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New Collaborations and Novel Innovations: The Role of Regional Brokerage and Collaboration Intensity

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Abstract

In this paper we investigate the role of brokers in the regional innovation network and its influence on innovative and collaborative outcomes. For this purpose, we make use of data from the European Patent Office and Eurostat in the period 1986-2015. We first build the regional collaboration network based on co-inventorship ties, then we identify the brokerage roles played by each region, using the original taxonomy proposed by Gould and Fernandez (1989), to disentangle their impact on innovation and collaboration. Finally, we investigate regional collaboration intensity and how it interacts with brokerage roles, highlighting its mediating effect. Our findings indicate that brokerage roles contribute to the extension of collaboration networks, but also that they are not efficient for the creation of innovation. Collaboration intensity, on the other hand, enhances both innovation and collaborative outcomes, and shows how a region can benefit from being a broker.

Keywords: brokerage, co-inventor collaboration, collaboration intensity, novel innovation, new collaboration

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1. Introduction

The literature in the field of economic geography has highlighted the importance of collaboration in regional innovation activities. According to Crescenzi et al. (2016), the level of collaboration among local inventors is a key indicator of a region's innovation performance. A network perspective can be used to study the complex relationship between regional collaboration and innovation, as it allows for the examination of how individual actors with different knowledge are connected. A region with a densely connected collaboration network is more likely to have greater access to new knowledge and opportunities, while a less connected region may experience inefficiency in innovation activities (Ahuja, 2000; Coleman, 1988; Jiang et al., 2019; Seo, 2019).

The concept of regional brokerage, which refers to a region's ability to act as a bridge between different knowledge sources, has been proposed as a way to explain the benefits and costs of regions in the global innovation network. According to the structural hole theory (Burt, 1992, 2005), a broker can fill gaps in the network by controlling knowledge flows and connecting otherwise disconnected agents. However, it is important to note that a broker region may not necessarily be the most connected region in the network, but rather an attractive potential collaborator (Allen, 2010).

Recent research in regional science has begun to explore the concept of regional brokerage and its effect on collaboration and innovation (Martinus et al., 2021). Within this body of literature, brokerage plays a central role in the economies of cities and regions (for a recent overview of latest research in regional studies, see Sigler et al., 2021). It has been featured in research on relational cities (Sigler, 2013), gateway cities (Scholvin et al., 2019), as well as in studies aiming to identify broker regions (Hennemann & Derudder, 2014). We contribute to this literature by applying a network perspective to the study of regional brokerage, and considering the role of collaboration intensity in determining the effect of regional brokers. External collaboration, as argued by Boschma (2005), allows regions to access new and non-redundant knowledge, which can help mitigate the coordination costs associated with their brokerage position.

Using data on inventors' collaboration within and between European regions, we identify a typology of three types of brokerage regions, and we look at innovation performance through brokerage within and between regions. To the best of our knowledge, brokerage role and collaboration intensity have not been considered together to see how they interact and influence innovation and collaborative activity at the regional level. This paper aims at generating a more accurate understanding of the brokerage role of regions, both with theoretical and policy implications, addressing the following research questions: How do regions conduct collaboration and what are the top brokerage regions? Which type of brokerage positions of regions enhance novel innovation and new collaboration? What is the mediating effect of regional collaboration intensity on brokerage, and how does this affect innovation and collaboration outcomes? To answer these questions, we make use of European Patent Office PATSTAT database and the Annual Regional Database of the European Commission's Directorate General for Regional and Urban Policy and we conduct an empirical analysis on European NUTS-3 regions between 1986 and 2015.

Our results can be summarised in three main findings. First, we confirm previous literature about brokerage roles being negatively associated with innovation but causing positive effect on collaborative output. Since nodes benefit from a dense collaboration network, the negative impact of brokers highlights that more structural holes hamper innovation output (Ahuja, 2000; Coleman, 1988; Jiang et al., 2019; Seo, 2019). On the other hand, brokerage positions are beneficial to attract new collaborations, which is in line with the point of view of Burt's theory (Burt, 1992, 1997) that emphasizes the potential of brokers for "closing the gap" with nodes with which they had not interacted before (Mitze & Strotebeck, 2019). Second, external collaboration has a positive impact on both innovative and collaborative outcomes. It is in fact beneficial for regional actors to collaborate with inventors from outside their region to increase the probability of accessing to new non-redundant knowledge. Finally, collaboration intensity positively moderates on the relationship between brokerage roles and innovation. This highlights the importance of external collaboration for regions to achieve innovation, via the favourable exploitation of their brokerage positions.

The paper is organized as follows. In section 2, we present our theoretical expectations regarding regional collaboration intensity and brokerage roles, grounded on the existing literature. In section 3, we describe the data, variables and the empirical strategy. Section 4 presents a descriptive overview of our main variable of interest. Section 5 presents findings from the econometric analysis. The concluding section provides a discussion and final remarks.

2. Theoretical framework

In the regional context, a region is a dynamic unit which interacts and exchange internal and external knowledge with other regions and within its own regional actors (Feldman & Kogler, 2010). The variability across regions, in terms of intensity of the innovation activity and outcome, could be explained by a lack of interactions among regional actors (especially firms, but also universities) or by a low centrality in the global innovation network. In this paper we explore these issues by focusing on the inter-regional collaboration network for innovation.

2.1. Collaboration intensity

Regions can be considered as nodes in the collaboration network, as well as clusters of local innovative actors and activities. The collaboration among these local actors eases the exchange of knowledge and ideas within the region in a condition of trust allowed by the physical proximity and the face-to-face interaction of the actors involved (Boschma, 2005). This “local buzz” (Bathelt et al., 2004), however can result in a local knowledge lock-in if the region is not also externally well-connected to innovative actors in other regions. These external connections, in fact, are essential in providing non-redundant knowledge which enriches the innovative atmosphere of the region (Broekel, 2012; Camagni, 1991). For example, according to Stojčić (2021), collaborating with domestic partners may not be as beneficial for commercializing novel products and services as collaborating with foreign rivals. This research suggests that collaborations with only foreign rivals can actually have a positive impact on the commercialization of incrementally novel innovations.

H1: Higher external collaboration intensity improves the regional innovation and collaborative outcomes.

Besides the degree of regional collaboration intensity, we also consider regions in the inter-regional innovation network. In this network, detailed in section 3.1, regions are the nodes and the edges are represented by co-patenting ties among inventors residing within different regions. As we just discussed, the degree of connectivity with the rest of the network can generate benefits for the regions, but this also depend on the position of the region in the overall network and on the role that it plays.

Several studies in the field of collaboration networks have underlined how broker positions exert a structural influence on knowledge networks (Boschma, 2005; Boschma & Frenken, 2006; Breschi &

Lissoni, 2001; De Prato & Nepelski, 2014; Glückler, 2007). A node in the position of broker connects different sources of knowledge, controlling the flow to and from its network, thus supporting its viability (Sapsed et al., 2007).

Brokerage nodes are not necessarily the most central nodes in the network. We define broker regions as those that link other region, belonging either to the same or to a different country, that are disconnected among each other. The different types of broker nodes allow us to understand the role those specific regions play in the transmission of external knowledge in their local network component.

2.2. Brokerage roles

Research on brokerage dates to the early 1920s with the foundational work of Simmel (1922), later reprised by Merton in the late 1950s (Merton, 1957) and by research on social networks as early as the 1980s. As brokerage roles have been studied for decades, the literature provides several definitions (Diani & McAdam, 2003; Ryall & Sorenson, 2007; Shi et al., 2009). In all definitions, brokers' main characteristic is the capacity to form a bridge between two disconnected nodes to compensate for connectivity weaknesses due to structural holes. Gould and Fernandez (1989; 1994) go beyond this general definition and propose a taxonomy of the different types of brokerage positions that a node can occupy. Their taxonomy consists of five different brokerage positions: i) *coordinator* brokers link individuals who are unconnected but belong to the same group; ii) *consultant* (or *itinerant*) brokers connect individuals co-located in the same external group; iii) *representative* brokers transfer externally information which is internal to their group; similarly, but with opposite direction, iv) *gatekeeper* brokers transfer external information inside their group; finally v) *liaison* brokers mediates between individuals belonging to different groups and are positioned outside both of them.

So far, the literature has paid very little attention to the impact of broker positions on the inventive performance at a more aggregate level. Notable exceptions include Breschi and Lenzi (2015) who focus on how the regional knowledge base can be renewed and expanded thanks to the gatekeeping position of individual inventors within networks of co-inventors. Before them, Graf and Krüger (2011) considered four regions in Germany and investigate whether patent applicants benefit from their gatekeeping position in terms of innovative production, finding inconclusive results. More recently, Le Gallo and Plunket (2020) analyse the inventor network of firms, showing how they benefit from their inventors' regional gatekeeping position in terms of inventive performance.

These studies have mainly focused on two types of brokerage positions, namely gatekeeper brokers and representative brokers, which have been also studied in innovation research at the organization level and at the geographic cluster level (Haas, 2015). In general, most of the regional economics literature focuses on specific clusters and on the impact that gatekeepers exert on the supply and dissemination of knowledge within the same clusters (Biggiero, 2002; Giuliani & Bell, 2005; Morrison, 2008; Morrison et al., 2013).

Our study extends the brokerage typology of Gould and Fernandez to the network across regions. We apply the notion of brokerage, which commonly indicates the idea that nodes are protagonists in the transfer of external knowledge in the group to which they connect, to the regional framework, thus considering a region in a brokerage position as a broker node in the collaboration network among regions.

On the one hand, broker regions are pivotal in providing the local innovation system with access to external knowledge. In this sense a broker would be attractive from a collaborative point of view, because it will allow to access valuable non-redundant knowledge (Burt, 2005). On the other hand, brokerage might entail costs for the region holding such a position. Maintaining the connection between regions which are unconnected among each other, obliges broker regions to operate in condition of uncertainty and to incur in high coordination costs. These costs might refer to the time and the resources devoted to maintaining these links (Giuliani & Bell, 2005), and, considering the organisations in which inventors are employed, to possible knowledge leaks in favour of rival regions (Khanna et al., 1998).

H2a: Regions that act as brokers in the inter-regional network increase their collaborative ties with other regions.

H2b: Regions that act as brokers in the inter-regional network demonstrate a reduced capacity for technological exploration in their innovation performance.

The effect that brokerage will generate on innovation in regions holding this position, will depend on the level of connectiveness to the rest of the network. A broker region which is well connected and open to collaboration to external partners will be able to take advantage from its favourable position in terms of accessibility to new knowledge, with respect to a peripheral region which would be more easily trapped in a lock-in cause by redundant knowledge.

H3: Collaboration intensity mitigates the negative effect on innovation for broker regions.

3. Data & Methods

To test our expectations, we use data from two main sources: the European Patent Office (EPO)'s PATSTAT database and the Annual Regional Database of the European Commission's Directorate General for Regional and Urban Policy (ARDECO).[1] We extracted all patent and economic indicators which refer to European NUTS-3 regions for the years 1986 to 2015. To create regional knowledge spaces (Kogler et al., 2013; Rigby, 2015) we make use of the 4-digits Cooperative Patent Classification (CPC) and five years windows in our observational period. We use this specific time window since the literature suggests that knowledge capital depreciates, and it loses its economic value within 5 years (Griliches, 1979, 1984). Burt (2000, 2002) employed a similar argument in his analysis of tie decay, discussing the tendency for collaborative relationships to weaken and eventually dissolve. Furthermore, this is a timeframe that has been used in many studies aiming at analysing technological impact of prior inventions (Ahuja, 2000; Gilsing et al., 2008; Henderson & Cockburn, 1996; Podolny & Stuart, 1995; Stuart & Podolny, 1996). This strategy allows us to depict the regional specialization in specific technological knowledge domains. To geo-locate the patents, we geocoded inventors' address and assigned them to NUTS-3 regions.

We divide European NUTS-e regions in two categories (metropolitan and non-metropolitan regions), using 2013 Eurostat concordance table.[2] As a result, in the analysis we will refer to a total of 274 metropolitan (hereafter metro) regions and 859 non-metropolitan (hereafter NUTS-3)

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[1] The ARDECO is a service provided by European Commission's Directorate General for Regional and Urban Policy that contains variables and indicators for EU regions.
[2] https://ec.europa.eu/eurostat/web/metropolitan-regions/background (last visited on February 2022).

regions. Finally, we collect from the ARDECO all regional level economic variables which we will use in the regressions as control variables to take into account regional difference.

3.1. Regional collaboration network

The regional collaboration network is created starting from the co-inventors' network, aggregating it to the regional level. For the aggregation to the regional level, we use the inventors-share, and not full counting, to control for the inventor size effects.

Patent	Region	Nb. of inventors	Region-share
Patent 1	Region A	3	0.6
	Region B	1	0.2
	Region C	1	0.2
Total Nb. of inventors		5	1

Patent	Region 1	Region 2	Region-share 1	Region-share 2	Region-share 1 + Region-share 2	(Region-share 1 + Region-share 2) / ∑ Region-share 1 + Region-share 2
Patent 1	Region A	Region B	0.6	0.2	0.8	0.4
	Region A	Region C	0.6	0.2	0.8	0.4
	Region B	Region C	0.2	0.2	0.4	0.2
∑ Region-share 1 + Region-share 2					2	1

Figure 1: Example of regional-share and weighted regional collaboration table

As an example, let us assume that patent 1 is co-invented by five inventors (Figure 1), three of them reside in the same region (region A) while the fourth inventor and the fifth inventor live in other regions (region B and C, respectively). If we use the full count of collaboration links, giving a value of 1 for each co-inventor linkage, region A has 6 linkages (each of the three inventors residing there collaborate with both inventors residing in the other two regions), while region B and region C have 4 linkages each (three linkages towards region A and one towards the remaining region). Thus, a total of 14 linkages would result from a single patent, which is higher than the number of linkages we would obtain from the mere regional collaboration. This can create biased results for patents with a higher number of co-inventors, and it can broaden the gap between regions with higher number of inventors and those with fewer of them.

To avoid this problem, we make use of the weighted regional collaboration, computed via the following procedure. First, we calculate, for each patent, the region-share by dividing the regional number of inventors for the total number of inventors (last column in the top table of Figure 1). Next, we compute the regional collaboration table by paring the regions involved in the patent production. Then, we compute the sum of the region-shares for each pair of regions, and we divide this value for the summation of regional-shares to obtain the proportion of the combination between two regions used for the patent creation (last column in the bottom table of Figure 1). Thanks to this process we obtain a weighted measure of the collaboration between regions.

3.2. Dependent variables

In the empirical analysis, we make use of two dependent variables: novel innovation (*Nov.INN*) and new collaboration (*New.COL*). *Nov.INN* is measured by the number of a focal region's patents in time window *t* which contain CPC classes that were not present in its patents in the previous time window *t–1* (Gilsing et al., 2008; Guan & Liu, 2016). To measure this variable, we compare technological profiles of each region between the two consecutive periods to obtain the number of patents containing CPC that had not been used before.[3] Our second dependent variable, *New.COL*, is measured by the number of regions collaborating with a focal one in time window *t*, which were not already collaborating in *t–1*. We thus computed the collaboration profile of each region and then compared it within two consecutive time windows.

3.3. Independent variables & moderator

The independent variables used in our models, along with the control variables that will be presented below, are calculated with a one-period lag.[4] Thus, our models estimate whether the

[3] We acknowledge that innovation can manifest differently in advanced and emerging innovation systems. Advanced systems tend to focus on creating new knowledge, where patents can be a useful measure of innovation, while emerging systems base their innovation on utilizing existing knowledge, such as through machinery, equipment, and expertise (Vujanović et al., 2022). Hence, patents are not a comprehensive measure of R&D efforts in an economy and are often considered an imperfect indicator. Despite this, patents are a widely used, formal, measurable output of the innovation system in literature for tracking the production of knowledge and technologies (Acs et al., 2002; Bergé et al., 2017; Françoso & Vonortas, 2022; Leydesdorff et al., 2015).
[4] In Tables B.7 and B.8 of the online Appendix B, we present a robustness check in which we re-estimate our models with the dependent variables calculated with a two-period lag.

characteristics at time *t* influence regional innovative and collaborative output at time *t+1*. Thanks to the creation of the regional collaboration network, described in section 3.1, we are able to classify regional nodes using the typology originally proposed by Gould & Fernandez (1989). To do so, we group regions in categories based on the country to which they belong. This allows us to measure three different brokerage roles (Figure 2):

- *Coordinator* (*COO*) regions collaborate with other unconnected regional nodes within the same country. These regions are in a key position to facilitate knowledge flows within their country.
- *Consultant* (*CON*) regions collaborate with other unconnected foreign regions which, in turn, belong to the same country. These regions play an important role in the information channel with another country.
- *Liaison* (*LIA*) regions collaborate with other unconnected foreign regions which, in turn, belong to different countries. These regions are highly internationalised as they transmit knowledge across several distinct jurisdictions.

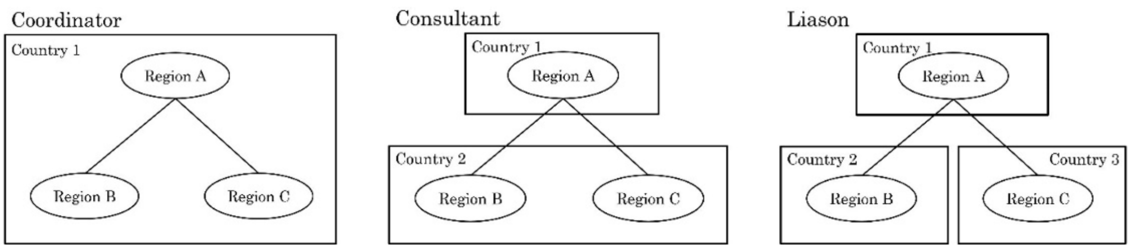

Figure 2: Regional Brokerage Roles

Once computed the regional collaboration network, we identify and classify regional brokerage roles using the "brokerage" function in the R package "SNA" (Butts, 2016). We thus first consider each triple of nodes A, B and C in the network such that A → B and A → C, but not B → C. In such cases, A is in a brokerage position with respect to B and C, because the flow of knowledge must pass through A. Second, we classify each broker node, assigning it to one of the three typologies presented above, based on the countries of the regions involved. Finally, we count for each regional node the number of the different brokerage positions that the region occupies.

Our moderator variable is *Collaboration Intensity (Coll.Int)*, which captures the intensity of regional internal (intra-regional) vs. external (inter-regional) collaboration patterns. *Coll.Int* is measured via an adapted version of the E–I index, or Krackhardt E/I ratio, proposed by Krackhardt and Stern (1988). It not only captures whether the regional collaboration pattern is either internally or externally oriented, but allows also to normalize the size effect of both. The index ranges between –1 and +1. If a region collaborates more internally, the value is closer to –1, while a region that has more external collaboration connections would display a value closer to 1. *Coll.Int* will thus tell us whether a region collaborates more with other regional economies (*Coll.Int* > 0) or if it mainly collaborates within its own regional economy (*Coll.Int* < 0).

$$Coll.Int = \frac{(External\ collaboration - Internal\ collaboration)}{(External\ collaboration + Internal\ collaboration)} \tag{1}$$

3.4. Control variables

While our analysis focuses on the relationship between inter-regional networks and innovation performance, other factors could also influence regions' propensity to patent and collaborate. To address this, we include several control variables in our models. First, we account for the level of technology advancement across regions. To do so, we use the Revealed Comparative Advantage (*RCA*) index (Hidalgo et al., 2007), which measures a region's comparative advantage in a particular technology based on the share of patents it holds in that technology relative to the share of patents held by all regions.

$$RCA_{r,i,t} = \frac{Patents_{r,i,t}}{\sum_i Patents_{r,i,t}} / \frac{\sum_r Patents_{r,i,t}}{\sum_r \sum_i Patents_{r,i,t}} \tag{2}$$

The index calculates the share of technology *i* in region *r*'s technological portfolio and the share of technology *i* in all regions. If the *RCA* of region *r* in technology *i* at time *t* ($RCA_{r,i,t}$) is greater than 1, this indicates that region *r* has a revealed comparative advantage in technology *i* at time *t*. We then count the number of technologies in which each region has a comparative advantage (i.e., *RCA* > 1). This enables us to control for the heterogeneity in technology profiles across regions, which may affect both their innovation performance and their collaboration patterns.

We then control for the economic conditions of regions using GDP per capita (*GDP*), employment per capita (*EMP*) and employment in manufactory (*EMP.M*). To account for the availability of human resources involved in innovation activities, we control for the number of inventors per capita (*INV*). Finally, we include two control variables to account for geographical specificities of regions which may influence innovative and collaborative outcomes: the number of adjacent regions (*Adj.Reg*) and a dummy for metropolitan regions (*Metro*). The first variable accounts for the geographical position of regions, in fact we expect more isolated regions to have fewer collaboration opportunities; while the latter account for the fact that metropolitan regions, defined as agglomerations of at least 250,000 inhabitants, have access to more skilled human resources and better infrastructures. Table 1 describes the variables used in the empirical analysis.

Table 1: Variables description and source

Variable	Description	Source
Dependent variables		
Nov.INN	Nb. of patents in *t* containing CPCs absent in *t–1*	PATSTAT
New.COL	Nb. of collaborating regions in *t,* unconnected in *t–1*	PATSTAT
Independent variables		
COO	Nb. of regional Coordinator positions	PATSTAT
CON	Nb. of regional Consultant positions	PATSTAT
LIA	Nb. of regional Liaison positions	PATSTAT
Moderator variable		
Coll.Int	Collaboration Intensity	PATSTAT
Control variables		
RCA	Nb. of technologies with RCA>1	PATSTAT
GDP	GDP per capita	ARDECO
EMP	Employment per capita	ARDECO
EMP.M	Employment in manufactory industry	ARDECO
INV	Nb. of inventors per capita	ARDECO
Adj.Reg	Nb. of adjacent regions	Eurostat
Metro	Dummy: 1 if metropolitan region; 0 otherwise	Eurostat

4. Regional collaboration network in the EU metro and NUTS-3 regions

Table A.1 in the online Appendix A summarises the top 5 brokering regions and their major firms for each period. Throughout the periods, it is always metro regions that are ranked as top 5 brokerage regions. Most of these are German metro regions such as Stuttgart, Frankfurt, Ruhgrebiet, and Munich; something that is perhaps not a surprise given that it is those regions that are also the location of many global manufacturing firms; headquarters. The exceptions are Paris and London that are perhaps not considered manufacturing centres, but nevertheless both are massive economic hubs for their respective countries and for the European economy in general.

Figure 3 illustrates the collaboration intensity and brokerage role relationship in 2011-2015. To recap, when collaboration intensity is close to –1, it indicates that regional collaborations mainly take place inside the region, while when it is close to +1 indicates that the majority of regional collaborations involve extra-regional partners. On the y-axis we report the average value of three brokerage roles normalized by the maximum value to rearrange all values between 0 and 1. Each data point represents either a metro or non-metro region, distinguished by the shape, while the size of the data point indicates patenting per capita. The top 15 regions for brokerage positions are labelled. Looking at the figure, it is possible to notice that all top brokerage regions are metro regions. Based on prior research (e.g., Balland et al., 2020; Krätke, 2007; Simmie, 2003), it is reasonable to presume that metro regions provide a more conductive environment for innovation activities, while also offering the sort of infrastructure (i.e., transport, telecommunication, etc.) that facilitates cooperation with inventors living in other, perhaps even more disconnected, regions.

In terms of collaboration intensity, however, no such a tendency is found either between metro and non-metro regions or high patenting and low patenting regions. For instance, Paris, London, and Milan are in the "within-regional" collaborator group, since a larger proportion of their regional collaboration activities happens inside their respective regional economies. Since metro regions have higher level of resources and inventors' endowments, the local inventors in those regions are most likely less in need of searching for collaboration opportunities at the outside. On the other hand, Frankfurt, Ruhrgebiet, and Manheim belong to the "inter-regional" collaborator group, whose regional collaboration is more focused on external partners. A possible explanation for this could be that some metro regions are located in what could be described as an agglomeration of metro regions. In this sense, they are situated in a dense network of spatial proximate urban centres, which might, in turn, make them a hub for transportation and thus more accessible and prone to engage in inter-regional collaboration activities. Collaboration intensity also varies irrespectively from the level of patenting pertaining to each region (represented in Figure 3 by the size of the data points).

This tells us that regional collaboration intensity varies regardless of its size or resources endowment.

Figure 4 presents the map of European regions showing the level of their brokerage role in 2011-2015. To ease readability of the visualization, all values are log-transformed, and a darker shade of colour indicates a greater value. As already discussed, metro regions show greater brokerage roles compared to the non-metro ones. Especially, metro regions that are geographically centre-located show comparably larger values, which obviously implies that their advantage in transportation and advanced infrastructure eases linking inventors from far-distance locations.

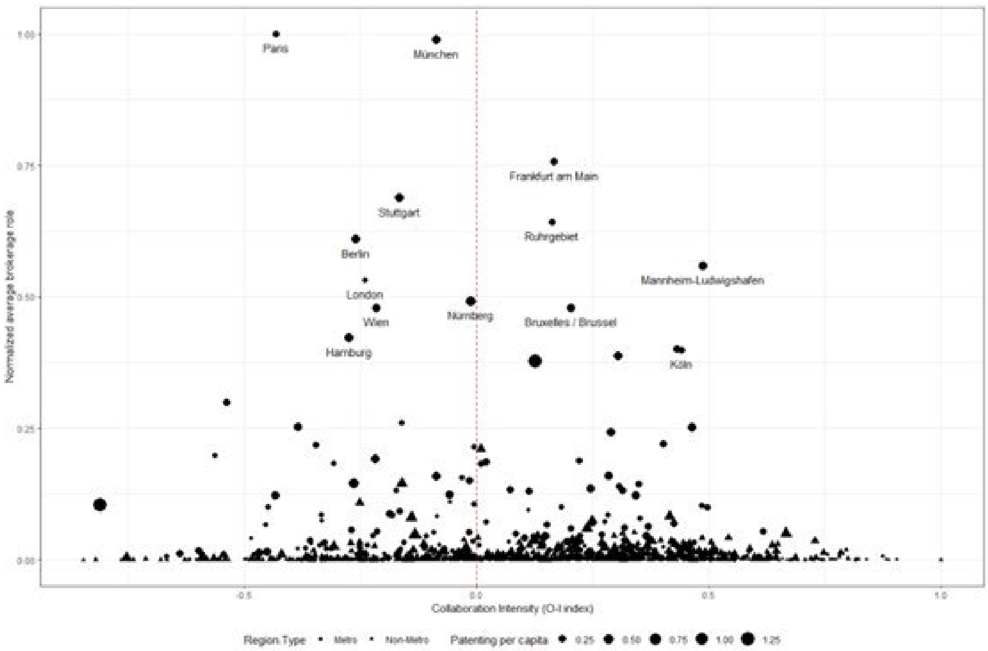

Figure 3: Collaboration intensity –brokerage role graph in 2011-2015

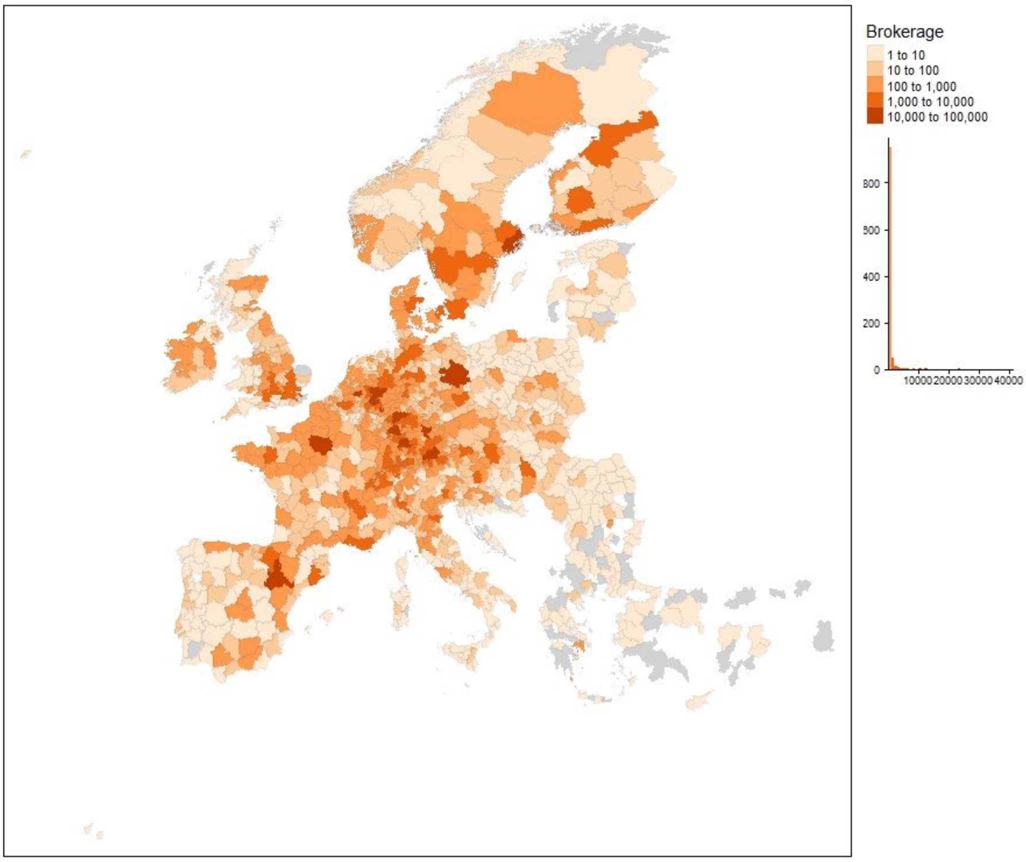

Figure 4: Brokerage map

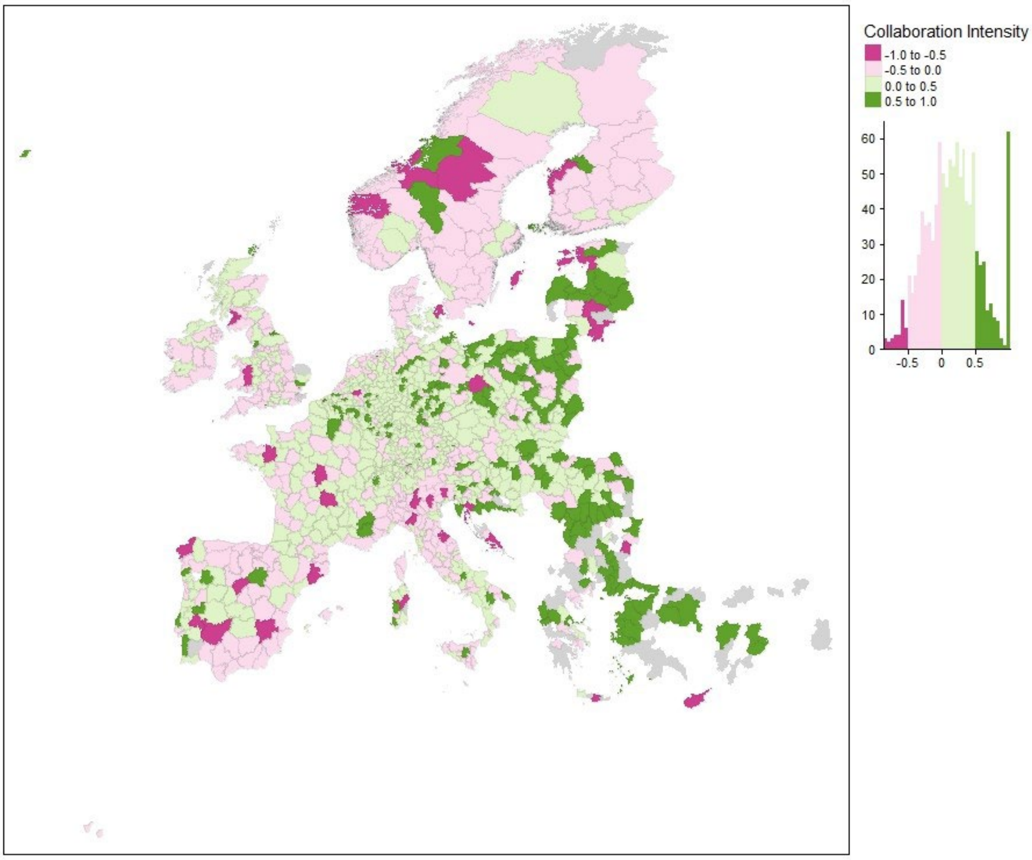

Figure 5: Collaboration intensity map

The collaboration intensity map (Figure 5) shows whether European regions rely proportionally more on external or internal collaboration. A greenish colour indicates a higher tendency of external collaboration activities while a pinkish colour refers to a higher tendency towards internal collaborations. Here we have a less clear distinction between metro and non-metro regions in terms of collaboration intensity. Regions with high levels of intra-regional collaboration (pink shades), outside of Scandinavia, are mainly Latin regions, which historically have a low degree of openness (Fukuyama, 1996), and are more likely inclined to individually develop internal resources and structures. In contrast, high levels of inter-regional collaboration involve two contrasting types of regions. First, it is some of the innovative regions of Germany and those in Benelux countries, where inter-regional, compared to intra-regional, cooperation is prevalent. Second, those regions of Central and Eastern Europe which are typically less known for innovation activities and thus seem to mainly collaborate with other knowledge intensive regions most likely due to their lack of internal resources and competencies (Hajek et al., 2014). In the latter case, the attitude to inter-regional collaboration in these regions is often the result of European projects which required them to collaborate to gain access to European funds.[5]

5. Results

The correlation between variables is presented in Table A.2 in the online Appendix A. The correlation between all variables is low except for *COO* and *LIA* roles. To avoid issues of multicollinearity, the estimations for these two variables were made separately. We conducted several tests to determine the appropriate estimation model before running our regression analysis. First, we performed a Hausman test which yielded a significant p-value, indicating that fixed effects should be used. Next, we conducted an F test and Lagrange Multiplier test to determine if time-fixed effects should be considered. Results from all models showed that including time-fixed effects improved the model fit, and thus we included time-fixed effects in our final model. In all models, we used robust standard errors in order to control for heteroscedasticity (Hoechle, 2007; Szymczak, 2018). Based on the recommendation of Long & Ervin (2000) for linear regression models, we used HC3

[5] To address the potential influence of Central and Eastern European regions on our results, we conducted a robustness check by including a dummy variable which takes a value of 1 for these regions. We report the results of this robustness check in Tables B.3 and B.4 in the online Appendix B, and found them to be consistent with our main results reported in Table 2 and Table 3 in section 5 of the paper.

(Heteroskedasticity-Consistent 3) robust standard errors clustered at the country level. Table A.3 in the online Appendix A provides the descriptive statistics for all the variables used in the empirical analysis.

Table 2: Regression result of fixed-effects model: Novel Innovation

	Dependent variable: Nov.INN				
	(1)	(2)	(3)	(4)	(5)
RCA	0.511***	0.517***	0.517***	0.499***	0.510***
	(0.025)	(0.024)	(0.025)	(0.026)	(0.025)
EMP.M	10.529***	10.440***	10.696***	11.237***	11.152***
	(0.946)	(0.929)	(0.927)	(0.922)	(0.931)
GDP	-1.369	-1.460	-1.323	-1.011	-1.159
	(1.116)	(1.108)	(1.084)	(1.116)	(1.087)
EMP	-5.627***	-5.652***	-5.842***	-6.579***	-6.425***
	(1.240)	(1.231)	(1.173)	(1.181)	(1.169)
INV	9.898***	9.659***	9.737***	10.142***	9.909***
	(0.751)	(0.725)	(0.743)	(0.764)	(0.742)
Adj.Reg	0.838***	0.893***	0.795***	0.852***	0.793***
	(0.247)	(0.243)	(0.244)	(0.246)	(0.246)
Metro	8.797***	8.591***	8.451***	8.446***	8.246***
	(1.508)	(1.465)	(1.395)	(1.445)	(1.370)
COO	-0.002***	-0.002***	-0.002***	-0.001**	-0.001**
	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)
CON	-0.005	-0.004	-0.002*		
	(0.004)	(0.004)	(0.001)		
LIA				-0.001**	-0.0004***
				(0.0003)	(0.0001)
Coll.Int	5.743***	4.812***	5.245***	5.831***	5.164***
	(1.106)	(1.037)	(1.090)	(1.102)	(1.057)
COO×Coll.Int		0.002**			
		(0.001)			
CON×Coll.Int			0.018***		
			(0.006)		
LIA×Coll.Int					0.002***
					(0.0004)
Time	Included	Included	Included	Included	Included
Observation	4,357	4,357	4,357	4,357	4,357
R^2	0.760	0.761	0.762	0.761	0.763
Adj R^2	0.759	0.760	0.761	0.760	0.762
F Stat	1,371.297***	1,253.516***	1,262.997***	1,382.701***	1,269.901***
	(df=10;4342)	(df=11;4341)	(df=11;4341)	(df=10;4342)	(df=11;4341)

Notes: All time-varying covariates are lagged one period; Robust standard errors in parenthesis; * p < 0.10, ** p < 0.05, *** p < 0.01

Table 2 reports the regression result of the model with novel innovation as a dependent variable. *RCA* reports positive and statistically significant coefficients. As expected, the more a region is specialized in technologies that are above the average level in comparison with other regions, the more it is likely to have stronger possibilities to introduce novel inventions. Similarly, the positive and significant coefficient of *INV* highlights that a higher inventors' endowment is needed to develop novel inventions. Regional economic indicators such as *EMP.M*, *GDP*, and *EMP*, however, show negative influence on novel innovation. We can infer that the larger regions with comparably greater productivity and human resources are much more likely to have large number of technologies already developed by the local inventors. As these regions have already developed large number of technologies, it becomes more difficult for them to develop new ones which have not been developed before. This is true especially if we compare them to the smaller regions, which present a smaller number of already developed technologies. In this light, these coefficients seem to provide a reasonable picture on their effect on novel innovation. *Adj.Reg* displays a positive coefficient, and this result emphasizes the importance of geographical location. Compared to either geographically isolated or partially sea-faced regions, those surrounded by more neighbouring regions have higher advantages in accessing new knowledge and human resources and to engage in collaboration activities. Finally, the positive coefficient of *Metro* implies that the positive effect on novel innovation is greater in metropolitan regions compared to non-metropolitan regions.

Examining now our main coefficients of interest, those regarding brokerage roles, we notice that they are all negative and significant. This indicates that the greater the regional engagement in broker activities is, the less the region is able to create novel inventions. We thus find evidence supporting our *H2b*. To interpret this result, we need to look more closely to the regional collaboration network. From a network perspective, a brokerage role does not require a high number of connections, but rather it implies connection to heterogeneous nodes that would not be connected without it. With the exception of the outliers of greater connectivity, it is often difficult to observe a node with both high connectivity and high brokerage roles. Imagine a region which collaborates frequently with other regions. It may collaborate once with 10 different regions, but it is much more common that it collaborates more than once with a smaller number of regions. It is indeed arguably more efficient to collaborate frequently with few others than interacting once with several different collaborators. Furthermore, it is likely that a region's collaborators also would interact among each other. Such phenomenon is known as the "small world" effect: a collaboration network is often built with a small number of connected nodes, and these nodes are likely to be relevant to each other. Therefore, we may assume that a brokerage node is less efficient in creating the new edges.

From our regional collaboration network's perspective, the regions with higher levels of brokerage roles are those that collaborate with other different regions that are unconnected amongst each other, hence they may be less efficient in creating novel inventions. Arguably, to conduct innovation the most important characteristic is the accessibility to resources, and, from a network perspective, broker regions are inefficient in this because their collaboration network is disconnected in some sense. A region in a broker position, in fact, does not necessarily also have a lot of connections. It is certainly the case for very big metro regions, such as Paris or London as highlighted earlier, but these represent more of an exception than a rule. This finding aligns with Coleman's (1988) position and the results of other relevant empirical studies (Ahuja, 2000; Jiang et al., 2019; Seo, 2019) that show how more structural holes, and hence more brokerage possibilities, reduce innovation output.

On the other hand, *Coll.Int* reports a positive and significant coefficient throughout the models, in line with our *H1*. This positive coefficient indicates that conducting more external collaboration contributes to achieving novel invention. It is in fact quite well known in the economic geography literature that external openness is indeed beneficial and can help in overcoming the possible shortcomings arising from a too dense local collaboration network (Bathelt et al., 2004). Interestingly, with respect to the existing literature, the interaction term of brokerage roles (*COO*, *CON*, and *LIA*) and *Coll.Int* is positive and significant.

As a moderator, *Coll.Int* can convert the negative effect of brokerage roles into a positive effect, as we hypothesized in *H3*. This result shows that a region can take advantage of its favourable brokerage position in the knowledge network in terms of creating novel innovation when it also has a high degree of extra-regional collaboration ties. From this buffering interaction effect, we may assume that the negative influence of brokerage roles can be overcome by the level of external collaboration. This finding allows us to expand the idea of the brokerage role to another aspect, collaboration intensity. As argued before, a brokerage region may not be efficient in producing novel invention, but if its collaboration activity relies more on other regions, then it can eventually benefit from its position.

Table 3: Regression result of fixed-effects model: New collaboration

	Dependent variable: New.COL				
	(1)	(2)	(3)	(4)	(5)
RCA	0.069***	0.070***	0.070***	0.066***	0.069***
	(0.017)	(0.017)	(0.017)	(0.018)	(0.017)
EMP.m	0.101	0.086	0.141	0.370	0.341
	(0.695)	(0.689)	(0.710)	(0.686)	(0.676)
GDP	-2.046**	-2.069**	-2.035**	-2.189**	-2.253**
	(0.799)	(0.798)	(0.795)	(0.886)	(0.878)
EMP	0.475	0.465	0.424	-0.098	0.148
	(0.915)	(0.911)	(0.931)	(0.878)	(0.819)
INV	2.346***	2.306***	2.314***	2.705***	2.624***
	(0.498)	(0.491)	(0.494)	(0.543)	(0.513)
Adj.Reg	0.444** (0.201)	0.455** (0.198)	0.434** (0.201)	0.522** (0.2055)	0.500** (0.203)
Metro	9.187***	9.145***	9.108***	9.576***	9.499***
	(0.980)	(0.973)	(0.979)	(1.087)	(1.055)
COO	0.003***	0.003***	0.003***	0.002***	0.002***
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
CON	0.008***	0.008***	0.009***		
	(0.0002)	(0.0002)	(0.002)		
LIA				0.0004*	0.001**
				(0.0002)	(0.0003)
Col.Int	2.834***	2.636***	2.714***	2.884***	2.830***
	(0.700)	(0.684)	(0.686)	(0.725)	(0.733)
COO×Col.Int		0.0004			
		(0.0004)			
CON×Col.Int			0.004		
			(0.007)		
LIA×Col.Int					0.001
					(0.0004)
Time	Included	Included	Included	Included	Included
Observation	4,242	4,242	4,242	4,242	4,242
R^2	0.672	0.672	0.673	0.650	0.652
Adj R^2	0.671	0.671	0.672	0.649	0.651
F Stat	866.557***	788.592***	790.574***	785.589***	719.949***
	(df=10;4227)	(df=11;4226)	(df=11;4226)	(df=10;4227)	(df=11;4226)

Notes: All time-varying covariates are lagged one period; Robust standard errors in parenthesis; * p < 0.10, ** p < 0.05, *** p < 0.01

Table 3 shows the regression result for the model with dependent variable *New.COL*. The coefficients of the control variables are positive and significant similarly to the previous table, except for *EMP.M* and *EMP*. While employment and share of manufacturing employment matters for the creation of novel innovation, they are not significant in determining new collaborations. This might be due to the fact that regions with strong manufacturing industries already have a dense collaboration network, and thus they are less likely to seek for new collaborators.

It is interesting and noteworthy that in the case of *New.COL*, the coefficients of all brokerage roles show positive and significant effects. This is in line with the expectations expressed in *H2a*. From a regional collaboration network's perspective, new collaboration is equivalent to connecting to a node that was unconnected before. From this point of view, a region with higher brokerage roles might be appealing to other regions as a new collaborator mainly because it is also connected to other regions with whom the new collaborators have no interaction otherwise. This explanation echoes the notions of structural hole theory (Burt, 1992, 1997), which shows how brokers are in a favourable position are the ones that attract new collaborators because it is through them that disconnected nodes (in our case: regions) can close the matrix gaps in the network. *Coll.Int*, again in line with *H1*, reports positive and significant coefficients, revealing how a higher orientation towards the outside of the region can also help it to expand its collaboration pool.

In this case, however, the interaction terms between the brokerage roles and *Coll.Int* are positive but not significant. This tells us that the brokerage role alone is a strong predictor for the region's ability to expand its collaboration network, regardless of the intensity of external collaboration. A brokerage region attracts new collaboration thanks to its partnering regions. In other words, the degree of internal or external collaboration of a brokerage region is insignificant with respect to its capacity of creating new collaboration, because the latter depends very much on whom a region interacts with in the first place.

To ensure the reliability of our findings, we conducted robustness checks that are reported in the online Appendix B. First, we added country fixed effects to our baseline regressions to control for country-specific heterogeneity. The additional regressions, presented in Tables B.1 and B.2 in the online Appendix B, confirmed the robustness of our results. Second, we addressed the possibility of different innovation patterns in Central and Eastern Europe by both adding the *CEE.Reg* dummy variable, which takes value 1 for regions in Central and Eastern Europe[6], and excluding these regions from our sample. The results, presented in Tables B.3 and B.4 and Tables B.5 and B.6, respectively, demonstrate the consistency of our estimations and show that our findings were not driven by the inclusion of these regions in our analysis. Finally, in Tables B.7 and B.8 of the online Appendix B, we present a robustness check in which we re-estimate our models with the dependent variables

[6] The dummy *CEE.Reg* takes a value of one for the group of eastern European regions in our sample, i.e.: Bulgaria, Czechia, Croatia, Hungary, Macedonia, Poland, Romania, Slovenia, and Slovakia.

calculated with a two-period lag, obtaining consistent results with respect to our baseline estimations. Overall, these additional robustness checks enhance the reliability of our results.

6. Conclusions

Our findings contribute to the existing literature on regional innovation and collaboration. First, our analysis demonstrates that regions' brokerage roles in collaboration activities can have both positive and negative effects on innovation outcomes. On one hand, acting as a broker can create opportunities for new collaborations and knowledge spillovers, but on the other hand, it may also hinder the creation of novel inventions by limiting the diversity of knowledge inputs. This insight clarifies why previous studies have found mixed results on the relationship between regional brokerage roles and innovation outcomes.

Second, we find that external collaboration intensity plays a crucial role in driving both novel innovation and new collaboration. While collaboration with external partners may be more challenging in terms of communication and workload management, our study supports the argument that external collaboration is preferable to local collaboration as it prevents local knowledge lock-in and stimulates the flow of new knowledge inputs. This finding deepens our understanding of the role of brokerage in collaboration and underscores the importance of collaboration intensity for achieving novel innovative outcomes.

The implications of our findings are relevant for policymakers seeking to support regional innovation activities. Our results suggest that creating a favorable environment for local inventors to engage in external collaborations, especially with those in different regions, could be key to promoting innovation. Policymakers can facilitate this by investing in assets that improve communication and collaboration, such as transportation and telecommunication technology, to overcome the geographical disadvantage of isolated regions. Our findings also highlight the importance of local inventors' capabilities and their inter-regional collaboration networks in enhancing innovation. While attracting external investments or firms is often seen as an effective way to boost regional development and knowledge spillovers, our study suggests that external collaborations can also play a central role in enhancing local innovation. Policymakers should therefore focus on creating policies that encourage and support external collaborations between regional inventors, as well as collaborations between regional inventors and those from outside the region. This would enable regions to take advantage of the brokerage role in collaboration and realize novel innovative outcomes.

In conclusion, our study highlights the importance of external collaboration in enhancing regional innovation activities. The findings suggest that policymakers should invest in measures that promote better collaboration, especially for regions with geographical disadvantages. Supporting local inventors in their efforts to engage in external collaborations can be a key strategy for fostering innovation. Moreover, our study underscores the need to take into account the collaboration intensity when assessing the outcomes of collaboration activities. Policymakers should be aware of the potential trade-off between creating a new collaboration network and generating novel innovations.

One limitation of our study, as mentioned in section 3.2, is the fact that the dependent variables are solely based on patent data, which may not capture all types of innovation and of collaboration. To complement our findings, future research could incorporate data from other sources to assess the effects of collaborations and brokerage on other forms of knowledge appropriation besides patents (e.g., scientific publications). This is especially important for emerging innovation systems, such as those in Central and Eastern European regions, which are known for being structurally weak and basing their innovation on knowledge use through machinery, equipment, and know-how (Vujanović et al., 2022). Therefore, future studies should aim to utilize alternative data sources to broaden the understanding of how collaboration and brokerage impact innovation in these specific contexts.

Overall, our study highlights the need for a nuanced understanding of the role of collaborations and brokerage in regional innovation networks. By recognizing the potential benefits and drawbacks of different types of collaborations, policymakers can make informed decisions to support innovation and economic development in their regions.

References

Acs, Z. J., Anselin, L., & Varga, A. (2002). Patents and innovation counts as measures of regional production of new knowledge. *Research Policy*, *31*(7), 1069–1085. https://doi.org/10.1016/S0048-7333(01)00184-6

Ahuja, G. (2000). Collaboration Networks, Structural Holes, and Innovation: A Longitudinal Study. *Administrative Science Quarterly*, *45*(3), 425–455.

Allen, J. (2010). Powerful City Networks: More than Connections, Less than Domination and Control. *Urban Studies*, *47*(13), 2895–2911. https://doi.org/10.1177/0042098010377364

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. *Nature Human Behaviour*, *4*(3), 248–254. https://doi.org/10.1038/s41562-019-0803-3

Bathelt, H., Malmberg, A., & Maskell, P. (2004). Clusters and knowledge: Local buzz, global pipelines and the process of knowledge creation. *Progress in Human Geography*, *28*(1), 31–56. https://doi.org/10.1191/0309132504ph469oa

Bergé, L. R., Wanzenböck, I., & Scherngell, T. (2017). Centrality of regions in R&D networks: A new measurement approach using the concept of bridging paths. *Regional Studies*, *51*(8), 1165–1178. https://doi.org/10.1080/00343404.2016.1269885

Biggiero, L. (2002). The Location of Multinationals in Industrial Districts: Knowledge Transfer in Biomedicals. *The Journal of Technology Transfer*, *27*(1), 111–122. https://doi.org/10.1023/A:1013156822541

Boschma, R. (2005). Proximity and Innovation: A Critical Assessment. *Regional Studies*, *39*(1), 61–74. https://doi.org/10.1080/0034340052000320887

Boschma, R., & Frenken, K. (2006). Why is economic geography not an evolutionary science? Towards an evolutionary economic geography. *Journal of Economic Geography*, *6*(3), 273–302. https://doi.org/10.1093/jeg/lbi022

Breschi, S., & Lenzi, C. (2015). The Role of External Linkages and Gatekeepers for the Renewal and Expansion of US Cities' Knowledge Base, 1990–2004. *Regional Studies*, *49*(5), 782–797. https://doi.org/10.1080/00343404.2014.954534

Breschi, S., & Lissoni, F. (2001). Knowledge Spillovers and Local Innovation Systems: A Critical Survey. *Industrial and Corporate Change*, *10*(4), 975–1005. https://doi.org/10.1093/icc/10.4.975

Broekel, T. (2012). Collaboration Intensity and Regional Innovation Efficiency in Germany—A Conditional Efficiency Approach. *Industry & Innovation*, *19*(2), 155–179. https://doi.org/10.1080/13662716.2012.650884

Burt, R. S. (1992). *Structural Holes: The Social Structure of Competition*. Harvard University Press.

Burt, R. S. (1997). The Contingent Value of Social Capital. *Administrative Science Quarterly*, *42*(2), 339–365.

Burt, R. S. (2000). Decay functions. *Social Networks*, *22*(1), 1–28. https://doi.org/10.1016/S0378-8733(99)00015-5

Burt, R. S. (2002). Bridge decay. *Social Networks*, *24*(4), 333–363. https://doi.org/10.1016/S0378-8733(02)00017-5

Burt, R. S. (2005). *Brokerage & Clusters*. Oxford University Press.

Butts, C. T. (2016). *sna: Tools for Social Network Analysis.* (R package version 2.4) [Computer software]. https://CRAN.R-project.org/package=sna

Camagni, R. (1991). *Innovation Networks: Spatial Perspectives*. Belhaven.

Coleman, J. S. (1988). Social Capital in the Creation of Human Capital. *American Journal of Sociology*, *94*(1988), S95–S120.

Crescenzi, R., Nathan, M., & Rodríguez-Pose, A. (2016). Do inventors talk to strangers? On proximity and collaborative knowledge creation. *Research Policy*, *45*(1), 177–194. https://doi.org/10.1016/j.respol.2015.07.003

De Prato, G., & Nepelski, D. (2014). Global technological collaboration network: Network analysis of international co-inventions. *The Journal of Technology Transfer*, *39*(3), 358–375. https://doi.org/10.1007/s10961-012-9285-4

Diani, M., & McAdam, D. (2003). *Social Movements and Networks*. Oxford University Press. https://doi.org/10.1093/0199251789.001.0001

Feldman, M. P., & Kogler, D. F. (2010). Stylized Facts in the Geography of Innovation. In *Handbook of the Economics of Innovation* (Vol. 1, pp. 381–410). Elsevier. https://doi.org/10.1016/S0169-7218(10)01008-7

Fernandez, R. M., & Gould, R. V. (1994). A Dilemma of State Power: Brokerage and Influence in the National Health Policy Domain. *American Journal of Sociology*, *99*(6), 1455–1491.

Françoso[1], M. S., & Vonortas, N. S. (2022). Gatekeepers in regional innovation networks: Evidence from an emerging economy. *The Journal of Technology Transfer*. https://doi.org/10.1007/s10961-022-09922-4

Fukuyama, F. (1996). *Trust: The social virtues and the creation of prosperity* (1. Free Press paperback ed). Free Press.

Gilsing, V., Nooteboom, B., Vanhaverbeke, W., Duysters, G., & van den Oord, A. (2008). Network embeddedness and the exploration of novel technologies: Technological distance, betweenness centrality and density. *Research Policy*, *37*(10), 1717–1731. https://doi.org/10.1016/j.respol.2008.08.010

Giuliani, E., & Bell, M. (2005). The micro-determinants of meso-level learning and innovation: Evidence from a Chilean wine cluster. *Research Policy*, *34*(1), 47–68. https://doi.org/10.1016/j.respol.2004.10.008

Glückler, J. (2007). Economic geography and the evolution of networks. *Journal of Economic Geography*, *7*(5), 619–634. https://doi.org/10.1093/jeg/lbm023

Gould, R. V., & Fernandez, R. M. (1989). Structures of Mediation: A Formal Approach to Brokerage in Transaction Networks. *Sociological Methodology*, *19*, 89. https://doi.org/10.2307/270949

Graf, H., & Krüger, J. J. (2011). The Performance of Gatekeepers in Innovator Networks. *Industry & Innovation*, *18*(1), 69–88. https://doi.org/10.1080/13662716.2010.528932

Griliches, Z. (1979). Issues in Assessing the Contribution of Research and Development to Productivity Growth. *The Bell Journal of Economics*, *10*(1), 92. https://doi.org/10.2307/3003321

Griliches, Z. (1984). *R&D, Patents, and Productivity* (N. B. of E. Research, Ed.). University of Chicago Press.

Guan, J., & Liu, N. (2016). Exploitative and exploratory innovations in knowledge network and collaboration network: A patent analysis in the technological field of nano-energy. *Research Policy*, *45*(1), 97–112. https://doi.org/10.1016/j.respol.2015.08.002

Haas, A. (2015). Crowding at the frontier: Boundary spanners, gatekeepers and knowledge brokers. *Journal of Knowledge Management*, *19*(5), 1029–1047. https://doi.org/10.1108/JKM-01-2015-0036

Hajek, P., Henriques, R., & Hajkova, V. (2014). Visualising components of regional innovation systems using self-organizing maps—Evidence from European regions. *Technological Forecasting and Social Change*, *84*, 197–214. https://doi.org/10.1016/j.techfore.2013.07.013

Henderson, R., & Cockburn, I. (1996). Scale , Scope , and Spillovers: The Determinants of Research Productivity in Drug Discovery. *The RAND Journal of Economics*, *27*(1), 32–59.

Hennemann, S., & Derudder, B. (2014). An Alternative Approach to the Calculation and Analysis of Connectivity in the World City Network. *Environment and Planning B: Planning and Design*, *41*(3), 392–412. https://doi.org/10.1068/b39108

Hidalgo, C. A., Klinger, B., Barabasi, A.-L., & Hausmann, R. (2007). The Product Space Conditions the Development of Nations. *Science*, *317*(5837), 482–487. https://doi.org/10.1126/science.1144581

Hoechle, D. (2007). Robust standard errors for panel regressions with cross-sectional dependence. *Stata Journal*, *7*(3), 281–312. https://doi.org/The Stata Journal

Jiang, J., Goel, R. K., & Zhang, X. (2019). Knowledge flows from business method software patents: Influence of firms' global social networks. *Journal of Technology Transfer*, *44*(4), 1070–1096. https://doi.org/10.1007/s10961-017-9645-1

Khanna, T., Gulati, R., & Nohria, N. (1998). The dynamics of learning alliances: Competition, cooperation, and relative scope. *Strategic Management Journal*, *19*(3), 193–210. https://doi.org/10.1002/(SICI)1097-0266(199803)19:3<193::AID-SMJ949>3.0.CO;2-C

Kogler, D. F., Rigby, D. L., & Tucker, I. (2013). Mapping Knowledge Space and Technological Relatedness in US Cities. *European Planning Studies*, *21*(9), 1374–1391. https://doi.org/10.1080/09654313.2012.755832

Krackhardt, D., & Stern, R. N. (1988). Informal Networks and Organizational Crises: An Experimental Simulation. *Social Psychology Quarterly*, *51*(2), 123. https://doi.org/10.2307/2786835

Krätke, S. (2007). Metropolisation of the European Economic Territory as a Consequence of Increasing Specialisation of Urban Agglomerations in the Knowledge Economy. *European Planning Studies*, *15*(1), 1–27. https://doi.org/10.1080/09654310601016424

Le Gallo, J., & Plunket, A. (2020). Regional gatekeepers, inventor networks and inventive performance: Spatial and organizational channels. *Research Policy*, *49*(5), 103981. https://doi.org/10.1016/j.respol.2020.103981

Leydesdorff, L., Alkemade, F., Heimeriks, G., & Hoekstra, R. (2015). Patents as instruments for exploring innovation dynamics: Geographic and technological perspectives on "photovoltaic cells". *Scientometrics*, *102*(1), 629–651. https://doi.org/10.1007/s11192-014-1447-8

Long, J. S., & Ervin, L. H. (2000). Using Heteroscedasticity Consistent Standard Errors in the Linear Regression Model. *The American Statistician*, *54*(3), 217–224. https://doi.org/10.1080/00031305.2000.10474549

Martinus, K., Sigler, T., Iacopini, I., & Derudder, B. (2021). The brokerage role of small states and territories in global corporate networks. *Growth and Change*, *52*(1), 12–28. https://doi.org/10.1111/grow.12336

Merton, R. K. (1957). *Social theory and social structure* (Enlarged ed., [Nachdr.]). Free Press.

Mitze, T., & Strotebeck, F. (2019). Determining factors of interregional research collaboration in Germany's biotech network: Capacity, proximity, policy? *Technovation*, *80–81*, 40–53. https://doi.org/10.1016/j.technovation.2018.11.001

Morrison, A. (2008). Gatekeepers of Knowledge within Industrial Districts: Who They Are, How They Interact. *Regional Studies*, *42*(6), 817–835. https://doi.org/10.1080/00343400701654178

Morrison, A., Rabellotti, R., & Zirulia, L. (2013). When Do Global Pipelines Enhance the Diffusion of Knowledge in Clusters? *Economic Geography*, *89*(1), 77–96. https://doi.org/10.1111/j.1944-8287.2012.01167.x

Podolny, J. M., & Stuart, T. E. (1995). A Role-Based Ecology of Technological Change. *American Journal of Sociology*, *100*(5), 1224–1260.

Rigby, D. L. (2015). Technological Relatedness and Knowledge Space: Entry and Exit of US Cities from Patent Classes. *Regional Studies*, *49*(11), 1922–1937. https://doi.org/10.1080/00343404.2013.854878

Ryall, M. D., & Sorenson, O. (2007). Brokers and Competitive Advantage. *Management Science*, *53*(4), 566–583. https://doi.org/10.1287/mnsc.1060.0675

Sapsed, J., Grantham, A., & DeFillippi, R. (2007). A bridge over troubled waters: Bridging organisations and entrepreneurial opportunities in emerging sectors. *Research Policy*, *36*(9), 1314–1334. https://doi.org/10.1016/j.respol.2007.05.003

Scholvin, S., Breul, M., & Diez, J. R. (2019). Revisiting gateway cities: Connecting hubs in global networks to their hinterlands. *Urban Geography*, *40*(9), 1291–1309. https://doi.org/10.1080/02723638.2019.1585137

Seo, I. (2019). Regions' technology brokerage patterns and dynamics for regional development. *Sustainability (Switzerland)*, *11*(9). https://doi.org/10.3390/su11092540

Shi, W., Markoczy, L., & Dess, G. G. (2009). The Role of Middle Management in the Strategy Process: Group Affiliation, Structural Holes, and Tertius Iungens. *Journal of Management*, *35*(6), 1453–1480. https://doi.org/10.1177/0149206309346338

Sigler, T. (2013). Relational Cities: Doha, Panama City, and Dubai as 21st Century Entrepots. *Urban Geography*, *34*(5), 612–633. https://doi.org/10.1080/02723638.2013.778572

Sigler, T., Neal, Z. P., & Martinus, K. (2021). The brokerage roles of city-regions in global corporate networks. *Regional Studies*, 1–12. https://doi.org/10.1080/00343404.2021.1950914

Simmel, G. (1922). *Conflict and the web of group affiliations*. Free Press. http://www.myilibrary.com?id=899370

Simmie, J. (2003). Innovation and Urban Regions as National and International Nodes for the Transfer and Sharing of Knowledge. *Regional Studies*, *37*(6–7), 607–620. https://doi.org/10.1080/0034340032000108714

Stojčić, N. (2021). Collaborative innovation in emerging innovation systems: Evidence from Central and Eastern Europe. *The Journal of Technology Transfer*, *46*(2), 531–562. https://doi.org/10.1007/s10961-020-09792-8

Stuart, T. E., & Podolny, J. M. (1996). Local Search and the Evolution of Technological Capabilities. *Strategic Management Journal*, *17*, 21–38.

Szymczak, S. (2018). Production fragmentation and employment. Country-industry level analysis based on WIOD 2016. *Collegium of Economic Analysis Annals*, *53*, 131–146.

Vujanović, N., Radošević, S., Stojčić, N., Hisarciklilar, M., & Hashi, I. (2022). FDI spillover effects on innovation activities of knowledge using and knowledge creating firms: Evidence from an emerging economy. *Technovation*, *118*, 102512. https://doi.org/10.1016/j.technovation.2022.102512

Appendices

A. Data information

Table A.1: Top 5 brokering regions and their major firms per period

Period	Region	Firm	Patents	Prop.
1986-1990	Munich (DE)	SIEMENS	4,175	0.59
1986-1990	Paris (FR)	THALES	1,076	0.07
1986-1990	Stuttgart (DE)	BOSCH	1,643	0.38
1986-1990	Frankfurt (DE)	AVENTIS	2,012	0.39
1986-1990	Ruhrgebiet (DE)	THYSSENKRUPP	341	0.17
1991-1995	Paris (FR)	ALCATEL	897	0.05
1991-1995	Munich (DE)	SIEMENS	3,992	0.52
1991-1995	Frankfurt (DE)	AVENTIS	1,426	0.28
1991-1995	Stuttgart (DE)	BOSCH	1,696	0.34
1991-1995	Ruhrgebiet (DE)	DEGUSSA	262	0.14
1996-2000	Paris (FR)	ALCATEL	1,940	0.09
1996-2000	Munich (DE)	SIEMENS	6,618	0.42
1996-2000	Frankfurt (DE)	CLARIANT	445	0.09
1996-2000	Stuttgart (DE)	BOSCH	4,751	0.47
1996-2000	London (UK)	UNILEVER	774	0.11
2001-2005	Paris (FR)	L'OREAL	1,707	0.07
2001-2005	Munich (DE)	SIEMENS	6,757	0.35
2001-2005	Frankfurt (DE)	CONTINENT	436	0.10
2001-2005	Stuttgart (DE)	BOSCH	5,603	0.45
2001-2005	Basel (CH)	ROCHE	1,089	0.25
2006-2010	Paris (FR)	CEA	2,015	0.07
2006-2010	Munich (DE)	SIEMENS	6,330	0.31
2006-2010	Berlin (DE)	BAYERHEALTH	340	0.11
2006-2010	Basel (CH)	ABBASEA	1,445	0.34
2006-2010	Frankfurt (DE)	CONTINENT	446	0.13
2011-2015	Paris (FR)	CEA	2,105	0.10
2011-2015	Munich (DE)	SIEMENS	6,162	0.39
2011-2015	Basel (CH)	ABBASEA	1,455	0.41
2011-2015	Frankfurt (DE)	HERAEUSDENTAL	320	0.14
2011-2015	Stuttgart (DE)	BOSCH	3,748	0.46

Notes: “Firms” indicates the major firm, those that display the highest number of patents in the observed timeframe. “Patents” indicates the firms’ total number of patents. “Prop.” indicates the proportion of patents assigned to a specific firm out of the total number of patents assigned to all firms and entities in the region. Regions are sorted by the average values of their three brokerage roles.

Table A.2: Correlation matrix

		1	2	3	4	5	6	7	8	9	10
1	COO										
2	CON	0.17									
3	LIA	0.49	0.82								
4	Coll.Int	0.01	-0.06	-0.06							
5	RCA	0.42	0.23	0.30	-0.20						
6	EMP.M	0.41	0.31	0.45	-0.20	0.38					
7	GDP	0.27	0.18	0.27	-0.21	0.57	0.08				
8	EMP	0.10	-0.03	-0.05	-0.03	0.20	0.19	0.12			
9	INV	0.45	0.42	0.42	-0.02	0.51	0.10	0.44	0.25		
10	Adj.Reg	0.33	0.16	0.24	0.00	0.31	0.31	-0.06	0.11	0.16	
11	Metro	0.31	0.20	0.26	-0.21	0.40	0.46	0.14	-0.03	0.18	0.12

Table A.3: Descriptive statistics

	Observation	Mean	Std. Dev.	Min	Max
Nov.INN	4,466	41.76	22.82	0	105
New.COL	4,466	61.73	48.49	0	313
COO	4,466	972.53	3,153.81	0	37,456
CON	4,466	71.15	433.41	0	9,810
LIA	4,466	1,018.09	4,768.91	0	109,202
Coll.Int	4,466	0.1	0.38	-0.92	1
RCA	4,466	71.76	47.5	1	226
EMP.M	4,466	188.86	266.7	4.22	3624.52
GDP	4,466	0.02	0.01	0	0.08
EMP	4,466	0.09	0.04	0.01	0.33
INV	4,466	0.16	0.23	0	3.78
Adj.Reg	4,466	5.11	2.1	0	16
Metro	4,466	0.27	0.44	0	1

B. Further results

Table B.1: Regression result of fixed-effects model: Novel Innovation (with country fixed effects)

	Dependent variable: Nov.INN				
	(1)	(2)	(3)	(4)	(5)
RCA	0.484***	0.490***	0.485***	0.471***	0.477***
	(0.025)	(0.024)	(0.025)	(0.026)	(0.025)
EMP.M	14.777***	14.591***	14.838***	15.287***	15.230***
	(1.114)	(1.092)	(1.121)	(1.120)	(1.044)
GDP	6..635***	6.596***	6.636***	7.427***	7.223***
	(1.174)	(2.182)	(2.201)	(2.158)	(2.184)
EMP	-12.773***	-12.747***	-12.894***	-13.522***	-13.500***
	(1.517)	(1.501)	(1.516)	(1.514)	(1.523)
INV	9.304***	9.101***	9.256***	9.496***	9.373***
	(0.749)	(0.729)	(0.743)	(0.749)	(0.737)
Adj.Reg	0.802***	0.854***	0.766***	0.819***	0.783***
	(0.254)	(0.250)	(0.253)	(0.250)	(0.249)
Metro	5.490***	5.356***	5.362***	5.105***	5.027***
	(1.426)	(1.401)	(1.372)	(1.406)	(1.356)
COO	-0.002***	-0.002***	-0.002***	-0.001***	-0.002***
	(0.0004)	(0.0003)	(0.0004)	(0.0004)	(0.0004)
CON	-0.009***	-0.009***	-0.006**		
	(0.003)	(0.003)	(0.003)		
LIA				-0.001***	-0.001***
				(0.0002)	(0.0002)
Coll.Int	4.077***	3.253***	3.743***	4.066***	3.562***
	(1.096)	(1.022)	(1.081)	(1.084)	(1.044)
COO×Coll.Int		0.002			
		(0.001)			
CON×Coll.Int			0.014*		
			(0.008)		
LIA×Coll.Int					0.001***
					(0.0004)
Time	Included	Included	Included	Included	Included
Country	Included	Included	Included	Included	Included
Observation	4,357	4,357	4,357	4,357	4,357
R^2	0.774	0.774	0.775	0.775	0.776
Adj R^2	0.772	0.772	0.773	0.772	0.774
F Stat	398.916***	389.878***	390.465***	400.815***	392.859***
	(df=37;4315)	(df=38;4314)	(df=38;4314)	(df=37;4315)	(df=38;4314)

Notes: All time-varying covariates are lagged one period; Robust standard errors in parenthesis; * p < 0.10, ** p < 0.05, *** p < 0.01

Table B.2: Regression result of fixed-effects model: New collaboration (with country fixed effects)

	Dependent variable: New.COL				
	(1)	(2)	(3)	(4)	(5)
RCA	0.054***	0.055***	0.054***	0.052***	0.052***
	(0.015)	(0.014)	(0.015)	(0.014)	(0.015)
EMP.m	3.859***	3.843***	3,861***	4.315***	4.313***
	(0.747)	(0.743)	(0.752)	(0.720)	(0.721)
GDP	2.990**	2.985**	2.990***	3.471**	3.462*** (1.374)
	(1.382)	(1.380)	(1.390)	(1.358)	
EMP	-4.451***	-4.441***	-4.453***	-5.149***	-5.149***
	(1.068)	(1.068)	(1.080)	(0.999)	(1.002)
INV	1.952***	1.936***	1.952***	2.106***	2.103*** (0.404)
	(0.405)	(0.395)	(0.405)	(0.409)	
Adj.Reg	-0.021	-0.016	-0.022	0.008	0.007
	(0.184)	(0.182)	(0.185)	(0.182)	(0.181)
Metro	6.492***	6.479***	6.489***	6.385***	6.382*** (10.838)
	(0.819)	(0.814)	(0.821)	(0.837)	
COO	0.002***	0.002***	0.002***	0.002***	0.002***
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0003)
CON	0.005**	0.005**	0.005		
	(0.002)	(0.002)	(0.003)		
LIA				0.0001	0.0001
				(0.0002)	(0.0003)
Col.Int	1.607***	1.526***	1.600***	1.633***	1.611***
	(0.515)	(0.467)	(0.536)	(0.521)	(0.538)
COO×Col.Int		0.0001			
		(0.0004)			
CON×Col.Int			0.0003		
			(0.008)		
LIA×Col.Int					0.001
					(0.0005)
Time	Included	Included	Included	Included	Included
Country	Included	Included	Included	Included	Included
Observation	4,242	4,242	4,242	4,242	4,242
R^2	0.754	0.754	0.754	0.747	0.747
Adj R^2	0.751	0.751	0.751	0.745	0.745
F Stat	346.998***	337.861***	337.791***	335.255***	326.376***
	(df=37;4200)	(df=38;4199)	(df=38;4199)	(df=37;4200)	(df=38;4199)

Notes: All time-varying covariates are lagged one period; Robust standard errors in parenthesis; * p < 0.10, ** p < 0.05, *** p < 0.01

Table B.3: Regression result of fixed-effects model with: Novel Innovation (with CEE.Reg dummy)

	Dependent variable: Nov.INN				
	(1)	(2)	(3)	(4)	(5)
RCA	0.495***	0.502***	0.502***	0.484***	5.818***
	(0.025)	(0.024)	(0.025)	(0.026)	(1.070)
EMP.M	11.621***	11.512***	11.772***	12.342***	0.494***
	(0.933)	(0.912)	(0.920)	(0.914)	(0.025)
GDP	-1.755	-1.750	-1.568	-1.048	12.253***
	(1.528)	(1.515)	(1.460)	(1.493)	(0.924)
EMP	-6.762***	-6.814***	-7.026***	-7.868***	-7.715***
	(1.339)	(1.328)	(1.254)	(1.265)	(1.253)
INV	10.702***	10.463***	10.536***	10.962***	10.727***
	(0.755)	(0.728)	(0.747)	(0.768)	(0.745)
Adj.Reg	0.819***	0.872***	0.774***	0.837***	0.775***
	(0.249)	(0.245)	(0.246)	(0.247)	(0.247)
Metro	7.992***	7.776***	7.617***	7.574***	7.367***
	(1.520)	(1.474)	(1.392)	(1.446)	(1.364)
CEE.Reg	0.752	0.998	1.097	1.503	1.513
	(2.238)	(2.916)	(2.179)	(2.207)	(2.183)
COO	-0.002***	-0.002***	-0.002***	-0.001***	-0.001***
	(0.0003)	(0.0003)	(0.0003)	(0.0004)	(0.0003)
CON	-0.005	-0.005	-0.003**		
	(0.004)	(0.004)	(0.001)		
LIA				-0.001***	-0.0004***
				(0.0003)	(0.0001)
Coll.Int	6.438***	5.492***	5.906***	6.513***	5.818***
	(1.122)	(1.051)	(1.106)	(1.117)	(1.070)
COO×Coll.Int		0.002*			
		(0.001)			
CON×Coll.Int			0.018***		
			(0.006)		
LIA×Coll.Int					0.002***
					(0.0004)
Time	Included	Included	Included	Included	Included
Observation	4,257	4,257	4,257	4,257	4,257
R^2	0.762	0.763	0.764	0.763	0.765
Adj R^2	0.761	0.762	0.763	0.762	0.764
F Stat	1,231.036***	1,134.461***	1,144.210***	1,242.702***	1,151.280***
	(df=11;4241)	(df=12;4240)	(df=12;4240)	(df=11;4241)	(df=12;4240)

Notes: All time-varying covariates are lagged one period; Robust standard errors in parenthesis; * p < 0.10, ** p < 0.05, *** p < 0.01

Table B.4: Regression result of fixed-effects model: New collaboration (with CEE.Reg dummy)

	Dependent variable: New.COL				
	(1)	(2)	(3)	(4)	(5)
RCA	0.063***	0.064***	0.064***	0.058***	0.062***
	(0.017)	(0.017)	(0.017)	(0.018)	(0.018)
EMP.m	0.389	0.373	0.425	0.692	0.662
	(0.711)	(0.705)	(0.725)	(0.701)	(0.692)
GDP	-2.637**	-2.640**	-2.595**	-2.769**	-2.836**
	(1.067)	(1.063)	(1.067)	(1.190)	(1.170)
EMP	0.470	0.456	0.408	0.065	0.117
	(1.001)	(0.997)	(1.022)	(0.932)	(0.902)
INV	2.578***	2.545***	2.547***	2.973***	2.894***
	(0.522)	(0.515)	(0.517)	(0.569)	(0.539)
Adj.Reg	0.458**	0.467**	0.448**	0.539**	0.516**
	(0.208)	(0.205)	(0.208)	(0.212)	(0.210)
Metro	9.243***	9.205***	9.160***	9.624***	9.545***
	(1.002)	(0.996)	(1.003)	(1.113)	(1.080)
CEE.Reg	-1.099	-1.053	-1.018	-1.073	-1.070
	(1.225)	(1.216)	(1.238)	(1.296)	(1.276)
COO	0.003***	0.003***	0.003***	0.002***	0.002***
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
CON	0.008***	0.008***	0.008***		
	(0.002)	(0.02)	(0.002)		
LIA				0.0004*	0.001**
				(0.0002)	(0.0003)
Col.Int	3.011***	2.835***	2.885***	3.041***	2.765***
	(0.737)	(0.722)	(0.721)	(0.765)	(0.706)
COO×Col.Int		0.0003			
		(0.0004)			
CON×Col.Int			0.004		
			(0.007)		
LIA×Col.Int					0.001
					(0.0004)
Time	Included	Included	Included	Included	Included
Observation	4,142	4,142	4,142	4,142	4,142
R^2	0.673	0.673	0.674	0.651	0.653
Adj R^2	0.672	0.672	0.672	0.65	0.651
F Stat	771.125***	707.332***	709.304***	699.303***	646.042***
	(df=11;4126)	(df=12;4125)	(df=12;4125)	(df=11;4126)	(df=12;4125)

Notes: All time-varying covariates are lagged one period; Robust standard errors in parenthesis; * p < 0.10, ** p < 0.05, *** p < 0.01

Table B.5: Regression result of fixed-effects model: Novel Innovation (without Central and Eastern European regions)

	Dependent variable: Nov.INN				
	(1)	(2)	(3)	(4)	(5)
RCA	0.435***	0.439***	0.441***	0.420***	0.429***
	(0.029)	(0.028)	(0.029)	(0.029)	(0.029)
EMP.M	11.885***	11.803***	12.020***	12.810***	12.718***
	(1.154)	(1.146)	(1.149)	(1.154)	(1.160)
GDP	-7.334***	-7.402***	-7.199***	-6.356***	-6.552***
	(1.789)	(1.784)	(1.767)	(1.766)	(1.750)
EMP	-1.813	-1.796	-2.026	-3.248*	-3.083**
	(1.436)	(1.435)	(1.403)	(1.414)	(1.398)
INV	10.709***	10.570***	10.557***	11.082***	10.878***
	(0.859)	(0.847)	(0.858)	(0.867)	(0.867)
Adj.Reg	1.124***	1.156***	1.085***	1.152***	1.101***
	(0.277)	(0.274)	(0.274)	(0.278)	(0.276)
Metro	12.322***	12.206***	11.980***	11.785***	11.627***
	(1.335)	(1.668)	(1.625)	(1.653)	(1.611)
COO	-0.002***	-0.002***	-0.002***	-0.001***	-0.002**
	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)
CON	-0.005**	-0.005**	-0.003*		
	(0.003)	(0.003)	(0.002)		
LIA				-0.001***	-0.001***
				(0.0002)	(0.0002)
Coll.Int	3.938***	3.306***	3.389***	4.067***	3.411***
	(1.285)	(1.236)	(1.261)	(1.281)	(1.234)
COO×Coll.Int		0.001			
		(0.001)			
CON×Coll.Int			0.016***		
			(0.005)		
LIA×Coll.Int					0.001***
					(0.0004)
Time	Included	Included	Included	Included	Included
Observation	3,876	3,876	3,876	3,876	3,876
R^2	0.682	0.683	0.684	0.685	0.686
Adj R^2	0.681	0.681	0.683	0.684	0.685
F Stat	829.388***	754.890***	760.998***	838.829***	767.048***
	(df=10;3860)	(df=11;3859)	(df=11;3859)	(df=10;3860)	(df=11;3859)

Notes: All time-varying covariates are lagged one period; Robust standard errors in parenthesis; * p < 0.10, ** p < 0.05, *** p < 0.01

Table B.6: Regression result of fixed-effects model: New collaboration (without Central and Eastern European regions)

	Dependent variable: New.COL				
	(1)	(2)	(3)	(4)	(5)
RCA	0.052***	0.053***	0.053***	0.046***	0.050***
	(0.019)	(0.018)	(0.019)	(0.019)	(0.019)
EMP.m	0.132	0.119	0.161	0.476	0.440
	(0.760)	(0.755)	(0.755)	(0.760)	(0.754)
GDP	-4.156***	-4.171***	-4.128***	-4.200**	-4.291**
	(1.186)	(1.188)	(1.195)	(1.273)	(1.270)
EMP	1.631*	1.631*	1.583	1.103	1.165
	(0.960)	(0.960)	(0.985)	(0.878)	(0.849)
INV	2.570***	2.551***	2.542***	3.024***	2.949***
	(0.539)	(0.532)	(0.532)	(0.564)	(0.542)
Adj.Reg	0.501** (0.212)	0.506** (0.212)	0.493** (0.212)	0.587***	0.566***
				(0.215)	(0.213)
Metro	10.880***	10.861***	10.808***	11.297***	11.233***
	(1.063)	(1.057)	(1.069)	(1.163)	(1.138)
COO	0.003***	0.003***	0.003***	0.002***	0.002***
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0003)
CON	0.008***	0.008***	0.008***		
	(0.0002)	(0.0002)	(0.002)		
LIA				0.0004*	0.001*
				(0.0002)	(0.0003)
Col.Int	2.551***	2.443***	2.431***	2.633***	2.352***
	(0.778)	(0.761)	(0.759)	(0.808)	(0.757)
COO×Col.Int		0.0002			
		(0.001)			
CON×Col.Int			0.003		
			(0.007)		
LIA×Col.Int					0.001
					(0.0005)
Time	Included	Included	Included	Included	Included
Observation	3,821	3,821	3,821	3,821	3,821
R^2	0.654	0.654	0.655	0.633	0.634
Adj R^2	0.653	0.653	0.653	0.631	0.632
F Stat	720.293***	654.792***	656.273***	655.109***	598.993***
	(df=10;3805)	(df=11;3804)	(df=11;3804)	(df=10;3805)	(df=11;3804)

Notes: All time-varying covariates are lagged one period; Robust standard errors in parenthesis; * p < 0.10, ** p < 0.05, *** p < 0.01

Table B.7: Regression result of fixed-effects model: Novel Innovation (two periods lag)

	Dependent variable: Nov.INN				
	(1)	(2)	(3)	(4)	(5)
RCA	0.482***	0.492***	0.490***	0.472***	0.486***
	(0.028)	(0.027)	(0.027)	(0.028)	(0.027)
EMP.M	12.330***	12.145***	12.469***	12.988***	12.802***
	(1.064)	(1.045)	(1.047)	(1.044)	(1.063)
GDP	-5.160***	-5.270***	-5.318***	-4.763***	-4.995***
	(1.367)	(1.354)	(1.336)	(1.362)	(1.339)
EMP	-4.546***	-4.481***	-4.737***	-5.416***	-5.160***
	(1.415)	(1.405)	(1.351)	(1.357)	(1.360)
INV	10.513***	10.194***	10.334***	10.704***	10.388***
	(0.785)	(0.759)	(0.777)	(0.785)	(0.763)
Adj.Reg	1.172***	1.229***	1.125***	1.157***	1.092***
	(0.279)	(0.276)	(0.277)	(0.278)	(0.279)
Metro	9.448***	9.227***	9.076***	8.974***	8.773***
	(1.724)	(1.690)	(1.629)	(1.666)	(1.603)
COO	-0.002***	-0.002***	-0.003***	-0.002***	-0.002***
	(0.0003)	(0.0003)	(0.0003)	(0.0004)	(0.0003)
CON	-0.008*	-0.007*	-0.004**		
	(0.004)	(0.004)	(0.002)		
LIA				-0.001***	-0.0005**
				(0.0003)	(0.0002)
Coll.Int	5.800***	4.768***	5.293***	5.836***	5.070***
	(1.300)	(1.266)	(1.287)	(1.292)	(1.253)
COO×Coll.Int		0.002**			
		(0.001)			
CON×Coll.Int			0.022***		
			(0.006)		
LIA×Coll.Int					0.002***
					(0.0004)
Time	Included	Included	Included	Included	Included
Observation	3,306	3,306	3,306	3,306	3,306
R^2	0.733	0.735	0.736	0.734	0.737
Adj R^2	0.732	0.733	0.735	0.733	0.736
F Stat	905.330***	828.010***	834.239***	910.499***	838.526***
	(df=10;3292)	(df=11;3291)	(df=11;3291)	(df=10;3292)	(df=11;3291)

Notes: All time-varying covariates are lagged two periods; Robust standard errors in parenthesis; * p < 0.10, ** p < 0.05, *** p < 0.01

Table B.8: Regression result of fixed-effects model: New collaboration (two periods lag)

	Dependent variable: New.COL				
	(1)	(2)	(3)	(4)	(5)
RCA	0.069***	0.069***	0.070***	0.064***	0.066***
	(0.021)	(0.021)	(0.021)	(0.022)	(0.021)
EMP.m	0.368	0.374	0.386	0.749	0.722
	(0.867)	(0.869)	(0.882)	(0.832)	(0.829)
GDP	-2.920***	-2.916***	-2.917***	-2.921***	-2.955***
	(0.963)	(0.965)	(0.957)	(1.023)	(1.033)
EMP	1.301	1.298	1.276	0.806	0.845
	(1.102)	(1.104)	(1.122)	(1.010)	(0.987)
INV	2.718***	2.729***	2.695***	3.054***	3.007***
	(0.586)	(0.584)	(0.591)	(0.621)	(0.596)
Adj.Reg	0.648***	0.646***	0.641***	0.720***	0.710***
	(0.235)	(0.234)	(0.238)	(0.239)	(0.237)
Metro	10.375***	10.383***	10.326***	10.659***	10.629***
	(1.160)	(1.161)	(1.180)	(1.260)	(1.250)
COO	0.003***	0.003***	0.003***	0.002***	0.002***
	(0.0002)	(0.0002)	(0.0002)	(0.0003)	(0.0003)
CON	0.008***	0.008***	0.008**		
	(0.002)	(0.002)	(0.004)		
LIA				0.0003	0.0004
				(0.0003)	(0.0004)
Col.Int	3.214***	3.250***	3.146***	3.344***	3.228***
	(0.893)	(0.895)	(0.889)	(0.904)	(0.845)
COO×Col.Int		-0.0001			
		(0.0005)			
CON×Col.Int			0.003		
			(0.011)		
LIA×Col.Int					0.0003
					(0.001)
Time	Included	Included	Included	Included	Included
Observation	3,259	3,259	3,259	3,259	3,259
R^2	0.622	0.622	0.623	0.607	0.608
Adj R^2	0.621	0.621	0.621	0.606	0.606
F Stat	534.543***	485.816***	486.373***	501.861***	456.744***
	(df=10;3245)	(df=11;3244)	(df=11;3244)	(df=10;3245)	(df=11;3244)

Notes: All time-varying covariates are lagged two periods; Robust standard errors in parenthesis; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$