# Inventors' working relationships and knowledge creation: a study on patented innovation

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**ABSTRACT:**

This study explores the knowledge-creation process that arises from inventors' working relationships and its impact on company innovation. Innovation is measured by a company's patenting activities. Our analysis is based on an original database built using OECD micro data obtained from patent applications at the European Patent Office (EPO). An empirical analysis was carried out on a body of firms located in the Italian region of Veneto. Our results reveal that the inventors' working relationships have a significant impact on a company's innovation – innovation which is also dependent upon both geography and timescales. Inventors' working relationships thus produce productivity effects, in terms of patenting activity, both in the short and long term and these impacts are also dependent upon geographical distance.

**KEYWORDS:** working relationships; knowledge creation; patenting activity; inventor productivity.
**JEL CLASSIFICATION:** O3, R1, J24.

## Relaciones laborales entre inventores y generación de conocimiento: un estudio sobre innovación patentada

**RESUMEN:**

Este estudio explora el proceso de generación de conocimiento que surge de las relaciones laborales entre inventores y su impacto en la innovación empresarial. La innovación se mide por la cantidad de patentes de una empresa. Nuestro análisis parte de una base de datos propia construida a partir de micro datos de la OECD obtenida a partir de solicitudes de patentes en la Oficina Europea de Patentes (EPO). Se realiza un análisis empírico sobre un grupo de empresas ubicadas en la región italiana de Véneto. Nuestros resultados revelan que las relaciones laborales entre inventores tienen un impacto significativo en la innovación empresarial, innovación que también depende tanto de la geografía como de la dimensión temporal. Las relaciones laborales entre inventores, por tanto, tienen un efecto sobre la productividad en términos de patentes, tanto a corto como a largo plazo, y este impacto depende también de la distancia geográfica.

**PALABRAS CLAVE:** Relaciones laborales; generación de conocimiento; patentes; productividad de inventores.
**CLASIFICACIÓN JEL:** O3, R1, J24.

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## 1. Introduction

In this article we explore the role of the inventors' working relationships and mobility in the process of enhancing knowledge creation and also in terms of innovation activity. What we mean by innovation is the registration of new patents at the European Patent Office (EPO).

Our analysis aligns with the literature on the knowledge-based view of a firm and the transfer of knowledge through the staff's working relationships and collaborations (Howells, 1996). Within the knowledge-based view of a firm, knowledge is treated as the most strategically important of the firm's resources and is viewed as residing within the individual (Grant, 1996). Therefore, the individual is central in the process of creating and storing knowledge: Knowledge is embodied in the individual (Nonaka, von Krogh, & Voelpel, 2006). It follows then, that one of the questions that arises from considering this paradigm is how to enhance the knowledge-creation process within a firm with this in mind.

At the core of the organisational knowledge-creation theory is the identification of the factors that enable knowledge creation for the purpose of improving innovation and learning (Nonaka & von Krogh, 2009; Nonaka et al., 2006; Von Krogh, Ichijo, & Nonaka, 2000). For the purposes of our analysis, it is fundamental to briefly define knowledge. According to the original definition by Polanyi (1966), knowledge is *tacit and explicit* along a *continuum.*[1] We can identify tacit knowledge with *knowing how,* and explicit knowledge with *knowing about* facts and theories. These two types of knowledge differ in relation to their transferability mechanisms – mechanisms for transference across individuals, space and time. Explicit knowledge is revealed through communication and it is usually formalized in documents such as patents, licences, R&D, procedures etc. Tacit knowledge is non-codified, disembodied know-how that is acquired via the informal assimilation of learned behaviours and procedures (Howells, 2002). All tacit knowledge is stored within individuals and it is revealed through its application (Grant, 1996; Howells, 1996; Mascitelli, 2000; Nonaka, 1994).

The first step in the process of knowledge creation is the sharing of tacit knowledge (von Krogh et al., 2000). The process starts when team members meet to share their knowledge (much of which is tacit) in order to work together on the same project. Then, tacit knowledge loses some of its 'tacitness' through the process of externalization (Nonaka & von Krogh, 2009). This conversion from tacit to explicit knowledge is important for the process of expanding knowledge. Several examples of the conversion of tacit knowledge into explicit knowledge are reported in the literature. Among the most cited, Flanagan, Eckert and Clarkson (2007) showed that the 'tacit overview knowledge' of senior designers was fundamental in facilitating communication across large-project teams. Nonaka and Takeuchi (1995) showed that a young engineer acquired tacit knowledge that allowed him to develop a new machine for producing bread – knowledge that he obtained from working side by side with a master baker at a nearby hotel.

Howells (1996) clearly described the fundamental role played by inter-firm and inter-organizational tacit know-how acquisition in the process of knowledge creation. Moreover, he explained how this inter-firm tacit knowledge acquisition can occur through across-firm staff collaborations and staff mobility. Staff working off site and collaborating with other firms can be a source of knowledge flows that enhance the firm's innovation capacity. In these cases, continuous interactions with staff working on inter-organizational projects can better facilitate the transfer of tacit knowledge – when compared to short and/or infrequent visits. On the other hand, 'the process of workers moving from one job environment with its set of innate tacit skills to a different working environment often facilitates this tacit knowledge transfer, but also enhances new tacit know-how learning as well' (Howells, 1996, p. 102). The hiring of new personnel is one of the central sources of knowledge acquisition and creation (Grant, 1996; Leonard & Sensiper, 1998).

[1] See Nonaka (1991, 1994) and Nonaka and von Krogh (2009) for a discussion.

Taking its cue from this literature, the main goal of this article is to verify whether across-firm staff working relationships and staff mobility are responsible for the knowledge creation that improves innovation. Specifically, we analyse the role played by inventors' working relationships and inventor 'mobility'. Then, two different channels of knowledge transmission and creation are studied. Concerning the former, and following the idea of von Krogh et al. (2000) discussed above, we assume that (by participating in innovation projects managed by different firms) inventors share their knowledge with colleagues with different innovation experiences. Then, inventors mutually absorb and transfer their tacit knowledge. This knowledge-sharing process creates knowledge that, finally, improves the innovation activity of the firms that the inventors collaborate with. Thus, we empirically test the hypothesis that the higher the number of inventors' collaborations, the higher the innovation output of the firms they work for becomes. Concerning the latter, following Grant's (1996) and Howells' (1996) ideas that personnel hiring facilitates knowledge creation, we assume that the inventors' new collaborations allow the transfer of inventor knowledge to the new firm. Thus, we test the hypothesis that stipulates that inventors collaborating for the first time with a new firm improve the firm's innovation by means of knowledge creation.

In the last fifteen years, some studies have focused on the effect of worker interactions/mobility on firm innovation and overall economic performance by looking at different perspectives, using alternative datasets and different empirical specifications. The contribution of Agrawal, Cockburn, and McHale (2006) underlines that 'an important component of the knowledge associated with patented inventions may be held tacitly by skilled engineers'. Tacit knowledge and not only codified knowledge appears to be important: it belongs to the researchers and engineers who take part in the patenting process and can be transferred through their social relationships. Such knowledge can spread when the inventors interact with other people, in particular with other inventors.[2] Singh and Agrawal (2011) showed that recruiting an individual from outside an organisation enhances a firm's access to external ideas. By employing patent data from the United States, they found that a recruit's prior ideas are used in the new firm by the recruit herself building upon her own prior ideas after arriving at her new firm. Moreover, regarding the temporal pattern of knowledge diffusion, they found that the role of the recruit persists over time to a surprising degree. In a recent article, Head, Li, and Minondo (2019), by studying academic citations and educational histories of mathematicians from the world's top 1,000 math departments, found that past colocation, alma mater relationships and advisor-mediated relationships are important elements that, together with co-authorships, help reduce the negative impact of geographic barriers on citation. The knowledge spillover channel has been recently analysed through immigration flows to the United States. Agrawal, McHale, and Oettl (2019) investigated whether the recruitment of foreign-trained scientists enhances U.S. science research or causes harm by displacing better-connected, domestically trained scientists. They developed a model that was simulated using bibliometrics data, assuming that every foreign-trained scientist displaces an appropriately matched domestically trained scientist. The simulation results do not show any evidence that foreign-trained scientists supplant better-connected, domestically trained scientists.

Using a survey of Finnish high-technology firms, Simonen and McCann (2008, 2010) studied the effect of worker mobility on the probability of innovation, taking into account the geographical extension of mobility (the same sub-region *versus* different sub-regions). They showed that human capital mobility improves innovation performance if it occurs between different areas. The geographical area of reference coincides with Finnish commuting areas and identifies Finland's local labour markets. Boschma, Eriksson, and Lindgreen (2009) addressed the issue of mobile workers' skill portfolios and its effect on a company's economic performance. They showed how worker mobility affects a company's economic performance

[2] This work followed the methodological approach of Jaffe and co-authors (Jaffe, 1986; Jaffe, Trajtenberg, & Henderson, 1993) which laid the foundations of a literature that analyses the issue of knowledge diffusion using databases containing patent registrations (Almeida & Kogut, 1999; Verspagen & Schoenmakers, 2004; Fischer, Scherngell, & Jansenberger, 2006; LeSage, Fischer, & Scherngell, 2007).

depending on the mix of geographical proximity and competences.[3] Boschma et al., (2009) argue that 'the effects of labor mobility on firm performance depend on whether new employees are recruited from the same region or from other regions'. Eriksson (2011) empirically confirmed these results.

Our study's contribution to the literature on the consequences of workers' professional relationships with patented innovation is distinguished by the following factors: first, a focus on inventors, who are the keepers of patented knowledge; secondly, a definition of mobility that allows for the transmission of tacit knowledge accumulated by inventors; and thirdly, the recognition of inventors' simultaneous working relationships as possible channels of knowledge transmission. These relationships are not codified by any agreement between firms; they depend on the professional activity of inventors, of which the firms they work for may not be aware. The focus of our study is interesting from a policy point of view. Indeed, by jointly evaluating the roles played by inventors' mobility and working relationships on companies' innovation activity, we are able to sketch some preliminary evaluations of policy strategies. We know that interfirm mobility is important for the circulation of ideas and knowledge diffusion. On the other hand, it depends on the recruitment of new personnel, which can be costly for a firm. Moreover, higher worker mobility can be detrimental for company investment in human capital because firms are worried about their inventors leaving. On the contrary, inventors' working relationships are a means of sharing and transferring knowledge that allows companies to take advantage of knowledge flow without additional cost. Moreover, knowledge transmission does not necessarily imply the departure of inventors from the company of origin.

Inventors' professional relationships are the focus of a recent contribution that studied how inventors' interactions affect productivity in innovation. Akcigit, Caicedo, Miguelez, Stantcheva, and Sterzi (2018) studied European inventors' productivity within the structure of inventor research teams and interactions with others. Differently from our contribution, their focus was on inventors' interactions within the same firm and interactions related to past co-inventorships. Thus, the relationships of inventors were codified by either belonging to the same firm or having been working in the past on the same patent through agreement between firms. Moreover, they studied inventors' individual productivity and not productivity at the firm or applicant level, as we do in our study. The results of Akcigit et al. (2018) are extremely interesting because they show that inventors' knowledge is built through interactions with others, and interactions are fundamental for enhancing individual productivity.

Due to data constraints, our study is unable to analyse the effects of social relationships that may arise from other sources aside from inventors' professional relationships. In fact, the database does not include information on the organisation's social capital or the inventors' social environment and social habits. However, we are aware of the role that social relationships in general may play in enhancing the flow of knowledge and innovation. The social capital literature provides some evidence on the topic. For example, Ruiz-Ortega, Parra-Requena, and García-Villaverde (2013), using survey data from companies with more than five employees in the footwear sector in Spain, showed that firms located in industrial districts have greater social capital and acquire more knowledge than firms outside these districts. However, the advantages of firms located in industrial districts were not confirmed when they focused on innovation performance. Differently, Parra-Requena, Ruiz-Ortega, García-Villaverde, and Rodrigo-Alarcón (2015) found that external social capital does affect innovativeness. In particular, firms with a high degree of trust and cognitive proximity in their relationships tend to develop innovativeness. Saint Ville, Hickey, Locher, and Phillip (2016) studied the role of social capital in developing agricultural knowledge networks and the ability of farming households to innovate in Caribbean smallholder farming communities. Their study's results support the view that, by utilising their social networks to increase their connection to a larger number of farmers, smallholders can improve their adaptive capacity to facilitate knowledge exchange,

[3] Developing the idea of Boschma and Iammarino (2009), Boschma et al. (2009) studied Swedish firm performance at plant level – measured by growth in labour productivity between 2001 and 2003 – as a function of labour mobility, as measured by the number of highly skilled job movers. They split mobility into intra-regional and inter-regional mobility according to the local labour market (LLM) definition. Boschma et al. (2009) define LLMs according to a specific commuting-minimising algorithm.

increase access to resources and connect to sources of support. Thus, social networks have a potentially significant role to play in improving smallholder agricultural system innovation in the Caribbean context.

A different approach to the study of social interaction and knowledge flow is embedded in the literature that employs agent-based simulation techniques to study the exchange of knowledge among employees and how organisations can encourage individual knowledge sharing behaviour. As an example, Wang, Gwebu, Shanker, and Troutt (2009) showed that the greater the personal benefit from contributions, the higher the levels of knowledge sharing. Kollock (1998) found that contribution to the sharing of knowledge is more likely when individuals have the ability to punish the defectors.

Our analysis was carried out on all firms established in Veneto, a north-eastern Italian region, who filed patents with the EPO in the pre-crisis period, 1998–2007. By limiting our study to one region, we were able to develop and document a precise procedure for cleaning the data that we may extend to the whole of Italy in the future. We chose Veneto because it is one of the most dynamic regions in Italy; historically, it has been characterised by its well-developed manufacturing industry composed of national and international companies. Veneto has also been characterised by a good technological profile and innovativeness. Whereas in the past, this was largely concentrated in big firms, nowadays, because of the delocalisation and deindustrialisation processes that have taken place in the region along with all advanced economies, industrial development is widespread across a wide number of small firms that are active both in traditional and more technologically advanced sectors. We deliberately limited the period of analysis to the pre-crisis years in order to avoid confounding factors from the crisis.

The paper is structured as follows. In Section 2, we describe the original dataset. Section 3 covers the empirical model and the constructed measures of inventor mobility and working relationships. The results are discussed in Section 4.

## 2. Data

We carried out the analysis on data from the OECD-REGPAT database (December 2010 edition). OECD-REGPAT is a database that includes two main types of micro data on patents: patent applications filed with the EPO in the period 1977–2007 and patent applications filed under the Patent Co-operation Treaty (PCT) at the international phase in the period 1977–2008. We chose to work only on that part of the database containing EPO applications because the PCT archive is much smaller than the EPO archive[4]. We therefore preferred to use the EPO archive to ensure that we included the largest possible number of firms and inventors innovating in the region.[5]

OECD-REGPAT is a very rich database: every record contains information on each patent application filed by one or more applicants, resulting from the contribution of one or more inventors. Every single record can be linked to information on each applicant and inventor participating in the project. The variables include the EPO application number, the application identifier, i.e., a surrogate key identifying patent applications, the EPO patent publication number and the priority year, i.e., the year of first filing. The priority year is the date closest to the actual date of invention and it is used as a proxy for the date of invention. Further information is related strictly to the inventors and applicants listed in each application. This information, together with patent data, allowed us to identify simultaneous and subsequent inventor working relationships and to measure the variables of interest (discussed in the next

[4] For the region of study, in the period covered by OECD-REGPAT (1977–2008), 8059 patent applications were filed under the EPO compared with 3621 filed under the PCT. The difference in the size of the two archives could be because it is much more expensive to file under the PCT than under the EPO.

[5] However, by choosing the EPO database, we excluded patent applications filed with the Italian Patent Office. This choice allows us to deal with patents that, on average, are expected to have a higher commercial value, since applying to the EPO is more expensive and time-consuming than applying to national patent offices only (Hoekman, Frenken, & Van Oort, 2009).

section). In other fields, for every applicant and every inventor we gathered their identification codes[6], full names and addresses, and country and NUTS3 regions of residence.

Despite the relative improvement in the data quality of recent OECD-REGPAT releases, the dataset presents serious problems for the identification of applicants and inventors.[7] To solve these problems, we made considerable efforts to clean the data and then to correctly identify the applicants and inventors through the unambiguous assignment of personal identification codes, addresses, municipalities of residence and company locations.[8]

After cleaning the data, the matrix we used for the study consisted of approximately 3500 inventors who, between 1998 and 2007, collaborated with over 2000 patent applicants in the Veneto region. In this period, the number of patent applications in the whole region exceeded 4700 applications.[9] At this stage, in addition to the original information available from the dataset, we were able to exactly identify any inventors and the applicants they collaborated with at any time, the inventor's correct residential address (street and city) and the location of each applicant in every year (street and city). This allowed us to establish inventors' exact patenting activity by year, applicant and city, and their new patenting activities at any time. Accordingly, by going back to the applicant with which an inventor cooperated, it was possible to measure the transmission of knowledge channels and the sharing that occurred through inventors' working relationships. We discuss these measures in the following section.

## 3. The empirical model

### 3.1. The variables of interest

Our main research goal was to test whether inventors' working relationships facilitate the sharing of tacit knowledge among inventors, giving rise to applicant-level positive knowledge effects that increase innovation activity. Before describing the measures of mobility and work relationships we constructed, we would like to specify a few matters related to the procedure of data construction. First, when building the measures of interest, the data on the Veneto region were matched to the whole OECD database in order to observe inventors' mobility and work relationships with applicants in the rest of Italy and in the world. At a later stage, data were delimited to the region of Veneto. Secondly, always in the phase of data construction, the whole original time series were kept in memory and used to construct a measure of the stock of patents at applicant level for the period prior to the one of interest.

As previously anticipated, we studied two different measures of inventors' working relationships. The first relates to the applicant's engagement of 'new' inventors, that is, inventors who had not worked for the applicant before. This *mobility* of inventors could provide a source of new knowledge for the applicant, increasing the firm's ability to patent (see the literature discussed in the Introduction). The second measure relates to the working relationships that inventors simultaneously have with different applicants in the absence of patenting agreements between the applicants themselves. Our hypothesis is that these relationships (which we call *connections*) help in sharing the knowledge among inventors and thus increase the amount of knowledge that inventors provide to each applicant that they work for. The

[6] Both identification codes are surrogate keys borrowed from the original PATSTAT database.

[7] This issue, known in the literature as the 'who is who' problem (Trajtenberg, Shiff, & Melamed, 2006), comes from two main kinds of errors that affect the correct identification of persons and firms. The first type of problem comes from erroneous or varied spelling of names of individuals, for example, Guiseppe instead of Giuseppe, Il'ya instead of Illya, Gian Carlo instead of Giancarlo or Jan-Douwe instead of Jan Douwe. The second type of error comes from writing the name of the applicant, usually a company, in various ways, for example, Glaxo, Glaxo Wellcome, GlaxoSmithKline or GSK. Additional problems arise in those cases where two different addresses are listed in relation to a single inventor. These cases need further investigation to decide whether there are two inventors with the same name or one inventor who has moved.

[8] Upon request, we can provide more details on the cleaning procedure.

[9] These applications are summed at the firm level by year. We ended up with around 3300 observations organized by firm and year.

number of inventors' *connections* for each applicant can be a proxy of the potential flow of knowledge from which the applicant may benefit. All things being equal, we can imagine that two applicants with the same number of inventors but with a different number of inventors' *connections* may benefit from different externalities and thus have different potential patenting outputs.[10]

Let us turn now to a more detailed description of these variables. *Mobility* was designed to capture the inflow of knowledge for which a mobile inventor can be responsible. This knowledge can be either strictly related to a specific patent the inventor developed in the past or more generic, i.e., related to the inventor's past research experience and the skills accumulated in his/her professional history. We defined a mobile inventor towards applicant $i$ at time $t$ as an individual being already registered in the dataset in correspondence with any applicant and any patent filed in any year $t - x$ (with $x > 0$), and participating at time $t$ in the production of a patent for applicant $i$ that he/she had not worked for before. Notice that, given our definition, an inventor who collaborates with two different applicants at the same time $t$ is not a mobile inventor. *Mobility* was then measured at firm $i$ in year $t$ as the sum of mobile inventors 'towards' firm $i$ at time $t$.

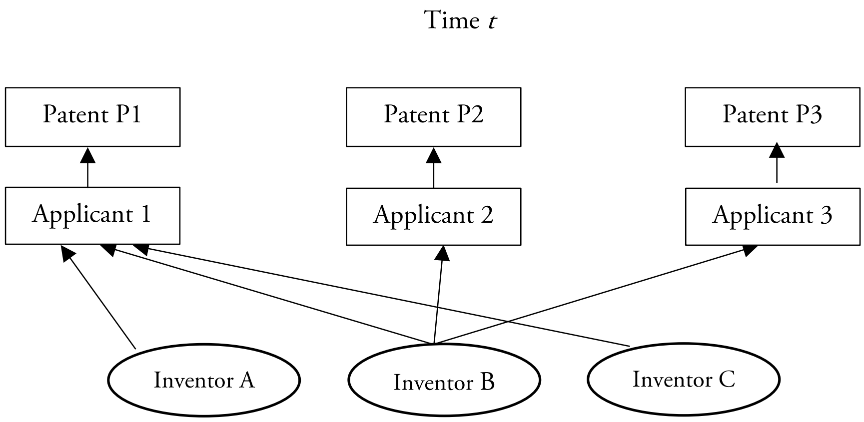
The measure of mobility that we propose can capture the transfer of any type of knowledge – specific or generic – that the inventor may be responsible for when he/she 'moves' to the 'new' applicant. Our measure is similar to the measures used in Simonen and McCann (2008, 2010) and Boschma et al. (2009), where the focus is on the potential effect of worker mobility to be detected at the destination firm. The difference between our study and these contributions relies on the data used and, consequently, on the types of workers under observation: in our case, solely inventors.

The *connections* variable was designed to capture the extent of applicant-level knowledge creation arising from inventors' current patenting collaborations. As previously explained, our hypothesis was that the greater the number of different applicant patenting projects the inventor participates in, the greater his/her knowledge and the potential externality for any applicant he/she works for. We measured *connections* of applicant $i$ at time $t$ as the number of applicants to which applicant $i$ is 'connected' at time $t$ through their inventors' working relationships. The *connections* variable was normalised by the number of inventors who took part in the considered patent and was constructed in such a way that it excludes multiple counting and those cases of inventors whose applicants co-participated in the same patent. This exclusion was motivated by the fact that we aimed to capture the potential effect of the flows of knowledge that arise only from inventor working relationships that are not related to co-operation agreements between the relative applicants. Let us go through a simple example to better understand the construction of *connections*.

Figure 1 shows the case of Applicant 1 who at time $t$ files Patent P1 in collaboration with Inventors A, B, and C. At the same time $t$, Inventor B is collaborating with Applicant 2 on Patent P2 and Applicant 3 on Patent P3. According to the definition of our measure, the Applicant 1 *connections* variable is equal to 2/3: two applicants (Applicants 2 and 3) linked to Applicant 1 through Inventor B, divided by the number of inventors working on Patent P1.

[10] We measure the *mobility* and *connections* variables without counting those relationships between applicants who belong to the same group of companies and controlling for cases of 'false' mobility due to changes of company type or name.

FIGURE 1.
An example of inventor–applicant working relationships




*Mobility* and *connections* constituted our 'basic' explicative variables. Later in this section, we go through the details of the geographical disaggregation of these variables and the dynamic specification of the model. Before doing that, we give a brief explanation of the dependent variables we used. We remind readers that our analysis aims to evaluate the potential effects of inventors' working relationships and mobility in terms of the production of patents at the applicant level.

The simplest variable of interest suitable for measuring the patented activity of each firm/applicant $i$ in any year $t$ is the *sum of patents*: the total number of patents registered at the EPO by applicant $i$ at time $t$. However, this measure of patenting activity may present some limits in representing real patent output when the company has partnered with other companies to carry out the patenting project. In these cases, the patent is the result of the effort of different entities and is shared by all of them, according to the quotas declared to the EPO. In these cases, a better measure of patented activity is given by the *weighted sum of patents* registered by firm $i$ at time $t$, where each patent of firm $i$ is weighted by the firm's participation share in the production of the patent. The *sum of patents* and the *weighted sum of patents* of each applicant $i$ in year $t$ are the two measures of patenting we used as dependent variables in the empirical analysis.

Table 1 summarises the distribution of the *sum of patents*, *mobility*, and *connections*. More than 20% of our observations record more than 1 patent application and almost 5% of cases registered 4 or more patents. Around 12% of observations record at least 1 mobile inventor, while *connections* are less frequent. Tables A1 and A2 in the Appendix include descriptive statistics for the variables of the estimated models.

According to the literature discussed in the Introduction, firm proximity can play an important role in driving knowledge spillovers and externalities. To investigate the geographical model of knowledge diffusion, we separated the geographical extent of *connections* and *mobility* by looking at the place of origin and destination for each relationship.[11] The idea was to evaluate whether a knowledge flow occurs according to the degree of geographical proximity between the origin and destination territory.

[11] As previously explained, we carried out this phase of data construction on the whole OECD-REGPAT database, including all countries. This allowed us to identify inventors' mobility and connections beyond the border of the region.

TABLE 1.
**Number of observations by number of patents, inventor *mobility* and *connections***

| | Observations (%) |
|---|---|
| *Number of patents* | |
| 1 | 2587 (78.8) |
| >1 | 696 (21.2) |
| *Of which* | |
| 2 | 415 (12.6) |
| 3 | 129 (3.9) |
| 4 | 65 (2) |
| 5+ | 87 (2.7) |
| *Mobility* | |
| 0 | 2900 (88.3) |
| 1 | 340 (10.4) |
| 2+ | 43 (1.3) |
| *Connections* | |
| 0 | 3055 (93) |
| 1 | 153 (4.7) |
| 2 | 49 (1.5) |
| 3+ | 26 (0.8) |
| *Total* | *3283 (100)* |

The territorial unit of reference we use is defined by the non-administrative territorial unit of the Local Labour System (LLS) as defined by the Italian Institute of Statistics in 1997 (a similar definition is used in Boschma et al. (2009) for Sweden). LLSs are constructed on commuter routes between home and work, as identified in the most recent population census. They are aggregations of municipalities that identify homogeneous labour markets and functional economic areas. As already argued in previous studies on the topic, LLSs are appropriate units for studying widespread urban areas as they most closely correspond with economic and functional areas and local labour markets (Boschma et al., 2009).

We defined *local*, *regional* and g*lobal* c*onnections* as follows: *local connections* exist when the applicants involved are located within the same LLS (intra-LLS *connections*); *regional connections* take place when inventors' working relationships connect applicants established in different LLSs of Veneto; *extra-regional connections* couple any applicant of Veneto to applicants established outside Veneto (either in Italy or a foreign territory). Similarly, we defined *local mobility* as when inventors 'move' inside the same LLS, *regional mobility* as when inventors move between firms/applicants located in different LLSs of Veneto and *extra-regional mobility* as when inventors 'move' to the observed applicant from firms located outside the region (either in Italy or a foreign territory).

The geographical specification of the variables of interest adds a further element to the analysis: the time needed for *connections* and *mobility* to affect patenting output. As shown in most recent contributions to the study of the effects of labour market relationships on the transfer of knowledge, relationships that occur within the same LLS may involve firms that are more closely 'related', in terms of production specialisation and worker competencies, than firms belonging to different LLSs or different regions/countries. Thus, the transfer of knowledge may be faster when relationships are within the same LLS than between different LLSs or regions/countries. For this reason, we add the time dimension to the geographical specification and end up with a time-space specification for both *connections* and *mobility.*[12]

Therefore, the different measures of the *connections* variable are evaluated both at the same time ($t$) the patenting output was observed and estimated (variable *connections*) and at different time lags (variables *connections lag i – j years*). When lagged, the *connections* variable measures relationships that occurred in the past – in years $t$ – *1*,.., $t$ – *i*, $t$ – *j* – and is meant to capture the lagged effect of knowledge diffusion. For simplicity, we grouped lagged *connections* at five-year intervals after carrying out robustness checks for different time intervals and making sure that the dynamics were satisfied regardless of the chosen interval.[13] As the *mobility* variable already measures the 'movement' of inventors between time $t$ and any time $t$ – $x$ (with $x > 0$), the temporal specification simply details the time interval (always at five-year intervals).

## 3.2. The econometric model

Our aim was to empirically test whether inventors' working relationships, measured by *connections* and *mobility*, are responsible for the sharing and creation of knowledge and whether or not they positively affect patenting. The econometric model was estimated for all firms that apply for a patent at any time $t$ in the period 1998–2007 and the dependent variable is one of the measures of patenting activity, as explained in the previous sections.

Data on patent applications of firm $i$ at any time $t$ are typical count data. The clear discrete nature of these data and the preponderance of small values suggest that we can improve on least squares with a model that accounts for those characteristics using the Poisson regression model.

A Poisson regression is a form of generalised linear model where the response variable is modelled as having a Poisson distribution; random variables with non-negative integer values are modelled as Poisson distributions. A random variable Y is said to have a Poisson distribution with the parameter $\mu$, $Y \approx P(\mu)$ if it takes integer values $y = 0, 1, 2, \ldots$ with the probability:

$$Pr\{Y = y\} = \frac{e^{-\mu}\mu^{y}}{y!} \tag{1}$$

For $\mu > 0$, the mean and the variance of this distribution can be shown to be: $E(Y) = var(Y) = \mu$. Since the mean is equal to the variance, any factor that affects one will also affect the other.

The Poisson regression model stipulates that a sample of $n$ observations $y_1, y_2, \ldots, y_n$ can be treated as realisations of independent Poisson random variables, with $Y_i \approx P(\mu_i)$ and $y_i$ taking integer values. A common transformation of the Poisson regression model is given by the log-linear Poisson model, where $\mu_i$ depends on a vector of explanatory variables $x_i$ through a log-linear model such as:

$$\log(\mu_i) = x_i'\beta \tag{2}$$

in which the regression coefficient $\beta$ represents the expected change in the log of the mean per unit change in the predictor $x_i$. In other words, increasing $x_i$ by one unit is associated with an increase of $\beta$ in the log of the mean.

By exponentiating equation (2), we obtained a multiplicative model for the mean itself:

$$\mu_i = \exp\{x_i'\beta\} \tag{3}$$

[12] As previously discussed, we worked on the original time-series of the database to construct the lagged measures of *mobility* and *connections*.

[13] Upon request, we can provide the tables with these estimations.

where the exponentiated regression coefficient $\exp\{\beta\}$ represents a multiplicative effect of the $j$-th predictor on the mean.

The problem with the Poisson regression model is that the assumption that the conditional mean and variance of $Y$ are equal may be too strong, given $X$. Inappropriate imposition of this restriction may produce spuriously small estimated standard errors. In addition, the model is based on the assumption that events occur independently over time.

A way to correct these issues is to allow for unexplained randomness by replacing equation (2) by the stochastic equation:

$$\log(\mu_i) = x_i'\beta + \varepsilon_i \tag{4}$$

where the error term is assumed to be normally distributed.

Equation (4) represents a natural generalisation of the Poisson regression model, where the error term can reflect a specification error such as unobserved omitted exogenous variables (Cameron & Trivedi, 1986). This also allows for cross-firm heterogeneity.

The generalised Poisson regression model is very similar to the non-negative binomial model. In fact, the two models differ only in the distribution of the error term: the error is assumed to be distributed according to a normal density function for the generalised Poisson regression and according to a gamma distribution in the non-negative binomial case. Actually, the negative binomial model is a more general model than the generalised Poisson regression because it allows for the variance to exceed the mean. However, under a specific assumption on a parameter of the gamma distribution, mean and variance converge and the non-negative binomial model becomes identical to the Poisson. In deciding which model to use, we took account of the distribution of the dependent variables of interest. It is clear that the distribution of the number of patents is not characterised by over dispersion. Indeed, its variance is lower than its mean. However, the variance becomes slightly larger than the mean when we derive the weighted sum of patents. However, as the difference between the variance and the mean was negligible, it was not appropriate to adopt the non-negative binomial model and we decided to use the generalised Poisson regression model.

Given the longitudinal dimension of our data, we estimated the model as the following:

$$\log(\mu_{it}) = cons + \alpha_t + \beta * connections_{it} + \delta * mobility_{it} + \gamma * patstock\_past_i + \varepsilon_i \tag{5}$$

where each applicant $i$ is observed in each year $t$ of the period 1998–2007.

The specification includes the above-discussed variables of interest, *connections* and *mobility*, together with the variable *patstock_past* measured at the applicant level. The variable *patstock_past* is defined as the stock of patents registered by each applicant in the decade prior to the period of interest (1988–1997). When estimating the model for the weighted sum of patents, we measured *patstock_past* by the weighted stock of patents (always registered in the period 1988–1997). The inclusion of the stock of patents and weighted stock of patents at the applicant level allows us to investigate the existence of persistence in patenting. According to the empirical evidence, pre-existing knowledge stocks are important for innovation (Roper & Hewitt-Dundas, 2008) and for patenting activities (Cefis & Orsenigo, 2001). Therefore, we expected the variable to have a positive and significant effect. To complete the model specification, random effects at the applicant level were also included to capture the role played by applicant unobservables, together with a time trend, $\alpha_t$.

We carried out the initial empirical analysis using the specification without geographical disaggregation but including the lagged variables (*base model*). In a second step, we added the geographical specification for the explicative variables (local, regional and global) and estimated the *geographical model*. Estimation results for the *base model* are reported in Table 2; those concerning the *geographical model* are shown in Table 3. We estimated both models using the two dependent variables: the *sum of patents* and the *weighted sum of patents*. Before estimating the different specifications, we carried out a correlation analysis to ensure that the explanatory variables were not causing multi-collinearity problems.[14]

## 4. Results

In this section, we discuss the results of the estimates of the econometric model illustrated in Section 3, which allows us to evaluate the effect of inventors' working relationships on patenting.[15]

We processed equation (5) to the two different specifications: the *base model* and the *geographical model*. We ran both specifications using the two alternative dependent variables: the *sum of patents* and the *weighted sum of patents*. Table 2 lists the estimated coefficients, the marginal effects and the usual statistics.

The general result that emerges from the different specifications of the base model is that there exists a growing trend in patent production: the higher the number of patents filed by the firm in the period 1988–1997, the higher the sum of patents produced yearly by the firm in the observed sample. This result indicates the existence of some degree of persistence in patenting activities at the firm level, confirming what previous empirical studies have shown (see for example, Cefis & Orsenigo, 2001).

We now turn to the results for the variables that measure inventor mobility and working relationships. The overall result is that both the *mobility* and *connections* variables can explain the production of patents. This is so even in the simple *base model* where the territorial extension of the relationships is not investigated. However, some caveats are necessary. Inventor mobility enhances patenting activity, but only when the period between when the patent was registered with the leaving applicant and filed with the destination applicant is not greater than five years. After five years, inventor mobility has no significant positive effect on innovation at the destination firm. This result shows that mobility has knowledge productivity effects if the contribution of the incoming inventor affects the production of new patents in the short term. Indeed, this outcome shows that the ability of an inventor to increase the patenting activity of a firm is negatively correlated to the time lag between the moment in which the inventor filed the last patent with the originating company and the time he records the first patent with the destination company. If this period is longer than five years, the incoming inventor will not significantly contribute to increase innovation in the 'recruiting' firm.

Now let us concentrate on the estimation results for inventors' patenting relationships measured by the variable *connections*. The variable has significant and positive effects on the creation of knowledge: coefficients and marginal effects are mostly significant, regardless of the time span that elapses between the year in which inventors' working relationships occurred and the year of observation of the company's patenting output.[16] However, this effect appears to increase over time: relations that occurred several years earlier (11–15 years) have a much higher marginal effect on the production of patents than relations that occurred in recent years (1–5 years) or in the same year of observation. As we see in the discussion of the geographical model, this outcome is partly due to the correlation between the time and the spatial extent of the area of influence of inventors' working relations. However, some caution has to be taken in interpreting the results. In fact, the increasing effect detected as the time lag increases may also be linked to inventors' characteristics, in particular to their working experience. Connections that are more distant in

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[14] We can provide the correlation matrix on request.

[15] We remind readers that, by construction, the *connections* and *mobility* variables are net of relationships occurring between applicants that belong to the same business group and net of 'false' mobility.

[16] The estimation results using 5-year lagged connections show some discontinuities of significance (1–5 and 11–15-year lags are significant while 6–10 and 16–20 year lags are not). This is probably due to a numerosity effect when grouping connections every five years. Indeed, when we initially ran the model with 1-year lagged connections, we found some regularities in the effect of 1-year lagged connections and an increasing effect of connections with time. Then, we decided to use 5-year lagged connections to reduce the length of tables. If there is interest, we can provide the tables with the results of the model with 1-year lagged connections.

time may be those of inventors with a longer working experience. Thus, the coefficient increases over time because it also captures the effect of the human capital that inventors accumulate over time.

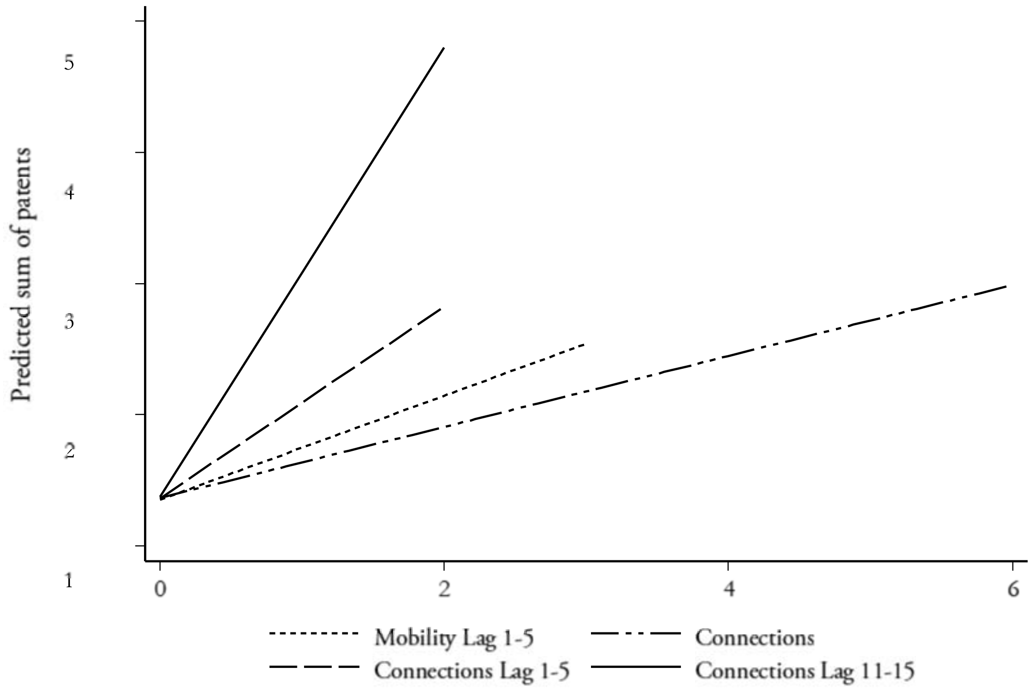
TABLE 2.
**Base model. Estimation results**

| | Dependent variable | | | |
|---|---|---|---|---|
| | Sum of patents$_{it}$ | | Weighted sum of patents$_{it}$ | |
| | **Coef.** | **Marg. effect** | **Coef.** | **Marg. Effect** |
| Time trend | 0.02*** | 0.03*** | 0.02*** | 0.03*** |
| | (0.01) | (0.01) | (0.01) | (0.01) |
| Stock of patents (1988–1997) | 0.02*** | 0.02*** | | |
| | (0.00) | (0.00) | | |
| Stock of weighted number of patents (1988–1997) | | | 0.02*** | 0.02*** |
| | | | (0.00) | (0.00) |
| **Mobility** | | | | |
| *Lag 1–5 years* | 0.09** | 0.13** | 0.09* | 0.11* |
| | (0.05) | (0.06) | (0.05) | (0.06) |
| *Lag 6–10 years* | 0.03 | 0.03 | 0.05 | 0.06 |
| | (0.09) | (0.12) | (0.09) | (0.12) |
| *Lag 11–15 years* | 0.04 | 0.05 | 0.07 | 0.09 |
| | (0.13) | (0.17) | (0.13) | (0.16) |
| *Lag 16–20 years* | –-0.24 | –0.32 | –0.23 | –0.28 |
| | (0.26) | (0.35) | (0.27) | (0.33) |
| **Connections** | 0.11*** | 0.15*** | 0.07* | 0.09* |
| | (0.04) | (0.05) | (0.04) | (0.05) |
| **Lagged connections** | | | | |
| *Lag 1–5 years* | 0.18** | 0.25** | 0.20** | 0.25** |
| | (0.08) | (0.11) | (0.09) | (0.11) |
| *Lag 6–10 years* | 0.16 | 0.21 | 0.15 | 0.19 |
| | (0.11) | (0.14) | (0.11) | (0.14) |
| *Lag 11–15 years* | 0.32** | 0.44** | 0.33** | 0.42** |
| | (0.14) | (0.19) | (0.15) | (0.18) |
| *Lag 16–20 years* | 0.27 | 0.36 | 0.22 | 0.28 |
| | (0.17) | (0.23) | (0.18) | (0.23) |
| Constant | –37.26*** | | –43.45*** | |
| | (10.85) | | (11.22) | |
| *Ln(μ)* | –2.54*** | | –2.33*** | |
| | (0.09) | | (0.09) | |
| Observations | | 3 283 | | 3 283 |
| Number of applicants | | 2 018 | | 2 018 |
| *Wald test Chi$^2$* | | 120.75*** | | 110.56*** |

Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.
**Note:** The variable *connections* is normalized by the number of inventors by firm and year.

To better summarise and understand the role played by the variables of the *base model* in explaining the production of patents, in Figure 2 we plot the line that interpolates the relationship between each variable with a statistically significant coefficient and the prediction of the dependent variable (predicted sum of patents). The graph clearly shows the positive relationship between the different variables of interest and the predicted sum of patents filed yearly at the EPO, confirming the importance of inventors' working relationships for the creation of new knowledge and patented innovation. The most significant effect is due to the *connections* variable, especially in the long term.

**FIGURE 2.**
**Base model. Linear interpolation of the *predicted sum of patents* in relation to *mobility* and c*onnections*.**




**Note:** only for statistically significant covariates

We can move now to the discussion of the estimation results for the geographical model (Table 3).

The geographical specification confirms the path dependency and the positive time trend of patenting: the time trend and the coefficients of the stock of patents in the period 1988–1997, whether weighted or unweighted, according to the dependent variable used, are significant, positive and stable. In general, the estimated coefficients of the *geographical model*, when significant, are greater than those predicted in the *base model*. This suggests that we underestimate the innovative effects of knowledge flows if we fail to consider the geographical dimension.

TABLE 3.
**Geographical model. Estimation results**

| | | Dependent variable | | | |
|---|---|---|---|---|---|
| | | Sum of patents$_{it}$ | | Weighted sum of patents$_{it}$ | |
| | | Coeff. | Marg. effect | Coeff. | Marg. effect |
| Time trend | | | 0.03*** | 0.02*** | 0.03*** |
| Stock of patents (1988–1997) | | 0.02*** | 0.02*** | | |
| Stock of weighted number of patents (1988–1997) | | | | 0.02*** | 0.02*** |
| **Mobility** | | | | | |
| *Local mobility* | *Lag 1–5 years* | 0.12* | 0.16* | 0.12* | 0.15* |
| | *6–10 years* | –0.03 | –0.04 | –0.01 | –0.01 |
| | *11–15 years* | 0.04 | 0.05 | 0.07 | 0.08 |
| | *16–20 years* | –0.21 | –0.28 | –0.21 | –0.26 |
| *Regional mobility* | *Lag 1–5 years* | 0.04 | 0.05 | 0.04 | 0.05 |
| | *6–10 years* | 0.08 | 0.11 | 0.08 | 0.11 |
| | *11–15 years* | –0.01 | –0.01 | 0.02 | 0.03 |
| | *16–20 years* | –0.28 | –0.33 | –0.22 | –0.25 |
| *Extra-regional mobility* | *Lag 1–5 years* | 0.14 | 0.19 | 0.12 | 0.15 |
| | *6–10 years* | 0.09 | 0.12 | 0.12 | 0.16 |
| | *11–15 years* | 0.10 | 0.14 | 0.13 | 0.18 |
| | *16–20 years* | –0.35 | –0.39 | –0.32 | –0.34 |
| **Connections** | | | | | |
| *Local connections* | | 0.12** | 0.16** | 0.08 | 0.10 |
| *Regional connections* | | 0.12 | 0.16 | 0.07 | 0.09 |
| *Extra-regional connections* | | 0.00 | 0.01 | –0.02 | –0.02 |
| **Lagged connections** | | | | | |
| *Local connections* | *Lag 1–5 years* | 0.18* | 0.24* | 0.19* | 0.24* |
| | *6–10 years* | 0.17 | 0.23 | 0.18 | 0.23 |
| | *11–15 years* | 0.71*** | 0.96*** | 0.72*** | 0.90*** |
| | *16–20 years* | 0.42 | 0.56 | 0.48 | 0.60 |
| *Regional connections* | *Lag 1–5 years* | 0.47* | 0.62* | 0.50** | 0.63** |
| | *6–10 years* | –0.21 | –0.28 | –0.35 | –0.44 |
| | *11–15 years* | –1.00 | –1.34 | –0.94 | –1.18 |
| | *16–20 years* | 0.06 | 0.08 | –0.14 | –0.17 |
| *Extra-regional connections* | *Lag 1–5 years* | –0.08 | –0.11 | –0.03 | –0.04 |
| | *6–10 years* | 0.30 | 0.40 | 0.30 | 0.38 |
| | *11–15 years* | 0.12 | 0.16 | 0.16 | 0.20 |
| | *16–20 years* | 0.43* | 0.57* | 0.44* | 0.56* |
| Constant | | –37.19*** | | –43.47*** | |
| *Ln(μ)* | | –2.57*** | | –2.36*** | |
| Observations | | 3 283 | | 3 283 | |
| Number of applicants | | 2 018 | | 2 018 | |
| *Wald test Chi²* | | 139.05*** | | 129.41*** | |

For reasons of space, standard errors are not reported. *** p<0.01, ** p<0.05, * p<0.1.
**Note:** The variable *connections* is normalized by the number of inventors by firm and year.

Regarding the measures of inventors' *mobility* and *connections*, the geographical model adds some interesting elements to the understanding of the mechanisms of the transfer of knowledge in the hands of inventors. For mobility, the results of the base model hold in the geographical specification: mobility significantly affects patenting only if the incoming inventor participates in some patenting output in the short term. However, the geographical specification clearly shows that inventor mobility affects the creation of knowledge at a very local level only if mobility occurs within the same LLS. *Connections*, in contrast, have local, regional and extra-regional effects and time plays some role in shaping these effects. While local connections significantly affect the innovation output in the very short term and in the medium to long term, regional connections have an effect in the medium term only and extra-regional connections in the long term. Thus, the geographical model seems to highlight the importance of time in determining the significant impact of working relationships that go beyond the LLS in spatial terms.[17]

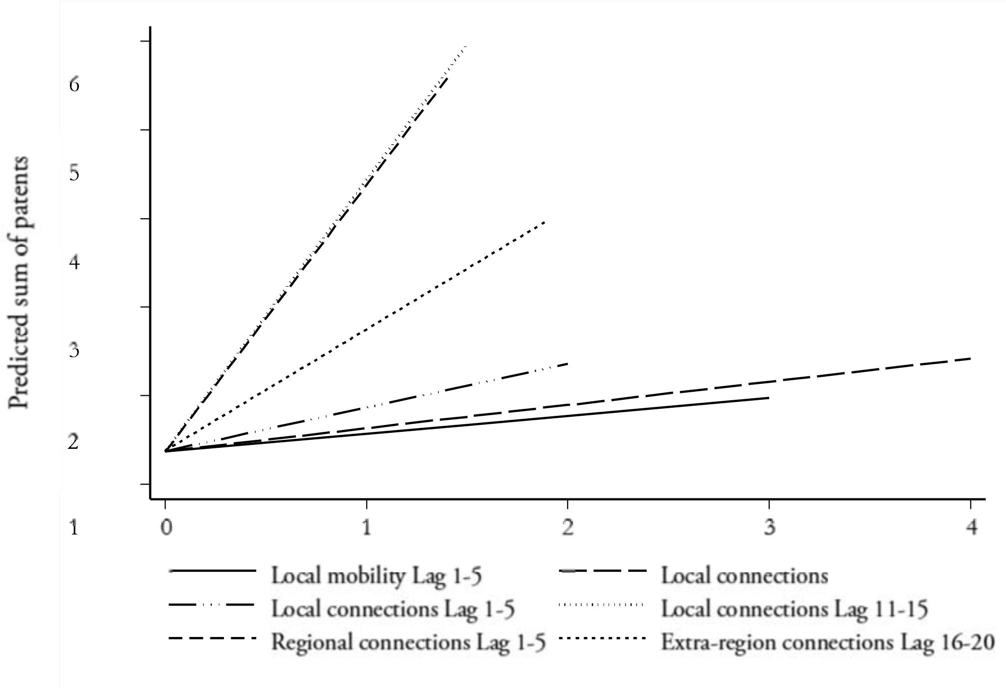
Turning to the size of the innovation effect, we can see that regional and extra-regional connections have innovation effects (marginal effects) sharply higher than the effects of local connections in the very short and the short term. This seems to support the outcomes of some empirical studies showing that human capital's working relationships improve knowledge creation and/or innovation if they occur between different areas.

In particular, our results fit well with Simonen and McCann (2008) who, working on a sample of Finnish high-technology firms, found that human capital inputs sourced from the local area are negatively associated with both product innovation and new products to market. On the other hand, human capital inputs acquired from other areas (and from the same sector) are positively related to product innovation. Simonen and McCann (2010) confirmed these results. They did not find evidence for a positive innovation role played by local labour markets. On the contrary, they detected a positive role played by human capital acquired from the same industry but from other regions. Also, Boschma et al. (2009), studying labour mobility in the entire Swedish economy, confirmed that the effects of labour mobility on firm performance depend on whether new employees are recruited from the same region or from other regions. However, since they were able to disentangle the types of skills of labour inflows, they showed that worker inflows from the same region contribute positively to plant performance when they are of unrelated skills with respect to internal skills. On the contrary, mobility across regions only has a positive effect on productivity growth when it concerns new employees with related skills.

We summarise the results of the geographical model in Figure 3. This shows the pairwise relationship between the predicted sum of patents and each variable with statistically significant effects. The figure clearly shows the positive relationship between the variables of interest and the predicted patenting activity, and how the spatial extent of inventors' relationships and time play a joint role in explaining the production of patents. Thus, the pattern of knowledge creation is not unique. For inventors' mobility, knowledge externalities occur in the short term and within very narrow boundaries (within LLSs). Otherwise, inventors' *connections* are responsible for knowledge externalities that spread beyond the local system where knowledge comes from.

[17] As for the base model (see Footnote 16), the regressions were first run with 1-year lagged connections. Then, since this model showed some regularities in the effects of 1-year lagged connections, we simplified the specification by grouping connections in 5-year lagged variables.

FIGURE 3.
**Geographical model. Linear interpolation of the *predicted sum of patents* in relation to *mobility* and *connections*.**




**Note:** only for statistically significant covariates

## 5. CONCLUSIONS

In this article, we study inventors' working relationships and mobility and their role in mediating the sharing of tacit knowledge. We evaluate the effects of these externalities on innovation, which we measure by patenting activity. This work fits into the branch of literature that highlights the role played by labour markets in the transmission of knowledge, in particular of knowledge tacitly held by individuals taking part in patenting processes.

The study adds something new to the literature. First, besides considering inventors' mobility, we also take into account a possible source of knowledge externality – inventors' working relationships (*connections*) – which has not been considered in any previous research. The peculiarity of these relationships is that they are not codified by any formal agreement between firms, unlike co-inventorships and multi-firm collaborations. As *connections* depend only on inventors' professional activities, the firms they work for may not be aware of them. Whereas inventors' *mobility* implies that inventors leave one firm to join a new one, *connections* highlight the working relationships that occur simultaneously and through multiple firms. This simultaneity gives rise to knowledge externalities across firms and can positively affect knowledge creation and the production of patents.

The article also explores the spatial extent and the dynamic pattern of the spread of knowledge and it contributes to the wide literature on knowledge externalities. To do so, we measured inventors' mobility and working relationships (*connections*). We took into account the territorial dimension, i.e., the LLS location of those firms involved by inventor's relationships/mobility. Thus, we captured the local, regional and extra-regional extent of the knowledge externalities and we measured their short- and long-term effects.

We carried out the analysis on the population of those firms located in Veneto which filed patents with the EPO in the pre-crisis period (1998–2007). After cleaning the data, we measured the patenting activity and the variables of interest year by year at the firm level. We ended up with an unbalanced panel of 2018 applicants filing at least one patent with the EPO in the period 1998–2007. We estimated the patenting model using a Poisson specification and exploited the panel dimension.

Our results confirm the role played by human capital in the transmission of knowledge. Specifically, inventors are responsible for positive externalities that benefit the companies with whom they patent. Such externalities, which arise and spread through labour relations and mobility, enhance companies' capacity for patenting. However, in general, *connections* have a higher positive impact on patenting activity than *mobility*.

By focusing on the spatial extent of inventors' *mobility* and *connections*, we have contributed to a better understanding of knowledge spillovers. In line with most of the literature on worker mobility and the transfer of knowledge, we found that the transfer of knowledge that occurs through inventors' mobility is localised and has a significant effect on patenting only within the borders of the specific LLSs where it takes place and when the production of new knowledge occurs in the short term. However, we also obtained original results because knowledge externalities that occur through inventors' working relationships have local, regional and extra-regional effects. This study shows the existence of a complex pattern of knowledge relationships, where both local and distant working relationships play a role in the transfer and creation of knowledge. Inventors' working relationships thus produce productivity effects, in terms of patenting activity, that are driven by factors related to the spatial extent of these relationships, in particular to the skill content of local and more extended relationships. Thus, not only local relationships, supported by physical proximity, but also distant relationships can be important for company performance. We contend that distant relationships can be relevant for the transfer of those skills that are not similar to those existing in the knowledge base of the firm but which are complementary to them. Although we could not control for inventors' competences and skills, our findings support previous research findings that company performances are affected by worker relationships, depending on a mix of geographical proximity and competences (Boschma et al., 2009; Eriksson, 2011).

Our results are of particular significance in relation to the territorial context of our study, the Veneto region. Strong local relations characterise the productive structure of Veneto, where face-to-face interactions are widespread and regularly occur, thus supporting a preliminary hypothesis of a localised knowledge diffusion, supported by territorial and physical proximity. However, our results emphasise that beyond the role of proximity in generating knowledge spillovers and productivity effects, working relationships among inventors channel knowledge diffusion on a much broader scale.

From a policy point of view, our results suggest that increasing investment to promote inventors' opportunities to connect with other firms' inventors can be a smart strategy to enhance knowledge transfer and creation inside firms. The channels of inventors' and researchers' professional relationships appear to be a more effective conduit of knowledge creation to positively affect firms' patenting activity than interfirm workers' mobility. This implies that, even in the presence of non-compete covenants, a company's innovation capacity can be enhanced through channels that include opportunities for its inventors to connect with other firms' inventors. Indeed, we think that a practical example of these types of policies is illustrated by the European Commission's Erasmus+ programme of recent years. With respect to the past, the programme presents interesting lines of intervention for the learning mobility of workers. Key Action 1 of the programme provides that organisations can engage in a number of development activities that include improvement of the professional skills of their staff through the arrangement to send or receive staff to or from participating countries.

Our study lacks some possible further analysis on the sector of activity and the geographical extent of the working relationships that affect innovation. Future research should focus on building a better understanding of the geographical extent of the benefits at industry level. Unfortunately, databases on patents do not provide information on the industrial sector that the applicant belongs to. Thus, this type of analysis would need to involve the merging of patent data with other databases.

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## APPENDIX

TABLE A1.
**Base model: descriptive statistics**

| | Mean | St. Dev. |
|---|---|---|
| Number of patents | 1.442 | 1.415 |
| Weighted number of patents | 1.365 | 1.434 |
| Stock of patents 1988–1997 | 1.886 | 8.832 |
| Stock of weighted sum of patents 1988–1997 | 1.863 | 8.738 |
| **Mobility** | | |
| Lag 1–5 years | 0.083 | 0.308 |
| Lag 6 to10 years | 0.029 | 0.173 |
| Lag 11 to 15 years | 0.013 | 0.118 |
| Lag 16 to 20 years | 0.004 | 0.070 |
| **Connections** | | |
| Number of connections# | 0.066 | 0.337 |
| Lag 1–5 years | 0.030 | 0.171 |
| Lag 6–10 years | 0.016 | 0.131 |
| Lag 11–15 years | 0.007 | 0.083 |
| Lag 16–20 years | 0.006 | 0.081 |

\# Normalized by the number of inventors by firm and year.

TABLE A2.
Geographical model: descriptive statistics

| | | Mean | St. Dev. |
|---|---|---|---|
| Number of patents | | 1.442 | 1.415 |
| Weighted number of patents | | 1.365 | 1.434 |
| Stock of patents (1988–1997) | | 1.886 | 8.832 |
| Stock of weighted sum of patents (1988–1997) | | 1.863 | 8.738 |
| Mobility | | | |
| *Local mobility* | *Lag 1–5 years* | 0.049 | 0.238 |
| | *6–10 years* | 0.016 | 0.132 |
| | *11–15 years* | 0.007 | 0.089 |
| | *16–20 years* | 0.003 | 0.058 |
| *Regional mobility* | *Lag 1–5 years* | 0.020 | 0.149 |
| | *6–10 years* | 0.006 | 0.080 |
| | *11–15 years* | 0.003 | 0.052 |
| | *16–20 years* | 0.001 | 0.030 |
| *Extra-regional mobility* | *Lag 1–5 years* | 0.012 | 0.119 |
| | *6–10 years* | 0.005 | 0.071 |
| | *11–15 years* | 0.003 | 0.055 |
| | *16–20 years* | 0.001 | 0.025 |
| Connections | | | |
| *Local connections* | | 0.046 | 0.265 |
| *Regional connections* | | 0.014 | 0.150 |
| *Extra-regional connections* | | 0.006 | 0.080 |
| Lagged connections | | | |
| *Local connections* | *Lag 1–5 years* | 0.020 | 0.149 |
| | *6–10 years* | 0.009 | 0.103 |
| | *11–15 years* | 0.003 | 0.049 |
| | *16–20 years* | 0.001 | 0.024 |
| *Regional connections* | *Lag 1–5 years* | 0.006 | 0.057 |
| | *6–10 years* | 0.004 | 0.052 |
| | *11–15 years* | 0.001 | 0.028 |
| | *16–20 years* | 0.003 | 0.062 |
| *Extra-regional connections* | *Lag 1–5 years* | 0.003 | 0.055 |
| | *6–10 years* | 0.003 | 0.057 |
| | *11–15 years* | 0.002 | 0.061 |
| | *16–20 years* | 0.002 | 0.046 |

# Normalized by the number of inventors by firm and year.