Q. 61 (3), 393–432. https://doi.org/10.1177/0001839216637849.
Tóth, G., Lengyel, B., 2021. Inter-firm inventor mobility and the role of co-inventor networks in producing high-impact innovation. J. Technol. Transf. 72 (1), 1. https://doi.org/10.1007/s10961-019-09758-5.
Tóth, G., Juhász, S., Elekes, Z., Lengyel, B., 2021. Repeated collaboration of inventors across European regions. Eur. Plan. Stud. 2, 1–21. https://doi.org/10.1080/09654313.2021.1914555.
Tubiana, M., Miguelez, E., Moreno, R., 2021. In knowledge we trust: learning-by-interacting and the productivity of inventors. Res. Policy 51 (1), 104388. https://doi.org/10.1016/j.respol.2021.104388.
Uzzi, B., Spiro, J., 2005. Collaboration and creativity: the small world problem. Am. J. Sociol. 111 (2), 447–504.
Uzzi, B., Mukherjee, S., Stringer, M., Jones, B., 2013. Atypical combinations and scientific impact. Science 342 (6157), 468–472. https://doi.org/10.1126/science.1240474.
van der Wouden, F., 2018. Exploring the Changing Structures of Inventor Collaboration in U.S. Cities Between 1836 and 1975 (PhD thesis). UCLA, Los Angeles.
van der Wouden, F., Rigby, D.L., 2019. Co-inventor networks and knowledge production in specialized and diversified cities. Pap. Reg. Sci. 98 (4), 1833–1853. https://doi.org/10.1111/pirs.12432.
Vicente, J., 2017. Network failures and policy challenges along the life cycle of cluster. In: Fornahl, D., Hassink, R. (Eds.), The Life Cycle of Clusters: A Policy Perspective. Edward Elgar Publishing, Cheltenham, UK, pp. 56–75.
Wagner, C.S., Whetsell, T.A., Mukherjee, S., 2019. International research collaboration: novelty, conventionality, and atypicality in knowledge recombination. Res. Policy 48 (5), 1260–1270. https://doi.org/10.1016/j.respol.2019.01.002.
Wang, J., 2016. Knowledge creation in collaboration networks: effects of tie configuration. Res. Policy 45 (1), 68–80. https://doi.org/10.1016/j.respol.2015.09.003.
Wang, J., Veugelers, R., Stephan, P., 2017. Bias against novelty in science: a cautionary tale for users of bibliometric indicators. Res. Policy 46 (8), 1416–1436. https://doi.org/10.1016/j.respol.2017.06.006.
Wanzenböck, I., Frenken, K., 2020. The subsidiarity principle in innovation policy for societal challenges. Glob. Transit. 2, 51–59. https://doi.org/10.1016/j.glt.2020.02.002.
Wanzenböck, I., Rocchetta, S., Kim, K., Kogler, D.F., 2022. Regional Dynamics of Technological Change: The Role of Organisations' Network Structure. DRUID Working Paper.
Watts, D.J., Strogatz, S.H., 1998. Collective dynamics of 'small-world' networks. Nature 393 (6684), 440–442. https://doi.org/10.1038/30918.
Weitzman, M.L., 1998. Recombinant growth. Q. J. Econ. 113 (2), 331–360. https://doi.org/10.1162/003355398555595.
White, H., 1980. A heteroskedasticity-consistent covariance matrix estimator and a direct test for heteroskedasticity. Econometrica 48 (4), 817. https://doi.org/10.2307/1912934.
Wuchty, S., Jones, B.F., Uzzi, B., 2007. The increasing dominance of teams in production of knowledge. Science 316 (5827), 1036–1039. https://doi.org/10.1126/science.1136099.
Yang, Z., Algesheimer, R., Tessone, C.J., 2016. A comparative analysis of community detection algorithms on artificial networks. Sci. Rep. 6, 30750. https://doi.org/10.1038/srep30750.
Zeileis, A., 2004. Econometric computing with HC and HAC covariance matrix estimators. J. Stat. Softw. 11 (10) https://doi.org/10.18637/jss.v011.i10.
Zeileis, A., Hothorn, T., 2002. Diagnostic checking in regression relationships. R News 2 (3), 7–10.
Zhou, T., Ren, J., Medo, M., Zhang, Y.-C., 2007. Bipartite network projection and personal recommendation. Phys. Rev. E Stat. Nonlinear Soft Matter Phys. 76 (4 Pt 2), 46115. https://doi.org/10.1103/PhysRevE.76.046115.