COLLABORATIVE PATENTS AND THE MOBILITY OF KNOWLEDGE WORKERS

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Abstract

This study explores the importance of the mobility of knowledge workers (i.e., inventors) for the formation of collaborative patents across different regional contexts. In particular, it looks at a sample of co-inventors in the biotechnology industry in Europe, and estimates the factors that speed up the years needed for collaboration. It tests and finds that collaborations between two separated inventors emerge faster if they were located in the same geographical area in the past, even after controlling for a large number of meaningful proximities between them. Furthermore, the empirical approach suggests that this 'previous co-location' premium becomes more valuable when other channels of interaction – social, cognitive, institutional, geographic – are weak or non-existent, and in fostering international technological collaborations.

Key words: biotechnology, collaborative patents, inventors, mobility, regions

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1. Introduction

This paper addresses the question of whether the mobility of high skilled workers across cities and regions fosters collaborative work and teamwork formation. Collaborative work is becoming increasingly decisive for innovation and knowledge production (Jones et al., 2008; Jones, 2010; Wuchty et al., 2007). New knowledge is more likely to flourish when recombining already existing ideas (Fleming, 2001; Nelson and Winter, 1982), so new inventions are increasingly the result of cooperation between organizations (Powell and Grodal, 2005; Singh and Fleming, 2010). As it has been repeatedly shown by the innovation management literature, inter-organizational cooperation networks positively influence firm innovation and performance (see Bergenholtz and Waldstrøm, 2011; and Najafian and Colabi, 2014, for a review of the literature). This is more so when connecting heterogeneous regional contexts, from which unusual combinations are more likely to arise and produce radical innovations (Bell and Zaheer, 2007; Zhou and Li, 2012).

However, teamwork formation tends to be geographically bounded, as proximity eases communication and saves time and coordination costs (Phelps et al., 2012). In contrast, knowledge accessed through local linkages might be less novel and less useful than knowledge transferred between geographically distant actors, with potentially harmful consequences – i.e., technological lock-in (Bell and Zaheer, 2007; Corredoira and Rosenkopf, 2010; David, 1993; Gittelman, 2007).

This paper focuses on knowledge workers – i.e., inventors – and their collaborative networks. Inventors are a special set of R&D employees who are arguably at the forefront of technological innovation. They usually possess highly relevant and valuable knowledge for the firm employing them, highly complex and of tacit nature, which makes them critical for the competitiveness of their employers (Miguelez and Fink, 2013). Although their individual networks do not necessarily overlap with inter-organizational ties (Sedita, 2008), firms can exploit the connections and relations of these key employees to access external knowledge and improve their innovation performance (Ellis, 2011; Wong and Ellis, 2002).

In particular, in this paper we look at inventors' mobility across different regional contexts and its influence on the formation of collaborative patents across the space. Inventors' geographical mobility bridges distant domains, enabling them to overcome localization constraints in their search for external knowledge.

To put these ideas into test, the paper reproduces and adapts Agrawal's et al. (2006) seminal 'enduring social capital' hypothesis ('Gone but not forgotten'). That is, informal ties, trust and mutual understanding, built after years of co-location in the same spatial context, may well survive the spatial separation of the individuals and be a source of knowledge diffusion. The tenet of this paper is that the enduring social capital between previously co-located knowledge workers is also conducive to teamwork formation between inventors located far apart, which in turn is a way to access distant pools of knowledge and insightful ideas. Put differently, it aims to study whether inventors located in different spatial contexts will connect more rapidly if they were co-located in the past. Very few papers have looked at the relationship between mobility and collaborations, despite their importance from the academic and policy perspectives.

Moreover, the study provides additional evidence on the determinants of team formation in patent production, with an emphasis on the role played by different types of similarities between the individuals involved (social, institutional, cognitive, organizational, and geographic).

The study makes use of microdata on European inventors who have applied for European Patent Office (EPO) patents in the biotechnology industry, over the period 1978-2005. Biotechnology refers to the "application of science and technology to living organisms, as well as parts, products and models thereof, to alter living or non-living materials for the production of knowledge, goods and services" (OECD, 2009). A conditional fixed-effect logit model is estimated to ascertain whether there exists a 'previous co-location premium' on the speed by which ties are built up across different regional contexts.

The remainder of the paper is organized as follows: Section 2 reviews previous studies, bringing together dispersed, but related, literature, and outlines the conceptual framework. Section 3 describes the empirical approach taken here and the data sources. Section 4 presents the results, and Section 5 presents the discussion and conclusions.

2. Background framework and contributions of the present analysis

The study of network formation has long attracted a great deal of interest from various research streams, spanning the limits across disciplines and sub-disciplines. For instance, in the innovation management literature, models of in-house firm innovation have been largely superseded by models emphasizing its interactive/open character, where firms do not work in isolation to produce knowledge (Huggins and Thompson, 2017; Laursen and

Salter, 2006, 2014; West et al., 2014). Thus, firms' innovativeness is not solely the result of their internal assets, but to a large extent their capacity to have access to external-to-the-firm knowledge resources (Kogut, 1988; Nieto and Santamaría, 2007). In the so-called 'open innovation' perspective (Chesbrough, 2003; West et al., 2014), firms draw knowledge and expertise from a wide range of external sources (Björk and Magnusson, 2009; Laursen and Salter, 2006, 2014), and thus innovation is the outcome of a constant process of interaction and recombination among different actors (Cruz-González et al., 2015; Doloreux, 2004; Weitzman, 1998).

If recombination of ideas is key to knowledge creation, networking should be an important facet of firm innovation (Obstfeld, 2005). Exploring this bridge there has been an increasing number of studies linking inter-organizational networks and firm innovation (Belderbos et al., 2004; Björk and Magnusson, 2009; D'Agostino and Moreno, 2018; Faems et al., 2005; Fukugawa, 2006; Hoang and Rothaermel, 2005; Laursen and Salter, 2006, 2014; Nieto and Santamaría, 2007; Rodríguez et al., 2018; Zeng et al., 2010). In this framework, scholars have also looked at the determinants of network formation and partner selection (Baum et al., 2010; Belderbos et al., 2018; Bergenholtz and Waldstrøm, 2011; Cowan et al., 2007; Howells et al., 2004; Johnston and Huggins, 2018; Miotti and Sachwald, 2003; Rajalo and Vadi, 2017; Sakakibara, 2002; Zaheer et al., 2010). These studies conclude that the formation of inter-organizational networks entails significant transaction costs. These are related to the selection of appropriate partners, as well as other costs associated to coordination, managing common projects, and partners' monitoring (Nieto and Santamaría, 2007). These costs are likely to be large as the geographic, social, and cognitive distance increase (Paier and Scherngell, 2011).

The evolutionary economic geography perspective has also looked at network formation (Boschma and Frenken, 2010), and two strands of literature stand out: the network structural effects perspective and the proximity perspective (Cassi and Plunket, 2015). The former emphasizes the importance of the amount of knowledge that each partner can access from the others in the network – their network position (Autant-Bernard et al., 2007). The latter argues that partnering decisions are based on the logic of 'homophily' (McPherson et al., 2001). 'Homophily' refers to the homogeneity of individuals' personal relations in a range of socio-demographic and personal characteristics. Among others, 'homophily' may refer to the same regional context. Much of what is valuable from potential partners is tacit and, therefore, can only be communicated as a highly contextual metaphor. Close geographical proximity enables frequent face-to-face interactions and enhances social capital formation. As a result, team formation is more likely to occur between individuals who are closely located.

Yet, other non-geographical similarities have been highlighted as producing the same type of outcomes – such as social proximity, cognitive proximity, institutional proximity, or organizational proximity (Boschma, 2005). All these proximities have some fundamental elements in common: they reduce uncertainty, help in solving coordination problems and lower the cost of identifying partners.

In this research strand, several empirical exercises have attempted to identify the determinants of team formation. Fafchamps et al. (2010) estimate network effects in co-authorship formation among economists over a twenty-year period. Their findings consistently show that collaborations between pairs of economists emerge faster if they are closer to each other in the network of co-authors. Time-variant characteristics such as the individuals' productivity or their propensity to collaborate, as well as the cognitive proximity between the pair, equally influence team formation. Network effects *vis-à-vis* geographic proximity motivate a growing number of studies, such as Mariani (2004), Ter Wal (2014), Cassi and Plunket (2015), for the case of European inventors of the chemical industry, biotech inventors in Germany, and genomics inventors in France, respectively. Their findings can be summarized as follows: social, organizational, institutional, and cognitive proximities between agents strongly influence network formation. Notwithstanding, no empirical analysis has succeeded in explaining the role of geographical distance away. Actually, geography plays even a more critical role when collaboration involves very different organizations (such as industry-university interactions) (Cassi and Plunket, 2015).

A parallel strand of literature at the cross-roads of labor economics and the economics of innovation has paid a great deal of attention to the mobility of knowledge workers and its strategic implications for firm performance and knowledge transfer (Almeida and Kogut, 1999; Corredoira and Rosenkopf, 2010; Singh and Fleming, 2010). Several studies emphasize that highly-skilled mobile employees extend firms' geographic reach in their search for distant, more valuable pools of knowledge (Rosenkopf and Almeida, 2003; Song et al., 2003). Hence, the geographical mobility of inventors may potentially bridge distant spatial contexts, enabling firms to overcome localization constraints in their search for external knowledge.

In a similar vein, other papers have argued that the benefits of physical proximity between inventors established through long periods of co-location are durable and manifest among people after they become separated (Breschi and Lissoni, 2009). Mobile skilled workers, by not breaking their ties with their former colleagues, favor the diffusion of knowledge and ideas across firms, regions and even countries. Kaiser et al. (2011) identify positive effects on firm's innovation of enterprises losing an employee hired by a competing firm, for the case of Denmark. Corredoira and Rosenkopf (2010) show a disproportionately larger number of citations from the sending to the receiving firm after an employee has left the former for the latter, for the case of US inventors. This 'outbound mobility' effect is even stronger when mobility occurs between geographically dispersed firms, since co-located organizations usually exploit other cross-firms interactions channels (Corredoira and Rosenkopf, 2010). According to the authors' views, the leaving employee probably stays in contact with former colleagues, constituting in this way a source of knowledge diffusion from the hiring to the sending firm. This same issue was also devised in the study of Agrawal et al. (2006). Exploring inventors' mobility across different Metropolitan Statistical Areas (MSAs), the authors find that knowledge flows are around 50% more likely to go to the innovator's prior location than if he had never lived there. Thus, social ties created during inventors' co-localization, which facilitate knowledge diffusion, persist even after the inventors' separation and are conducive to knowledge flows. Oettl and Agrawal (2008) study builds upon the same idea. The authors estimate a fixed-effects negative binomial model to analyze backward knowledge flows between countries from the departing innovator to their former co-located colleagues. Indeed, mobile knowledge workers provide access to distant knowledge pools that neither the receiving firm and country nor the source firm and country might otherwise enjoy.

3. Research design

3.1. Estimation framework

This section describes the way in which the influence of the focal variable – the ‘previous co-location’, in the speed by which collaborative patents form across the space, is assed. A fixed-effects conditional logit model is estimated, which enables controlling for important time-invariant confounders. The paper looks at inventors’ co-patents across different European regions – basically NUTS3 regions, though robustness analysis includes NUTS2 regions. (NUTS is the French acronym *Nomenclature d'Unités Territoriales Statistiques*). Hence, it is of particular interest with respect to this paper to know what makes collaborations among inventors emerge faster, conditional upon not residing in the same region and not having co-patented before.

For each pair of inventors, a link is formed if and only if the associated payoffs are expected to be positive, $\pi_t^{ij} > 0$. This in turn depends upon i’s and j’s observable time-variant and non-observable time-invariant characteristics, X_t and γ^{ij} respectively, as well as a well-behaved error term, ε:

$$\Pr_t^{ij} = \Pr(\pi_t^{ij} > 0) = \beta_n \cdot X_t + \gamma^{ij} + \varepsilon_t^{ij}, \qquad (1)$$

where n stands for the number of regressors included in the model. The i’s and j’s observable features refer to i’s individual characteristics, j’s individual characteristics, as well as a set of proximities between the two – social, institutional, cognitive, organizational and geographic. In addition, a dummy variable reflecting whether the two individuals were spatially co-located in the past (valued 1) or not (valued 0) is introduced. This will test the main hypothesis of the paper, that is, the existence of the ‘previous co-location' effect. Thus, the latent payoffs of collaborating at time t are described by the following expression:

$$\pi_t^{ij} = \beta_t^i \cdot X_t^i + \beta_t^j \cdot X_t^j + \beta_t^{ij,\text{proximities}} \cdot X_t^{ij,\text{proximities}} + \beta_t^{ij,\text{co-location}} \cdot X_t^{ij,\text{co-location}} + \gamma^{ij} + \varepsilon_t^{ij}. \qquad (2)$$

The coefficient of interest, $\beta_t^{ij,\text{co-location}}$, will reflect co-inventorship changes attributed to mobility. As is customary in the related literature, a logit model is used to estimate the latent payoff.

Denote y_t^{ij} as the observed dependent variable, defined as a dummy taking the value 1 if a given pair of inventors collaborate at time t and 0 otherwise, conditional upon not having collaborated before, $t-s$. More formally, the specific data-generating process is expressed as follows:

$$\Pr(y_t^{ij} = 1 \mid y_{t-s}^{ij} = 0) = \frac{\exp(\beta_{t,n} \cdot X_{t,n} + \gamma^{ij})}{1 + \exp(\beta_{t,n} \cdot X_{t,n} + \gamma^{ij})}, \qquad (3)$$

where $y_{t-s}^{ij} = 0$ stands for the fact that the pair has never collaborated before. The r.h.s. variables are lagged to avoid simultaneity bias. Thus, the probability of forming a tie in time t will be a function of a number of regressors computed within rolling time windows of five or ten years, from, respectively, t-5 to t-1 and t-10 to t-1. γ^{ij} is a pair-wise fixed-effect that takes on board all time-invariant unobservable characteristics that a cross-sectional setting cannot account for. The introduction of pair-wise fixed-effects is highly valuable, since this allows a better identification of the influence of time-variant variables on the likelihood to observe a tie between inventors at time t. Note, importantly, that due to the introduction of fixed-effects, all the pairs potentially co-authors that never collaborated drop out, because the fixed-effects model requires time variation of the dependent variable – therefore, this information cannot be used. In this way, the model specifically estimates the effect of previous co-location on the number of years needed to collaborate. The way in which the variables are built is explained in detail in the following subsection.

3.2. Data sources and variables construction

Firstly, all EPO patent applications were retrieved for the period 1978 to 2005, having at least one technology class code corresponding to biotechnology. The REGPAT OECD database, January 2010 edition, is used (Maraut, 2008). Among the numerous information contained in patent data, is included the technology or technologies into which the patent is classified. Thus, the front page of an EPO patent contains a number of codes corresponding to the International Patent Classification (IPC) allowing the classification of patents onto different broad technologies. The technological classification of patents by Schmoch (2008) is followed to select and retrieve biotechnology patents. This means retrieving all patents which IPC codes starting with one of the following 4-digit strings: C07G, C12M, C12N, C12P, C12Q, C12R, or C12S. Afterwards, all the information regarding the inventors having at least one biotechnology patent and contained in the database is retrieved. Only inventors reporting a European postal address are considered. If an inventor has patented from Europe and also while residing abroad, all the information concerning his years in a non-European country is disregarded. Note that a single ID for each inventor and anyone else is missing in the database. However, in order to draw the spatial mobility and co-patenting history of inventors, it is necessary to identify them individually. This paper uses their name and surname, as well as other useful details contained in the patent document, for singling out individual inventors using patent documents. In brief, it first cleans, harmonizes and codes all the inventors' names and surnames. Afterwards, it tests whether each pair of names belongs to the same individual, using a wide range of characteristics, such as their address, the applicants and groups of applicants of their patents, their self-citations, or the technological classes to which their patents belong – up to 15 different tests were run (a detailed explanation of the chosen disambiguation process is presented in Appendix 1).

3.2.1. Dependent variable

All the realized ties during the whole period of analysis are scrutinized, building up all the possible pairs, that is, all the couples of inventors that have a co-patent. All ties occurring within the same region are removed. The pairs in which at least one of the inventors has only one patent are also disregarded. It is noteworthy that the interest is in knowing whether there exists a collaboration premium due to being co-located (residing in the same region) in the past. To that end, one needs to exploit the information concerning the inventors' past location. Similarly, all the pairs in which the focal co-patent is the first patent for at least one of the inventors of the pair are dropped, even if he has additional subsequent patents. Again, this is done because there is a need to observe patenting history before the date of the focal co-patent.

Each pair of inventors is considered active from the first year in which both inventors have a patent to the last year in which both of them have a patent as well. Note, however, that for now the only interest is in the determinants of the inventors' first collaboration, hence the years after their first collaboration are removed. Suppose that they have a co-patent at year t, t_{ij}. Therefore, the variable y_{ij} takes value 1 if $t = t_{ij}$, and 0 if $t < t_{ij}$. That is, for each pair, there will be a sequence from the first time they patent independently until their common co-patent, resulting in an unbalanced panel. Overall, there are 7,376 pairs of inventors forming linkages across NUTS3 regions. On average, the pairs take 4.5 years from their independent patenting to their common co-patent, ranging from a minimum of 2 years to a maximum of 21 years.

3.2.2. Explanatory variables

All the explanatory variables are built within time-windows of five years, in line with other studies (Breschi and Lenzi, 2016; Cassi and Plunket, 2014, 2015; Fleming et al., 2007b, 2007a; Lobo and Strumsky, 2008; Schilling and Phelps, 2007). The underlying assumption behind this choice is that the potentially existent social capital between two given inventors starts depreciating after five years if it is not fed with new interactions. Yet, any previous study has tested whether this is an acceptable assumption, so regressions using rolling time-windows of ten years will be also shown. Recall that the r.h.s. variables are lagged by one year to avoid biases due to system feedbacks. Thus, a set of explanatory variables computed from year t-5 to t-1 (and from t-10 to t-1) explains the formation of collaborative patents in year t. In consequence, all years of the dependent variables corresponding to the period 1978-1982 (1978-1987) are removed, since a 5-year (10-year) window lag for the explanatory variables cannot be computed from the raw data. All the explanatory variables are built using information from the REGPAT OECD database, January 2010 edition, unless otherwise noted.

Previous co-location: a dummy variable valued 1 if the two inventors resided in the same NUTS3 region in the period t-5 to t-1 (t-10 to t-1), and 0 otherwise, tests the main hypothesis of the present paper. The variable is re-built each year, and therefore it shows time variation for a reasonable proportion of the observations, making the conditional fixed-effects logit regression suitable to identify its effect (Allison, 2005, 2009) – although, as shown in the descriptive statistics section, this variable is relatively sparse compared to other binary ones included in the analysis.

Social proximity: to compute this variable, one starts by defining the co-inventorship network, from t-5 to t-1 (t-10 to t-1), where inventors are nodes and co-patents are the links between these nodes. Afterwards, computation is made of the shortest path between every pair of inventors of the sample for each time window, p_t^{ij}, that is, the shortest geodesic distance between the two. Consider the following example: if inventors i and j have both co-invented with z, but not between them, their shortest path is 2. Recall that the focus is on the determinants of first co-patenting, so the minimum shortest path possible between pairs of inventors is always 2. If two inventors do not have any common co-author, at any geodesic distance, their shortest path is infinite. For this reason, it is better to work with the inverse of the geodesic distance, that is, social proximity, defined as

$$s_t^{ij} = \frac{1}{p_t^{ij}} \tag{4}$$

which varies between 0 and 0.5. Social proximity equals 0.5 if the two inventors share at least one common co-inventor, and equals 0 when they are not connected at all.

Cognitive proximity: to proxy cognitive proximity this study uses an index of technological similarity as suggested in Jaffe (1986). Thus, the study computes the uncentered correlation between individuals' vector of technological classes in the form of:

$$t_{ij} = \frac{\sum f_{ih} f_{jh}}{\left(\sum f_{ih}^2 \sum f_{jh}^2\right)^{1/2}} . \qquad (5)$$

In (5), f_{ih} stands for the share of patents of one technological class h according to the IPC classification of the inventor i, and f_{jh} for the share of patents of one technological class h of the inventor j. Values of the index close to the unity would indicate that a given pair of inventors share almost the same fields of research, and values close to 0 means that they do not share research expertise at all.

Institutional proximity: proxied with a dummy variable valued 1 if the couplet of inventors used to work for the same type of applicant (company, university, non-profit organization, or hospital) according to their patent portfolio within the period t-5 to t-1 (t-10 to t-1), and 0 otherwise. Information on applicants' classification is retrieved from the EEE-PPAT database (Van Looy, 2006) and merged with the sample.

Organizational proximity: when the inventors of the pair have worked for the same organization in the past, they are a priori more willing to collaborate; that is to say, knowledge workers are more likely to form ties within organizational boundaries. This variable is proxied with a dummy taking the value 1 if the pair of inventors share at least one common applicant according to their patent portfolio within the period t-5 to t-1 (t-10 to t-1), and 0 otherwise. Harmonized and coded applicants' data are retrieved from the HAN database (Thoma et al., 2010), and merged with the sample.

Geographic proximity: This study proxies this variable as the linear distance (in hundreds km) between the centroids of each of the NUTS3 regions where each of the inventors involved in the pair reside, in each moment of time.

As the estimations could be compromised if time-varying features of the individual inventors have an impact on the likelihood to observe a tie, additional variables derived from the raw database are included.

Productivity: More productive innovators tend to attract other inventors to work with them. Omitting individuals' ability to produce patents may lead to inconsistent results. To proxy individuals' ability, q_t^i, the study includes the number of patents of each inventor through the time-window t-5 to t-1 (t-10 to t-1), weighted by the number of citations each patent has received, to account for heterogeneity in patent quality and relevance – citations data are retrieved from the OECD Citations database, January 2010. Note that the dependent variable is undirected, hence the same regressors are needed, irrespective of the order of indexation. The regressors are entered in a symmetrical way as in Fafchamps et al. (2010), that is, the average productivity

$$\bar{q}_t^{ij} = \frac{q_t^i + q_t^j}{2}, \tag{6}$$

and the absolute difference in productivity,

$$\Delta q_t^{ij} = \left| q_t^i - q_t^j \right|. \quad (7)$$

Degree centrality: One also needs to control for observed time-varying individuals' propensity to collaborate. The concept of *preferential attachment* states that highly connected actors are more likely to attract additional connections (Barabási and Albert, 1999). To that end, the innovators' degree centrality is computed, dc_t^i, within each time-window t-5 to t-1 (t-10 to t-1). Degree centrality corresponds to the number of co-inventors a given inventor has in a given time period. Again, this variable is introduced symmetrically as the average degree centrality,

$$\overline{dc}_t^{ij} = \frac{dc_t^i + dc_t^j}{2}, \quad (8)$$

and the absolute difference in degree centrality,

$$\Delta dc_t^{ij} = \left| dc_t^i - dc_t^j \right|. \quad (9)$$

3.3. Descriptive statistics

This section presents summary figures of the phenomena under study. Firstly, Table I provides an overview of the biotechnology sector in the EPO and some figures of the final dataset. From that table one learns the following main findings: first, the biotech industry accounts for 6.77% of all European inventors throughout the whole period (1978-2005), but only for 3.71% of the patents, which seems to indicate the importance of research teams in inventive activity – making the present analysis worthwhile. Only 37.36% of inventors (19,459) are multi-patent – and therefore constitute the focal group of analysis – of which only 9.15% are mobile across the space – report more than one NUTS3 region of residence. The number of observed cross-regional pair-wise linkages is, respectively, for NUTS3 and NUTS2, 70,852 and 49,351. However, after the necessary restrictions are imposed, as described above, the focal group of analysis reduces to 7,376 and 4,902 pairs (respectively, 10.41% and 9.94%), which represents the 10.53% of all biotech inventors. This percentage is apparently low, indeed. Note, however, that these 5,484 inventors have, on average, larger number of patents per inventor, larger number of co-authors, and accumulate more citations to their work, witnessing the importance and economic impact of this subgroup for inventive activity and knowledge diffusion.

INSERT TABLE I ABOUT HERE

Table II goes one step further in the analysis of this subgroup. It shows summary figures of the number of patents per inventor, number of co-authors and citations received, broken down into two groups: geographically mobile inventors (those with more than one NUTS3 region of residence) and non-mobile inventors. Noticeably, mobile inventors are more productive, have more co-inventors, and their work is more valuable, according to the number of citations received. The figures indicate that mobile innovators differ systematically in their observable characteristics from those who do not move across regions. Clearly, controlling for such features in the econometric analysis is pivotal.

INSERT TABLE II ABOUT HERE

Table III provides summary statistics of the variables used in the present analysis for the case of linkages across NUTS3 regions (NUTS2 linkages figures can be provided upon request), when the explanatory variables are computed on rolling time-windows of five years (upper panel) and when they are computed on time-windows of ten years (lower panel). Tables A2.1 and A2.2 in the Appendix display the correlation matrix. Other than the high correlations between both productivity measures and between both degree centrality measures, the correlation among the focal independent variables is, in general, sufficiently small and collinearity does not pose a significant problem in the estimations. These high correlations are not a serious concern to the extent that these four variables are only used to control for confounding individuals' features that might bias the point estimates of the focal variable in the present analysis. To ensure that this is not an issue, all the estimations are repeated including either one or the other highly correlated variables each time. No remarkable change is worthy of report.

INSERT TABLE III ABOUT HERE

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4. Results

4.1. Fixed-effects conditional logit estimation

This section turns to examining the estimation results. Recall that an unbalanced panel is estimated, first from 1983 to 2005 (5-year rolling time-windows), then from 1987 to 2005 (10-year windows). Conditional logit methods are used to drop out the fixed-effect (Chamberlain, 2010). Note that potential spurious correlation between r.h.s. variables and the dependent one due to non-stationary panels may arise. This may happen because the dependent variable is by construction a sequence of zeros followed by a single 1. Any regressor exhibiting a trend will mechanically create a correlation with the dependent variable (see Fafchamps et al., 2010). Unit root tests for panel data are performed to identify regressors that exhibit a trend (Harris and Tzavalis, 1999; Im et al., 2003). There is some evidence of trend only for the case of the productivity and the degree centrality variables. To address this issue, these four variables are included in first differences in all the estimations. Table IV reports the fixed-effects logit estimations for the linkages formed across different spatial contexts – NUTS3 regions in Europe (5-year windows). Note that all the proximities considered (social, cognitive, institutional, organizational, and geographic) are significant and with the expected sign, confirming prior evidence on the role of different, more meaningful types of proximities to explain agents' knowledge interactions and teamwork formation. Results concerning productivity and collaboration propensity of inventors (their degree centrality) are in accordance with the theory. Thus, both the average productivity and the average connectivity enhance knowledge linkages formation. That is, the more productive or central, on average, are two given inventors, the faster the collaborations will emerge. The absolute difference of both variables is, however, negative and significant. That is to say, the speed by which network formation emerges falls when inventors are dissimilar in terms of their productivity and their propensity to collaborate.

‘Previous co-location’ is the main variable under scrutiny in the present inquiry. The associated coefficient is positive and significant throughout all the estimations of Table IV. This finding holds even when controlling for a large number of potential time-varying confounders as well as for pair-wise time-invariant fixed-effects. Thus, there exists a premium derived from being co-located in the past on the speed by which collaborative patents arise between currently non-co-located individuals, all else being equal. This result confirms the main hypothesis: informal ties between individuals, shared trust and mutual understanding, built after years of co-location and shared spatial context, may well survive the spatial separation of the individuals and be a source of knowledge interaction and teamwork formation among knowledge workers.

Further, to see not only the statistical, but also the economic significance of these results, column (ii) presents the computed marginal effects, evaluated at the means – except for the case of dummy variables, evaluated at the change from 0 to 1. Thus, the table shows that having shared a common spatial context in the past 5 years increases the speed by which cross-regional collaborative patents emerge by around 5.8%, holding other covariates at the reference points. This result may seem unimportant at first sight. In order to make these figures comparable, note that the marginal effect of institutional proximity – they worked for the same type of institution in the recent past – is around 5.6%, whilst having worked for the same organization around 5%. Given that the mean likelihood that two inventors collaborate in a given year is 22%, this 5.8% implies a relative increase of 26.4%, which is sizeable.

INSERT TABLE IV ABOUT HERE

Column (iii) introduces interactions between the ‘previous co-location’ dummy and four proximities – social, cognitive, institutional and organizational. The parameter of the interaction terms determines whether previous co-location and the four proximities considered are complements or substitutes in fostering collaborative patents. Three out of four coefficients are negative and strongly significant. That is to say, previous co-location and social, cognitive, and institutional proximities are substitutes in fostering the speed by which alliances emerge across different spatial contexts. This implies that the effect of having co-inhabited together in the past is especially important when inventors are farther apart in the co-inventorship network, when they did not previously work in similar technological fields, and when they did not previously work for the same type of applicant. The interaction with organizational proximity is not significant, suggesting the absence of substitution effects. Finally, column (iv) adds also the interaction between the focal variable in this study and geographic distance. The coefficient is positive and significant, indicating strong substitution effects – recall that the coefficient of geographic distance is negative. Interestingly, adding the latter interaction term reduces the significance of the interaction with social proximity, which seems to suggest substitution effects between social networks and geography, too (Agrawal et al., 2008; Breschi and Lissoni, 2009).

Table V repeats the analysis in Table IV, but using 10-year time windows to compute the explanatory variables. The estimated coefficients point to the same conclusions as for the case of the 5-year windows estimates – with the exception of geographic distance, which is not significant anymore. However, marginal effects (column (ii)) show that all the explanatory variables, including the ‘previous co-location’ one, decrease their importance with respect to the baseline regressions. These latter results seem to suggest that the effects of all proximities considered and the main focal variable, the ‘previous co-location’ effect, erodes relatively quickly over time, and the social capital between two given inventors starts depreciating relatively soon. In consequence, the remaining of the paper will focus on the results for time windows of five years, although the complete set of results can be provided on request.

INSERT TABLE V ABOUT HERE

4.2. International mobility

Table VI interacts the ‘previous co-location’ variable (and the other proximities/distances considered) with two dummies indicating whether (1) the collaboration occurs across countries, 0 otherwise; and (2) the collaboration takes place within national boundaries, 0 otherwise, so to create an international and a national group and compare the estimated coefficients. The logic behind is testing the role of the international mobility of inventors as means to access foreign knowledge resources through diaspora networks (Agrawal et al., 2011; Breschi et al., 2017; Foley and Kerr, 2013; Kerr and Kerr, 2018; Kerr, 2008; Miguelez, 2016), as opposed to the mobility occurring within countries. Because of their familiarity with local market needs, diasporas provide information about business opportunities in their homelands, and thus are critical in providing access to relevant information otherwise inaccessible because of cultural, language, institutional, administrative, or geographical barriers. As Foley and Kerr (2013) posit, internationally mobile inventors in host countries possess the language skills and cultural sensitivity necessary to promote international collaborations between their home and host countries.

Column (i) shows estimated coefficients for all the proximities/distances considered, plus the focal variable of this study, split between international and national collaborations. Column (ii) presents the marginal effects for, respectively, international and national collaborations. The way to read this table is comparing coefficients for, say, social proximity in column 'International' with coefficients in column 'National'. The results indicate that cognitive and institutional proximities are statistically equivalent for the international and national cases – according to Wald tests on differences between coefficients, which do not reject the null hypothesis of the two estimated coefficients to be equal (provided on request). Meanwhile, social and organizational proximities are critical for the international case, and have more nuanced effects for the national one, which points to the role of professional networks and multinational firms in diffusing knowledge and connecting people across national borders. Similarly, the 'previous co-location' effect is substantially more important for the international case too. Finally, substitutability relationships arise only for the case of the national sample (column (iii)), except for the case of institutional proximity.

INSERT TABLE VI ABOUT HERE

4.3. Robustness analysis

This section summarizes complementary estimations performed in order to ensure the robustness of the main results. First, for the case of some countries of Europe, the NUTS3 administrative borders do not correspond to meaningful regions where economic interactions take place within relatively confined boundaries, but to arbitrary parts of them. In order to see whether the choice of the spatial scale bias the results the former analysis is repeated, but only considering those pair-wise linkages across different NUTS2 regions. Fortunately, as illustrated in column (i) of Table VII, most of the results and qualitative conclusions remain unaltered with respect to the former estimations. Note that most of the computed marginal effects (column (ii)) decrease the size of the coefficient, being 'previous co-location' the exception – which is actually larger. Thus, it seems that the importance of having shared a common spatial and social context in the past is especially beneficial when the chances to meet and interact reduce substantially.

INSERT TABLE VII ABOUT HERE

Finally, column (iii) mimics the identification strategy suggested by Fafchamps et al. (2010) in order to provide reassurance to the results encountered so far. Although the data set is rich in observed characteristics of the inventors, many dimensions which are likely to affect teamwork formation decisions remain unobserved. If these unobserved factors are correlated with the outcome, the estimated mobility-collaboration relationship would be biased. According to the authors, the factors conditioning an initial collaboration may differ from those conditioning a subsequent one. The underlying logic is that, if the listed omitted variables are relevant and drives the results concerning the 'previous co-location' premium, then there is no reason to think that they do not drive the results for subsequent collaborations. As in Fafchamps et al. (2010), the study runs a counterfactual-type experiment, by testing the role of 'previous co-location' on subsequent collaboration, conditional upon having collaborated before. While this type of experiment does not completely resolve for the omission of relevant variables, the potential qualitative results of this exercise may give support to the previous findings. Column (iii) re-estimates the baseline model (Table IV, column (i)) for the subsample of subsequent collaborations. The point estimates of the 'previous co-location' variable decreases dramatically, while the standard error increases, making strongly non-significant the effect of this variable. Admittedly, the sample size of this specification is considerably lowered and, therefore, the results should be interpreted with care.

5. Discussion and conclusions

5.1. Theoretical implications

The empirical evidence shown here confirms that there exists a premium derived from being co-located in the past on the speed by which collaborative patents arise between currently non-co-located individuals. That is to say, inventors residing in different regions in Europe are more likely to collaborate if they lived in the same area in the past, and at least one of them moved to another region. This result is in line with previous literature addressing the role of mobility on knowledge diffusion (Agrawal et al., 2006; Oettl and Agrawal, 2008) as well as the role of informal social relationships on network formation and diffusion of ideas. The results therefore empirically support the idea that the spatial and highly contextual conditions in which interactions take place and social capital is built up are important for economic outcomes, as largely discussed in economic geography and innovation economics (Storper and Venables, 2004). Its effects manifest through agents that shared this same context but are not currently co-located.

This analysis looks also at the role of different proximities (social, cognitive, institutional, organizational, and geographic). These are significant and with the expected sign, confirming prior evidence on the role of different, more meaningful types of proximities to explain agents' knowledge interactions and teamwork formation (Cassi and Plunket, 2014, 2015; Mariani, 2004). This adds to the theoretical developments in different fields highlighting the different ways in which agents interact, access and transmit information, and eventually innovate (Boschma, 2005). Even though the different proximities correlate, and all of them partially overlap with geographical space, understanding the different conditions under which they operate is important from theoretical, managerial and policy perspectives.

Importantly, this study finds the 'previous co-location' effect to be more valuable when other interaction channels – social, cognitive, and institutional proximities, as well as geographic distance – are weak or non-existent. That is to say, the advantages of not breaking the ties with their former social contexts tend to decline when inventors share other types of proximities. Again, understanding the boundary conditions of the 'previous co-location' premium is critical to figure out the way in which the different interaction means of accessing knowledge operate. The exception is organizational proximity, for which no effect (or slightly complementary effect) is found. This latter finding is in line with recent evidence by Breschi et al. (2017), who find a complementary relationship between inventors' migration and firm boundaries with respect to international knowledge flows.

These differential effects also emerge when splitting the analysis between international and national collaborations: results show that the 'previous co-location' premium is particularly relevant when institutional, administrative and geographical barriers are more acute and other interaction channels are less likely to be exploited – i.e. across national boundaries. This idea is also supported when the study focuses on networks between NUTS2 regions, for which larger effects for the 'previous co-location' variable are found, indicating its relevance especially when the chances to meet and interact reduce substantially. In line with Corredoira and Rosenkopf (2010), proximate agents may exploit other interaction channels and, therefore, the 'previous co-location' premium becomes more valuable when these channels are less likely to be available. Importantly, one cannot rule out the importance of other equally important explanations, such as the role of cultural differences across European countries, which may explain part of this result too. Cultural differences across countries have been found important to hinder international trade flows (Boisso and Ferrantino, 1997; Felbermayr and Toubal, 2010) as well as international firm expansion and the organizational structure of multinational firms (Hennart and Larimo, 1998; Hofstede, 1983; Johanson and Vahlne, 1977; Kogut and Singh, 1988; Rugman and Verbeke, 2003, 2001; for an overview see: Tung and Verbeke, 2010), because they increase transaction costs of doing business abroad. The social capital between previously co-located knowledge workers might overcome these barriers and facilitate interactions across different cultural contexts.

5.2. Managerial and policy implications

The results presented here bring about two important lines of implications: from a policy viewpoint, they go against recent trends towards restricting geographical mobility in Europe, as the formation of teams able to advance knowledge and innovation could be seriously harmed. They also suggest a more positive view on the allegedly negative effects of the drain of brains that some regions may suffer. If the local social and economic tissue is able to maintain the links with its emigrated skilled workers, positive returns in the form of collaborative teams across the space are more likely to emerge. As for firms' recruitment strategies, again the results go against organizations' efforts to contain labor flows of highly skilled workers (Marx et al., 2009; Rogers and Larsen, 1984), as allowing people to leave may result in a source of external social capital for the firm. Even if the approach of this paper is at the regional level, firm level analysis seems to support this view too (Kaiser et al., 2011; Corredoira and Rosenkopf, 2010).

5.3. Limitations and future research

Admittedly, the empirical evidence presented here is limited to one single industry in Europe, and looks at the mobility and networking patterns of inventors only. This could affect the generalizability of the conclusions since, as discussed earlier, inventors are a quite specific type of R&D workers, arguably at the forefront of technological innovation, and highly valuable assets for the firm employing them. However, it is plausible that the 'previous co-location' effect could emerge across other groups of highly-skilled workers too, for which knowing 'who' is as important as knowing 'how'. And for which the local buzz is as critical as the global pipelines emerging from ties among members of epistemic communities (Bathelt et al., 2004; Gittelman, 2007). Further research could address this issue.

Other potential limitations may affect the study's results. First and foremost, as it uses only EPO data, one cannot observe potential links between inventors in patents applied to national offices – or if they co-authored a scientific article. If they were abundant, that could invalidate the present results. Similarly, the choice of the biotechnology field is not exempt of controversies, as it is a highly patenting industry, as compared to other sectors like machinery or the food industry. Finally, cultural differences across countries, but also across regions, could be an important missing variable in the present analysis, as an increasing literature, particularly in the international business field, has repeatedly shown (Hennart & Larimo, 1998; Kogut & Singh, 1988). The relationship between cultural differences and economic interactions between countries and regions is an interesting avenue of research that could be addressed in the near future. In the same vein, and in relation to the former point, future projects could address the mobility of knowledge workers at the international level, and study the effects of ethnic/national proximity in the diffusion of knowledge and the formation of alliances across individuals, firms, and territories.

5.4. Conclusions

This paper bridges different strands of studies, including the innovation networks, the innovation management and the economic geography literatures, to put forward the 'enduring social capital' hypothesis (Agrawal et al., 2006) in the context of teamwork formation. That is, informal ties, trust and mutual understanding, built after years of co-location in the same spatial context, may well survive the spatial separation of the individuals and be a source of teamwork formation. Previous studies have not inspected the relationship between mobility and team formation and, therefore, it constitutes an important contribution to the existent literature. The results of the paper align with previous studies looking at mobility, diffusion and network formation, as well as on the role of informal social relationships for network formation and diffusion of ideas.

References

Agrawal, A., Cockburn, I., McHale, J., 2006. Gone but not forgotten: knowledge flows, labor mobility, and enduring social relationships. Journal of Economic Geography 6, 571–591. https://doi.org/10.1093/jeg/lbl016

Agrawal, A., Kapur, D., McHale, J., 2008. How do spatial and social proximity influence knowledge flows? Evidence from patent data. Journal of Urban Economics 64, 258–269. https://doi.org/10.1016/j.jue.2008.01.003

Agrawal, A., Kapur, D., McHale, J., Oettl, A., 2011. Brain drain or brain bank? The impact of skilled emigration on poor-country innovation. Journal of Urban Economics 69, 43–55. https://doi.org/10.1016/j.jue.2010.06.003

Allison, P.D., 2009. Fixed effects regression models. SAGE publications.

Allison, P.D., 2005. Fixed Effects Regression Methods for Longitudinal Data Using SAS. SAS Institute, Cary, NC.

Almeida, P., Kogut, B., 1999. Localization of Knowledge and the Mobility of Engineers in Regional Networks. Management Science 45, 905–917. https://doi.org/10.1287/mnsc.45.7.905

Autant-Bernard, C., Billand, P., Frachisse, D., Massard, N., 2007. Social distance versus spatial distance in R&D cooperation: Empirical evidence from European collaboration choices in micro and nanotechnologies*. Papers in Regional Science 86, 495–519. https://doi.org/10.1111/j.1435-5957.2007.00132.x

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

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, 31–56. https://doi.org/10.1191/0309132504ph469oa

Baum, J.A.C., Cowan, R., Jonard, N., 2010. Network-Independent Partner Selection and the Evolution of Innovation Networks. Management Science 56, 2094–2110. https://doi.org/10.1287/mnsc.1100.1229

Belderbos, R., Carree, M., Lokshin, B., 2004. Cooperative R&D and firm performance. Research Policy 33, 1477–1492. https://doi.org/10.1016/j.respol.2004.07.003

Belderbos, R., Gilsing, V., Lokshin, B., Carree, M., Fernández Sastre, J., 2018. The antecedents of new R&D collaborations with different partner types: On the dynamics of past R&D collaboration and innovative performance. Long Range Planning 51, 285–302. https://doi.org/10.1016/j.lrp.2017.10.002

Bell, G.G., Zaheer, A., 2007. Geography, Networks, and Knowledge Flow. Organization Science 18, 955–972. https://doi.org/10.1287/orsc.1070.0308

Bergenholtz, C., Waldstrøm, C., 2011. Inter-Organizational Network Studies—A Literature Review. Industry and Innovation 18, 539–562. https://doi.org/10.1080/13662716.2011.591966

Björk, J., Magnusson, M., 2009. Where Do Good Innovation Ideas Come From? Exploring the Influence of Network Connectivity on Innovation Idea Quality. Journal of Product Innovation Management 26, 662–670. https://doi.org/10.1111/j.1540-5885.2009.00691.x

Boisso, D., Ferrantino, M., 1997. Economic Distance, Cultural Distance, and Openness in International Trade: Empirical Puzzles. Journal of Economic Integration 12, 456–484.

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

Boschma, R., Frenken, K., 2010. The spatial evolution of innovation networks. A proximity perspective. Handbook of evolutionary economic geography 120–135.
Breschi, S., Lenzi, C., 2016. Co-invention networks and inventive productivity in US cities. Journal of Urban Economics 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. Journal of Economic Geography 9, 439–468. https://doi.org/10.1093/jeg/lbp008
Breschi, S., Lissoni, F., Miguelez, E., 2017. Foreign-origin inventors in the USA: testing for diaspora and brain gain effects. J Econ Geogr 17, 1009–1038. https://doi.org/10.1093/jeg/lbw044
Cassi, L., Plunket, A., 2015. Research Collaboration in Co-inventor Networks: Combining Closure, Bridging and Proximities. Regional Studies 49, 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, 395–422. https://doi.org/10.1007/s00168-014-0612-6
Chamberlain, G., 2010. Binary Response Models for Panel Data: Identification and Information. Econometrica 78, 159–168. https://doi.org/10.3982/ECTA8419
Chesbrough, H., 2003. Open innovation: the new imperative for creating and profiting from innovation. Harvard Business School Press: Cambridge, MA.
Corredoira, R.A., Rosenkopf, L., 2010. Should auld acquaintance be forgot? the reverse transfer of knowledge through mobility ties. Strategic Management Journal 31, 159–181. https://doi.org/10.1002/smj.803
Cowan, R., Jonard, N., Zimmermann, J.-B., 2007. Bilateral Collaboration and the Emergence of Innovation Networks. Management Science 53, 1051–1067. https://doi.org/10.1287/mnsc.1060.0618
Cruz-González, J., López-Sáez, P., Navas-López, J.E., Delgado-Verde, M., 2015. Open search strategies and firm performance: The different moderating role of technological environmental dynamism. Technovation 35, 32–45. https://doi.org/10.1016/j.technovation.2014.09.001
D'Agostino, L.M., Moreno, R., 2018. Exploration during turbulent times: an analysis of the relation between cooperation in innovation activities and radical innovation performance during the economic crisis. Ind Corp Change 27, 387–412. https://doi.org/10.1093/icc/dtx035
David, P.A., 1993. Intellectual property institutions and the panda's thumb: patents, copyrights, and trade secrets in economic theory and history, in: Global Dimensions of Intellectual Property Rights in Science and Technology. National Academies Press.
Doloreux, D., 2004. Regional networks of small and medium sized enterprises: evidence from the Metropolitan Area of Ottawa in Canada. European Planning Studies 12, 173–189. https://doi.org/10.1080/0965431042000183923
Ellis, P.D., 2011. Social ties and international entrepreneurship: Opportunities and constraints affecting firm internationalization. J Int Bus Stud 42, 99–127. https://doi.org/10.1057/jibs.2010.20
Faems, D., Van Looy, B., Debackere, K., 2005. Interorganizational Collaboration and Innovation: Toward a Portfolio Approach*. Journal of Product Innovation Management 22, 238–250. https://doi.org/10.1111/j.0737-6782.2005.00120.x

Fafchamps, M., van der Leij, M.J., Goyal, S., 2010. Matching and Network Effects. Journal of the European Economic Association 8, 203–231. https://doi.org/10.1111/j.1542-4774.2010.tb00500.x
Felbermayr, G.J., Toubal, F., 2010. Cultural proximity and trade. European Economic Review 54, 279–293. https://doi.org/10.1016/j.euroecorev.2009.06.009
Fleming, L., 2001. Recombinant Uncertainty in Technological Search [WWW Document]. URL http://pubsonline.informs.org/doi/abs/10.1287/mnsc.47.1.117.10671 (accessed 11.24.13).
Fleming, L., King, C., Juda, A.I., 2007a. Small Worlds and Regional Innovation. Organization Science 18, 938–954. https://doi.org/10.1287/orsc.1070.0289
Fleming, L., Mingo, S., Chen, D., 2007b. Collaborative brokerage, generative creativity, and creative success. Administrative Science Quarterly 52, 443–475.
Foley, C.F., Kerr, W.R., 2013. Ethnic Innovation and U.S. Multinational Firm Activity. Management Science 59, 1529–1544. https://doi.org/10.1287/mnsc.1120.1684
Fukugawa, N., 2006. Determining Factors in Innovation of Small Firm Networks: A case of Cross Industry Groups in Japan. Small Bus Econ 27, 181–193. https://doi.org/10.1007/s11187-006-0010-2
Gittelman, M., 2007. Does Geography Matter for Science-Based Firms? Epistemic Communities and the Geography of Research and Patenting in Biotechnology. Organization Science 18, 724–741. https://doi.org/10.1287/orsc.1070.0249
Harris, R.D.F., Tzavalis, E., 1999. Inference for unit roots in dynamic panels where the time dimension is fixed. Journal of Econometrics 91, 201–226. https://doi.org/10.1016/S0304-4076(98)00076-1
Hennart, J., Larimo, J., 1998. The Impact of Culture on the Strategy of Multinational Enterprises: Does National Origin Affect Ownership Decisions? J Int Bus Stud 29, 515–538. https://doi.org/10.1057/palgrave.jibs.8490005
Hoang, H., Rothaermel, F.T., 2005. The Effect of General and Partner-Specific Alliance Experience on Joint R&D Project Performance. ACAD MANAGE J 48, 332–345. https://doi.org/10.5465/AMJ.2005.16928417
Hofstede, G., 1983. Dimensions of national cultures in fifty countries and three regions. Expiscations in cross-cultural psychology 335–355.
Howells, J., James, A.D., Malik, K., 2004. Sourcing external technological knowledge: a decision support framework for firms. International Journal of Technology Management 27, 143–154. https://doi.org/10.1504/IJTM.2004.003949
Huggins, R., Thompson, P., 2017. Entrepreneurial networks and open innovation: the role of strategic and embedded ties. Industry and Innovation 24, 403–435. https://doi.org/10.1080/13662716.2016.1255598
Im, K.S., Pesaran, M.H., Shin, Y., 2003. Testing for unit roots in heterogeneous panels. Journal of Econometrics 115, 53–74. https://doi.org/10.1016/S0304-4076(03)00092-7
Jaffe, A.B., 1986. Technological Opportunity and Spillovers of R & D: Evidence from Firms' Patents, Profits, and Market Value. The American Economic Review 76, 984–1001. https://doi.org/10.2307/1816464
Johanson, J., Vahlne, J.-E., 1977. The Internationalization Process of the Firm-A Model of Knowledge Development and Increasing Foreign Market Commitments. Journal of International Business Studies 8, 23–32.
Johnston, A., Huggins, R., 2018. Partner selection and university-industry linkages: Assessing small firms' initial perceptions of the credibility of their partners. Technovation. https://doi.org/10.1016/j.technovation.2018.02.005

Jones, B.F., 2010. Age and Great Invention. Review of Economics and Statistics 92, 1–14. https://doi.org/10.1162/rest.2009.11724
Jones, B.F., Wuchty, S., Uzzi, B., 2008. Multi-University Research Teams: Shifting Impact, Geography, and Stratification in. Science 322, 1259–1262. https://doi.org/10.1126/science.1158357
Kaiser, U., Kongsted, H.C., Rønde, T., 2011. Labor Mobility, Social Network Effects, and Innovative Activity (IZA Discussion Paper No. 5654). Institute for the Study of Labor (IZA).
Kerr, S.P., Kerr, W.R., 2018. Global Collaborative Patents. The Economic Journal. https://doi.org/10.1111/ecoj.12369
Kerr, W.R., 2008. Ethnic Scientific Communities and International Technology Diffusion. Review of Economics and Statistics 90, 518–537. https://doi.org/10.1162/rest.90.3.518
Kogut, B., 1988. Joint ventures: Theoretical and empirical perspectives. Strat. Mgmt. J. 9, 319–332. https://doi.org/10.1002/smj.4250090403
Kogut, B., Singh, H., 1988. The Effect of National Culture on the Choice of Entry Mode. J Int Bus Stud 19, 411–432. https://doi.org/10.1057/palgrave.jibs.8490394
Laursen, K., Salter, A., 2006. Open for innovation: the role of openness in explaining innovation performance among U.K. manufacturing firms. Strat. Mgmt. J. 27, 131–150. https://doi.org/10.1002/smj.507
Laursen, K., Salter, A.J., 2014. The paradox of openness: Appropriability, external search and collaboration. Research Policy, Open Innovation: New Insights and Evidence 43, 867–878. https://doi.org/10.1016/j.respol.2013.10.004
Lobo, J., Strumsky, D., 2008. Metropolitan patenting, inventor agglomeration and social networks: A tale of two effects. Journal of Urban Economics 63, 871–884. https://doi.org/10.1016/j.jue.2007.07.005
Maraut, S., 2008. The OECD REGPAT Database: A Presentation. OECD.
Mariani, M., 2004. Research Collaborations Among Inventors and the Location of R&D in the European Chemical Industry, in: Cesaroni, F., Gambardella, A., Garcia-Fontes, W. (Eds.), R&D, Innovation and Competitiveness in the European Chemical Industry. Springer US, Boston, MA, pp. 119–143.
Marx, M., Strumsky, D., Fleming, L., 2009. Mobility, Skills, and the Michigan Non-Compete Experiment. Management Science 55, 875–889. https://doi.org/10.1287/mnsc.1080.0985
McPherson, M., Smith-Lovin, L., Cook, J.M., 2001. Birds of a Feather: Homophily in Social Networks. Annual Review of Sociology 27, 415–444. https://doi.org/10.1146/annurev.soc.27.1.415
Miguelez, E., 2016. Inventor Diasporas and the Internationalization of Technology. World Bank Econ Rev lhw013. https://doi.org/10.1093/wber/lhw013
Miguelez, E., Fink, C., 2013. Measuring the International Mobility of Inventors: A New Database (WIPO Economic Research Working Paper No. 8).
Miotti, L., Sachwald, F., 2003. Co-operative R&D: why and with whom?: An integrated framework of analysis. Research Policy 32, 1481–1499. https://doi.org/10.1016/S0048-7333(02)00159-2
Najafian, M., Colabi, A.M., 2014. Inter-Organizational Relationship and Innovation: A Review of Literature. Global Business and Management Research: An International Journal 6, 52.
Nelson, R.R., Winter, S.G., 1982. An evolutionary theory of economic change. Belknap Press of Harvard Univ. Press, Cambridge, Mass. [u.a.

Nieto, M.J., Santamaría, L., 2007. The importance of diverse collaborative networks for the novelty of product innovation. Technovation 27, 367–377. https://doi.org/10.1016/j.technovation.2006.10.001
Obstfeld, D., 2005. Social Networks, the Tertius Iungens Orientation, and Involvement in Innovation. Administrative Science Quarterly 50, 100–130. https://doi.org/10.2189/asqu.2005.50.1.100
OECD, 2009. OECD Biotechnology Statistics 2009. Paris.
Oettl, A., Agrawal, A., 2008. International labor mobility and knowledge flow externalities. Journal of International Business Studies 39, 1242–1260. https://doi.org/10.1057/palgrave.jibs.8400358
Paier, M., Scherngell, T., 2011. Determinants of Collaboration in European R&D Networks: Empirical Evidence from a Discrete Choice Model. Industry & Innovation 18, 89–104. https://doi.org/10.1080/13662716.2010.528935
Phelps, C., Heidl, R., Wadhwa, A., 2012. Knowledge, Networks, and Knowledge Networks: A Review and Research Agenda. Journal of Management 0149206311432640. https://doi.org/10.1177/0149206311432640
Powell, W.W., Grodal, S., 2005. Networks of innovators. The Oxford handbook of innovation 56–85.
Raffo, J., Lhuillery, S., 2009. How to play the “Names Game”: Patent retrieval comparing different heuristics. Research Policy 38, 1617–1627. https://doi.org/10.1016/j.respol.2009.08.001
Rajalo, S., Vadi, M., 2017. University-industry innovation collaboration: Reconceptualization. Technovation 62–63, 42–54. https://doi.org/10.1016/j.technovation.2017.04.003
Rodríguez, A., Nieto, M.J., Santamaría, L., 2018. International collaboration and innovation in professional and technological knowledge-intensive services. Industry and Innovation 25, 408–431. https://doi.org/10.1080/13662716.2017.1414752
Rogers, E.M., Larsen, J.K., 1984. Silicon Valley fever: Growth of high-technology culture. Basic books New York.
Rosenkopf, L., Almeida, P., 2003. Overcoming Local Search Through Alliances and Mobility. Management Science 49, 751–766. https://doi.org/10.1287/mnsc.49.6.751.16026
Rugman, A.M., Verbeke, A., 2003. Extending the theory of the multinational enterprise: Internalization and strategic management perspectives. Journal of International Business Studies 34, 125–137.
Rugman, A.M., Verbeke, A., 2001. Subsidiary-specific advantages in multinational enterprises. Strategic Management Journal 22, 237–250.
Sakakibara, M., 2002. Formation of R&D consortia: industry and company effects. Strat. Mgmt. J. 23, 1033–1050. https://doi.org/10.1002/smj.272
Schilling, M.A., Phelps, C.C., 2007. Interfirm Collaboration Networks: The Impact of Large-Scale Network Structure on Firm Innovation. Management Science 53, 1113–1126. https://doi.org/10.1287/mnsc.1060.0624
Schmoch, U., 2008. Concept of a technology classification for country comparisons. Final report to the World Intellectual Property Organization (WIPO), Fraunhofer Institute for Systems and Innovation Research, Karlsruhe.
Sedita, S.R., 2008. Interpersonal and Inter-organizational Networks in the Performing Arts: The Case of Project-Based Organizations in the Live Music Industry. Industry and Innovation 15, 493–511. https://doi.org/10.1080/13662710802373833

Singh, J., Fleming, L., 2010. Lone Inventors as Sources of Breakthroughs: Myth or Reality? Management Science 56, 41–56. https://doi.org/10.1287/mnsc.1090.1072
Song, J., Almeida, P., Wu, G., 2003. Learning–by–Hiring: When Is Mobility More Likely to Facilitate Interfirm Knowledge Transfer? Management Science 49, 351–365. https://doi.org/10.1287/mnsc.49.4.351.14429
Storper, M., Venables, A.J., 2004. Buzz: face-to-face contact and the urban economy. J Econ Geogr 4, 351–370. https://doi.org/10.1093/jnlecg/lbh027
Ter Wal, A.L.J., 2014. The dynamics of the inventor network in German biotechnology: geographic proximity versus triadic closure. J Econ Geogr 14, 589–620. https://doi.org/10.1093/jeg/lbs063
Thoma, G., Torrisi, S., Gambardella, A., Guellec, D., Hall, B.H., Harhoff, D., 2010. Harmonizing and combining large datasets-An application to firm-level patent and accounting data. National Bureau of Economic Research.
Tung, R.L., Verbeke, A., 2010. Beyond Hofstede and GLOBE: Improving the quality of cross-cultural research. Journal of International Business Studies 41, 1259–1274.
Van Looy, B., 2006. Data production methods for harmonized patent statistics : patentee sector allocation. [WWW Document].
Weitzman, M.L., 1998. Recombinant Growth. The Quarterly Journal of Economics 113, 331–360. https://doi.org/10.1162/003355398555595
West, J., Salter, A., Vanhaverbeke, W., Chesbrough, H., 2014. Open innovation: The next decade. Research Policy, Open Innovation: New Insights and Evidence 43, 805–811. https://doi.org/10.1016/j.respol.2014.03.001
Wong, P.L., Ellis, P., 2002. Social Ties and Partner Identification in Sino-Hong Kong International Joint Ventures. J Int Bus Stud 33, 267–289. https://doi.org/10.1057/palgrave.jibs.8491016
Wuchty, S., Jones, B.F., Uzzi, B., 2007. The Increasing Dominance of Teams in Production of Knowledge. Science 316, 1036–1039. https://doi.org/10.1126/science.1136099
Zaheer, A., Gözübüyük, R., Milanov, H., 2010. It's the Connections: The Network Perspective in Interorganizational Research. ACAD MANAGE PERSPECT 24, 62–77.
Zeng, S.X., Xie, X.M., Tam, C.M., 2010. Relationship between cooperation networks and innovation performance of SMEs. Technovation 30, 181–194. https://doi.org/10.1016/j.technovation.2009.08.003
Zhou, K.Z., Li, C.B., 2012. How knowledge affects radical innovation: Knowledge base, market knowledge acquisition, and internal knowledge sharing. Strat. Mgmt. J. 33, 1090–1102. https://doi.org/10.1002/smj.1959

Appendix 1: Inventors' disambiguation

This Appendix describes the methodology to identify individual inventors from patent data using information listed in applications to the EPO, accessed through the OECD REGPAT database, January 2010 edition. A three-step procedure is followed (Raffo and Lhuillery, 2009): the parsing stage, the matching stage, and the filtering stage.

The parsing stage: It corrects all the corrupted characters from the inventor name and inventor address fields; it replaces all the non-corrupted accentuated characters with their non-accentuated counterparts, upper cases all the characters and drops slashes, hyphens, accents, diereses, and so on. It extracts an arbitrary list of surname modifiers from this same field – i.e., 'Prof.', 'Dr.', 'Prof.-Dr.', 'Ing.', 'Jr.', 'PhD.', 'Chem.'.

The name matching stage: The second step consists in encoding the strings of the name and surname to minimize spelling problems. The Soundex algorithm is used. Soundex encodes by using the first letter of each string followed by a number of digits representing the phonetic categories of the next consonants. The vowels and the consonants H, W and Y are ignored, and adjacent letters from the same category are encoded with a single digit. The 0 is used when the string finishes before the whole number of digits has been used. Then all records sharing the same Soundex-modified name and surname are grouped as potentially the same inventor.

The filtering stage: Using information contained in the patent document, all the pairs of records for which the Soundex code is the same are compared, and assigned an arbitrary score to each comparison. Then, all the scores of each individual comparison are added up, which produces a “similarity score” for pairs of inventors with the same Soundex code. Then this is compared with a pre-determined numerical threshold, which is used to decide whether two records belong to the same inventor or not. The information used to compare records with the same Soundex code is as follows:

- Same middle name Soundex-code
- Same surname modifier (if it exists)
- Same affiliation (if it exists)
- Rare surname+name Soundex-code
- Same street and building number
- Same ZIP code
- Same city
- Same NUTS2 and/or NUTS3 regions
- Same applicant code
- Same company code (if it exists)
- Same group code (if it exists)
- Same technological class (4 digits)
- Same technological class (6 digits)
- Same technological class (12 digits)
- Self-citation

Appendix 2: Correlation matrixes

Table A2.1. Correlation matrix, linkages across NUTS3, 5-eyar time window

	1	2	3	4	5	6	7	8	9	10
1. Cross-regional co-patents	1									
2. Social proximity	0.19	1								
3. Cognitive proximity	0.20	0.42	1							
4. Institutional proximity	0.18	0.46	0.66	1						
5. Geographic distance	0.15	0.60	0.45	0.62	1					
6. Organizational proximity	-0.01	-0.14	0.03	-0.06	-0.20	1				
7. Previous co-location	0.02	0.12	0.07	0.11	0.15	-0.10	1			
8. Average productivity	0.12	0.15	0.19	0.20	0.16	-0.01	0.03	1		
9. Abs. diff. productivity	0.04	0.05	0.03	0.03	0.04	-0.01	0.01	0.82	1	
10. Average centrality	0.16	0.19	0.19	0.20	0.17	0.00	0.03	0.60	0.47	1
11. Abs. diff. centrality	0.09	0.06	0.06	0.06	0.06	0.00	0.01	0.49	0.50	0.88

Note: Correlations involving variables 8 to 11 are computed using their first differences transformation.

Table A2.2. Correlation matrix, linkages across NUTS3, 10-eyar time window

	1	2	3	4	5	6	7	8	9	10
1. Cross-regional co-patents	1									
2. Social proximity	0.16	1								
3. Cognitive proximity	0.21	0.36	1							
4. Institutional proximity	0.21	0.41	0.55	1						
5. Geographic distance	0.15	0.58	0.35	0.53	1					
6. Organizational proximity	-0.01	-0.17	0.03	-0.06	-0.23	1				
7. Previous co-location	0.02	0.14	0.08	0.13	0.18	-0.11	1			
8. Average productivity	0.13	0.15	0.17	0.19	0.15	-0.01	0.04	1		
9. Abs. diff. productivity	0.05	0.05	0.03	0.04	0.04	0.00	0.02	0.81	1	
10. Average centrality	0.19	0.19	0.19	0.21	0.16	-0.01	0.04	0.64	0.47	1
11. Abs. diff. centrality	0.10	0.07	0.06	0.07	0.06	0.00	0.02	0.52	0.53	0.85

Note: Correlations involving variables 8 to 11 are computed using their first differences transformation.

Tables

Table I. Summary figures

Absolute number of inventors in biotech (1978-2005)	52,081
Share of inventors in biotech	6.77%
Number of patents in the biotech industry	38,624
Share of patents in the biotech industry	3.71%
Average number of patents per inventor	2.19
Average co-authors per inventor	5.11
Average number of citations received per inventor	0.83
Number of multi-patent inventors	19,459
Geographically mobile inventors (NUTS3)	1,781
Share mobile inventors over multi-patent inventors	9.15%
Total number of potential ties	1,356,189,240
Total number of realized ties	124,681
Realized ties across different NUTS3 regions	70,852
Realized ties across different NUTS2 regions	49,351
Observed ties under analysis (NUTS3)	7,376
Observed ties under analysis (NUTS2)	4,902
Final set of inventors under study	5,484
Share of biotech inventors under study	10.53%
Average number of patents per inventor final dataset	6.78
Average number of co-authors per inventor final dataset	6.10
Average number of citations received per inventor final dataset	3.22

Note: Recall that the final dataset refers to the final number of inventors used in the empirical analysis, retrieved after the necessary restrictions were imposed, as previously described.

Table II. Two-group mean comparison. Mobile vs. non-mobile innovators

	Mobile inventors	Non-mobile inventors	Absolute difference
Observations	1,383	4,101	
Average # of patents per inventor	8.79	6.11	2.68***
Average # of co-authors per inventor	7.25	5.71	1.55***
Average # of citations per inventor	3.99	2.97	1.02***

Notes: *** p<0.01, ** p<0.05, * p<0.1.

Table III. Summary statistics, unbalanced panel, linkages across NUTS3

	# obser.	Mean	Std. Dev.	Min	Max
5-year time window					
Cross-regional co-patents	33,005	0.22	0.42	0	1
Social proximity	33,005	0.09	0.17	0	0.50
Cognitive proximity	33,005	0.38	0.40	0	1
Institutional proximity	33,005	0.50	0.50	0	1
Organizational proximity	33,005	0.29	0.45	0	1
Geographic distance	33,005	2.82	3.89	0.02	71.68
Previous co-location	33,005	0.06	0.24	0	1
Average productivity	33,005	1.15	1.52	0	21.55
Abs. diff. productivity	33,005	1.49	2.44	0	41.17
Average centrality	33,005	6.74	9.13	0	128
Abs. diff. centrality	33,005	9.12	15.09	0	236
10-year time window					
Cross-regional co-patents	30,336	0.23	0.42	0	1
Social proximity	30,336	0.11	0.18	0	0.50
Cognitive proximity	30,336	0.47	0.39	0	1.00
Institutional proximity	30,336	0.64	0.48	0	1
Organizational proximity	30,336	0.34	0.47	0	1
Geographic distance	30,336	2.91	3.93	0.02	71.68
Previous co-location	30,336	0.07	0.25	0	1.00
Average productivity	30,336	1.63	1.94	0	25.36
Abs. diff. productivity	30,336	2.06	3.12	0	42.51
Average centrality	30,336	9.21	11.05	0	157
Abs. diff. centrality	30,336	12.04	17.84	0	246

Note: Descriptive figures do not include variables in first differences.

Table IV. Collaborative patents, linkages across NUTS3, 5-year time windows

	(i)	(ii)	(iii)	(iv)
	Logit	Marginal Effects	Logit	Logit
Social proximity	1.982***	0.331***	2.152***	2.130***
	(0.168)	(0.0401)	(0.179)	(0.179)
Cognitive proximity	0.799***	0.133***	0.825***	0.824***
	(0.0765)	(0.0173)	(0.0792)	(0.0791)
Institutional proximity	0.338***	0.0564***	0.388***	0.390***
	(0.0643)	(0.0111)	(0.0665)	(0.0665)
Organizational proximity	0.297***	0.0496***	0.322***	0.317***
	(0.0715)	(0.0115)	(0.0753)	(0.0753)
Geographic distance	-0.0521***	-0.00870***	-0.0539***	-0.0548***
	(0.0160)	(0.00295)	(0.0160)	(0.0161)
Previous co-location	0.345***	0.0575***	2.516***	2.222***
	(0.118)	(0.0162)	(0.216)	(0.227)
Average productivity	0.0858***	0.0143***	0.0849***	0.0828***
	(0.0256)	(0.00448)	(0.0256)	(0.0257)
Abs. diff. productivity	-0.0476***	-0.00796***	-0.0465***	-0.0455***
	(0.0141)	(0.00248)	(0.0142)	(0.0142)
Average centrality	0.0396***	0.00661***	0.0392***	0.0396***
	(0.00480)	(0.00097)	(0.00483)	(0.00484)
Abs. diff. centrality	-0.00458*	-0.000765*	-0.00422	-0.00437*
	(0.00262)	(0.000444)	(0.00263)	(0.00264)
Previous co-location* Social			-1.119**	-0.864*
			(0.491)	(0.504)
Previous co-location* Cognitive			-1.053***	-1.057***
			(0.300)	(0.304)
Previous co-location* Institutional			-1.763***	-1.814***
			(0.296)	(0.299)
Previous co-location* Organizational			0.201	0.190
			(0.251)	(0.254)
Previous co-location*Geographic				0.220***
				(0.0623)
Pairwise fixed-effects	yes		yes	yes
Observations	33,005		33,005	33,005
Pairs of inventors	7,376		7,376	7,376
McFadden's Adjusted R-squared	0.141		0.149	0.150
Log-likelihood	-8428		-8348	-8340

Notes: *** p<0.01, ** p<0.05, * p<0.1. Standard errors in parentheses.

Table V. Collaborative patents, linkages across NUTS3, 10-year time windows

	(i)	(ii)	(iii)	(iv)
	Logit	Marginal Effects	Logit	Logit
Social proximity	0.787***	0.022***	1.024***	1.013***
	(0.197)	(0.00709)	(0.210)	(0.210)
Cognitive proximity	1.715***	0.0482***	1.730***	1.730***
	(0.114)	(0.00928)	(0.118)	(0.118)
Institutional proximity	0.991***	0.0279***	1.055***	1.056***
	(0.0884)	(0.00525)	(0.0918)	(0.0918)
Organizational proximity	1.013***	0.0285***	1.002***	0.994***
	(0.107)	(0.00490)	(0.112)	(0.112)
Geographic distance	-0.0339*	-0.000955*	-0.0343*	-0.0364**
	(0.0176)	(0.000567)	(0.0177)	(0.0181)
Previous co-location	0.697***	0.0196***	3.854***	3.715***
	(0.158)	(0.00275)	(0.379)	(0.387)
Average productivity	0.114***	0.00321***	0.111***	0.111***
	(0.0279)	(0.000996)	(0.0279)	(0.0279)
Abs. diff. productivity	-0.0640***	-0.00180***	-0.0616***	-0.0618***
	(0.0150)	(0.000542)	(0.0150)	(0.0150)
Average centrality	0.0517***	0.00145***	0.0520***	0.0520***
	(0.00483)	(0.00145)	(0.00484)	(0.00484)
Abs. diff. centrality	-0.00712***	-0.0002**	-0.00714***	-0.00708***
	(0.00264)	(0.0000849)	(0.00265)	(0.00265)
Previous co-location* Social			-2.151***	-2.061***
			(0.542)	(0.548)
Previous co-location* Cognitive			-1.208***	-1.202***
			(0.392)	(0.394)
Previous co-location* Institutional			-2.361***	-2.365***
			(0.410)	(0.411)
Previous co-location* Organizational			0.292	0.261
			(0.319)	(0.320)
Previous co-location*Geographic				0.114
				(0.0705)
Pairwise fixed-effects	yes		yes	yes
Observations	33,005		33,005	33,005
Pairs of inventors	7,376		7,376	7,376
McFadden's Adjusted R-squared	0.244		0.249	0.249
Log-likelihood	-6854		-6805	-6813

Notes: *** p<0.01, ** p<0.05, * p<0.1. Standard errors in parentheses.

Table VI. Collaborative patents, linkages across NUTS3, 5-year time windows, national vs. international

	(i)		(ii)		(iii)	
	Logit		Marginal Effects		Logit	
	International	National	International	National	Int'l	National
Social proximity	3.300***	1.863***	.0590**	0.0333**	3.482***	1.988***
	(0.497)	(0.182)	(0.0304)	(0.0166)	(0.526)	(0.193)
Cognitive proximity	0.713***	0.834***	0.01276*	0.0149**	0.706***	0.868***
	(0.144)	(0.0903)	(0.00696)	(0.00749)	(0.145)	(0.0944)
Institutional proximity	0.413***	0.305***	0.00739*	0.00546*	0.457***	0.364***
	(0.124)	(0.0753)	(0.004005)	(0.00291)	(0.125)	(0.0786)
Organizational proximity	0.839***	0.222***	0.0150**	0.003967*	0.839***	0.248***
	(0.189)	(0.0795)	(0.0074)	(0.00229)	(0.200)	(0.0838)
Geographic distance	0.258***	-0.211***	0.00461**	-0.00378**	0.257***	-0.221***
	(0.0429)	(0.0343)	(0.00222)	(0.00197)	(0.0435)	(0.0348)
Previous co-location	1.275***	0.256**	0.0228***	0.00457*	3.844***	2.074***
	(0.461)	(0.122)	(0.00562)	(0.00273)	(1.245)	(0.241)
Previous co-location* Social					-0.905	-0.812
					(1.626)	(0.539)
Previous co-location* Cognitive					-0.0632	-1.094***
					(1.250)	(0.320)
Previous co-location* Institutional					-2.795**	-1.738***
					(1.109)	(0.316)
Previous co-location* Organizational					0.841	0.171
					(0.841)	(0.275)
Previous co-location* Geographic					-0.0631	0.443***
					(0.131)	(0.142)
Includes controls (1)	yes				yes	
Pairwise fixed-effects	yes				yes	
Observations	33,005				33,005	
Pairs of inventors	7,376				7,376	
McFadden's Adjusted R2	0.147				0.156	
Log-likelihood	-9813				-8282	

Notes: *** p<0.01, ** p<0.05, * p<0.1. Standard errors in parentheses. (1) The controls included in all regressions are: Average productivity, Abs. diff. productivity, Average centrality, and Abs. diff. centrality.

Table VII. Fixed-effects conditional logit estimations. Robustness analysis

	(i)	(ii)	(v)
	NUTS2		Subsequent collaborations
	Logit	Marginal Effects	Logit
Social proximity	1.798***	0.1702***	0.642*
	(0.216)	(0.0382)	(0.379)
Cognitive proximity	0.854***	0.0809***	0.145
	(0.0906)	(0.0171)	(0.385)
Institutional proximity	0.425***	0.0403***	-0.731
	(0.0931)	(0.0099)	(0.494)
Organizational proximity	0.359***	0.0334***	0.118
	(0.0750)	(0.00885)	(0.544)
Geographic distance	-0.00677	-0.00064	-0.0611**
	(0.0198)	(0.00192)	(0.0301)
Previous co-location	0.915***	0.0866***	0.296
	(0.198)	(0.00981)	(0.198)
Average productivity	0.0969***	0.00917**	0.0200
	(0.0322)	(0.00355)	(0.0560)
Abs. diff. productivity	-0.0487***	-0.004607**	-0.0466
	(0.0180)	(0.00194)	(0.0396)
Average centrality	0.0326***	0.00309***	-0.0638***
	(0.00596)	(0.000803)	(0.00824)
Abs. diff. centrality	-0.00124	-0.000118	0.0252***
	(0.00328)	(0.000312)	(0.00656)
	yes		yes
Observations	21,683		3,846
Pairs of inventors	4,902		762
McFadden's Adjusted R2	0.140		0.0509
Log-likelihood	-5568		-1267

Notes: *** p<0.01, ** p<0.05, * p<0.1. Standard errors in parentheses. Columns (i) and (ii) – marginal effects – show the results corresponding to linkages across NUTS2 regions. Column (iii) and (iv) – marginal effects – correspond to linkages across NUTS3 regions, but computing the explanatory variables over 10-year time windows. The observations corresponding to the years 1983 to 1987 are not included in the estimations (iii) and (iv).