Proximity of Inventors and Knowledge Flows

Paola Giuri
Laboratory of Economics and Management
Sant'Anna School of Advanced Studies
giuri@sssup.it

Myriam Mariani
CESPRI and IEP, Università Commerciale Luigi Bocconi
myriam.mariani@uni-bocconi.it

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This paper contributes to understanding the role of geographical proximity in knowledge interactions. By using survey data on 6,945 patents of European inventors, we study the geographical breadth of knowledge exchange in the form of meetings, discussions and, more generally, circulation of ideas that inventors develop during the inventive process. We start by showing that interactions with geographically close individuals are fewer and less important than interactions across regions. We then explore two issues concerning the geographical extent of knowledge interactions. First, is there a "Silicon Valley effect", i.e. do local interactions develop in technological active and richer regions (the technological clusters) more than elsewhere? Second, is the spatial dimension of interactions shaped by the characteristics of the inventors who set them up? Our results show that, after controlling for many factors, the importance of local interactions is not correlated with being located in the technological clusters. Differently, inventors' personal background is key in explaining the geographical extent of knowledge ties. Specifically, interactions tend to be local when the research project has a low scientific content and the inventors are young and have a low level of education. By contrast, the higher the experience and the educational background of the inventors, the wider and more dispersed geographically are the research networks. This suggests that local links are established because of the individual inadequacy to enter into broader research networks. Implications for the design and effectiveness of regional policies to stimulate technological development arise compared to actions directed to individual "openness".

1. Introduction

Since Marshall (1920) a large amount of research has been devoted to theorize and prove the existence, extent and merits of geographically localized knowledge spillovers as one of the advantages of regional agglomeration economies. The basic idea is that there are geographic boundaries to knowledge flows and that physical proximity among individuals foster communication and makes it easier to access information produced by others, therefore reducing the complexity and uncertainty of production and research activities (for a survey, see Doring and Schnellenbach, 2006; Feldman, 1999). Moreover, compared to manufacturing, inventive activities benefit the most from co-location, particularly in skilled and R&D-intensive industries (Audretsch and Feldman, 1996) and in sectors that rely more on new economic knowledge, practice and learning-by-doing (Pavitt, 1987; Maskell, 2001).

Knowledge spillovers have important economic implications. On the one hand, the fact that knowledge spills over from the source that generates it to other parties might lower the incentive to produce it in the first place, and encourages free-riding on others' research efforts. On the other hand, by generating increasing returns, spillovers foster economic growth (e.g. Romer, 1990; Grossman and Helpman, 1991). Moreover, as the ability to exchange knowledge is geographically constrained, innovative and economic activities tend to be geographically concentrated. This contributes to shape the geographical distribution of innovative and economic activities and, at the same time, it increases inequality among regions and countries (Saxenian, 1994; Verspagen, 1997; Swann *et al.* 1998).

The importance of knowledge spillovers has encouraged scholars in economic and managerial disciplines to document them and to study their boundaries (see, for example, Jaffe, 1989; Acs et al. 1994 among others; Jaffe, Trajtenberg and Fogarty, 2000; Funke and Niebuhr, 2005). A seminal paper in this direction, on which a large number of later contributions are based, is by Jaffe et al. (1993). They use US patent citations and a matching method that controls for the pre-existing distribution of production activities, and show that knowledge spillovers are geographically concentrated between and within countries (for Europe see Verspagen, 1997; Verspagen and De Loo, 1999).[1]

In spite of this research that provides evidence about the existence and benefits of locally bounded knowledge spillovers, some recent contributions are more skeptical. There is concern, for example,

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[1] For a discussion on the use of patent citations as measures of knowledge flows: Jaffe et al. (1993), Ameida and Kogut (1999), Hall et al. (2001), Jaffe and Trajtenberg (2002).

about the use of patent citations to measure spillovers, as Alcacer and Gittelman (2006) show that an important fraction of patent citations are included by the examiners rather than inventors (see also Jaffe *et al.*,1998, Harhoff et al., 2005). Precisely, this share is about 41% for USPTO patents. This problem is especially relevant for patents issued by the EPO, because 93% of patent citations are generated by the examiner or search officer. This makes patent citations a noisy measure of the extent and direction of the knowledge flows.

Moreover, even if one trusts citations as a measure of knowledge flows, in a 2005 paper, Thompson and Fox Kean revisit the Jaffe et al. (1993) work and, by using patent citations, find no evidence of regional spillovers. To check the robustness of the Jaffe et al. analysis they use finer criteria to select the control sample of patents – which is critical in order to control for the pre-existing patterns of industrial activities – and find that this eliminates the intra-national location of knowledge spillovers (at the level of the State and Consolidated Metropolitan Statistical Areas). Only international location effects remain. By using a different identification methodology that compares the geographic matching of a sample of US cited and citing patents in the two alternative settings in which citations are added by inventors and by examiners, Thompson (2004) finds evidence of a modest location effect, with inventors' citations being more likely to match the intra-national location of the cited patents compared to examiners' citations.[2]

Not only has the measurement of knowledge spillovers been discussed, but also the traditional notion of spillovers as merely being "in the air" is now debated against other mechanisms whereby individuals and their personal networks shape the direction and geographical breadth of knowledge flows. For example, Zucker et al. (1998 and 1999) show that what might appear to be localized knowledge spillovers in the US biotechnology industry is in fact a pure market mechanism through which star scientists are either employees or collaborators of biotechnology companies in the regions. Almeida and Kogut (1999) use US patent citations of important semiconductor inventions and find that the location of knowledge spillovers varies across regions and they tend to be located in only three out of the thirteen regions that they analyzed. In addition, they suggest that an important mechanism by which knowledge is transferred in semiconductors is inter-firm mobility of

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[2] More generally on agglomeration economies Klepper (2002) studied the US automobile industry and argues that firm competencies rather than regional agglomeration economies are the drivers of the evolution and location of the industry. Buenstorf and Klepper (2005) examine the geographical distribution of firm entry in the U.S. tire industry and find little evidence of agglomeration economies shaping the regional patterns of firm origination. Rather, the regional distribution of firm birth reflects the distribution of potential founders with adequate competencies.

Cassiman and Veugelers (2002) show that when knowledge spillovers are important inputs for the invention process, firms in the Belgian manufacturing industry are also likely to engage in cooperative R&D agreements.

human capital that embodies knowledge. Likewise, others take the inventor as the unit of analysis and show that knowledge flows and regional co-location is in fact driven by the underlying social networks among researchers (e.g. Breschi and Lissoni, 2004; Singh, 2005; Fleming et al. 2007).

This paper provides new evidence on the extent to which knowledge flows are geographically localized, and the factors that affect the probability that they are bounded within specific regions. To do so it exploits new data collected from a survey of 9,550 European patents (i.e. the PatVal-EU survey) and, by using information drawn directly from the inventors solves the problems highlighted above about the measurement and mechanisms through which knowledge spillovers take place. First, by introducing a novel indicator of knowledge exchange as provided by the inventors, it limits the problem of using indirect indicators like patent citations.

Second, it focuses on a form of knowledge exchange that mimics closely the idea of "marshallian" knowledge spillovers. As a matter of fact, the output of a research project is a positive function of the inputs that it employs. They consist of the firm/inventor own knowledge and, to the extent in which it/he can appropriate it, knowledge produced by others. External knowledge, in turn, can be either acquired through contractual agreements (i.e. market transactions) or by means of informal interactions that are not explicitly regulated by any market transaction. In the latter case, there are increasing returns in the production of new knowledge, as the input is acquired at no cost. By asking the inventors to report on interactions such as meetings, discussions, and more generally, circulation of ideas that were important for the research leading to the patent, and by excluding interactions that end up in co-inventorship, we try to capture these informal types of knowledge exchange. Moreover, by asking them about interactions that were important for the development of a patent, we focused on knowledge that was actually used as an input in the research project.

Third, our study employs indicators for the individual characteristics of the inventors who set up the interactions. This is an important novelty of the paper as we can understand the relative importance of location factors vis-à-vis inventors' individual characteristics on the probability to enter into local/broader networks of research during the inventive process.

The empirical analysis consists of two stages. It first analyses the importance of geographical proximity among individuals to establish interactions during the inventive process. The data indicate that interactions with individuals external to the inventor's organization are not common, and that local interactions are much less important than interactions that involve distant ties. This is true across European regions and types of organizations, suggesting that local knowledge flows are not a major factor in this process. Second, by means of multiple correlation analysis, the paper explores the idea that local interactions take place in technological active regions ("vibrant regions" by using Almeida and Kogut, 1999) to a greater extent than elsewhere. We call this the “Silicon Valley effect”. In addition, it investigates to what extent the spatial dimension of such links is shaped by the characteristics of the individual inventors. After controlling for the distribution of inventive activities and for inventor, patent, firm and technology characteristics, the results show that the technological features of the location do not affect the importance of local interactions during the inventive process. There is a mild evidence of local interactions to be more important than distant ties only when regions develop a marked comparative advantage in the specific technological sector in which the inventor performs research. This is however extremely rare in Europe, as it concerns less than 10% of the regions in our sample. We find, however, that key factors in explaining the geographical breadth of knowledge interactions are the nature of the research and the characteristics of the inventors. Specifically, the higher the scientific content of the research conducted, the greater the importance of distant interactions. Likewise, the higher the level of education and the age of the inventors are, the higher the propensity to engage in geographically wide interactions, suggesting that local ties are likely to be the output of the individual inadequacy to set up larger networks.

The remainder of the paper is organized as follows. Section 2 discusses our measure of knowledge spillovers and provides descriptive statistics about their geographical extension and importance for the inventors. Section 3 introduces the hypotheses and the variables used in the ordered probit regressions. Section 4 discusses the results. Section 5 concludes. Appendix 1 shows the ISI-INPI-OST list of technological classes used in the paper. Appendix 2 describes the robustness checks.

2. Our measure and the geographical extent of knowledge interactions

As discussed above, an important novelty of this paper is that it tries to document the importance of “marshallian” knowledge spillovers without resorting to indirect indicators like patent citations. Since knowledge flows are invisible and they leave “[…] no paper trial” (Krugman 1991), we collected direct information from patent inventors, and we asked them about the importance of geographical proximity for setting up knowledge interactions with other people during the inventive process. This was done by means of the PatVal-EU survey that interviewed the inventors of 9,550 patents granted by the European Patent Office (EPO) between 1993 and 1998, and located in Denmark, France, Germany, Hungary, Italy, the Netherlands, Spain, the United Kingdom. The survey provides information on the individual inventors, the invention process and the resulting patents. Giuri et al. (2006) report the details of the survey and key descriptive statistics.

This paper uses information on a sub-sample of 6,945 patents that we obtained by excluding data with missing answers in the survey and French patents. This is because the PatVal-EU survey in France was conducted by asking some questions to the inventors while others to the managers of the applicant organisations. In order to avoid potential biases in our analysis we decided not to use the French sample. In any case, when we perform the empirical analysis by including it, our results do not change significantly.

For the purpose of studying the importance of geographically localized knowledge spillovers we asked the inventors to rate the importance of interactions with other people during the invention process. More specifically, by using a scale from 0 (not used) to 5 (very important), they indicated the importance of meetings, discussions and, more generally, circulation of ideas for the research leading to the patent. They also specified the geographical extent of the interactions and whether they took place among people affiliated to the inventor's organization or with individuals affiliated to different organizations. In the end, the answer to this question provided information about the importance of four types of interactions: (1) interactions with people *External* to the organization and geographically *Close*; (2) interactions with people *External* to the organization and geographically *Distant*; (3) interactions with people *Internal* to the organization and geographically *Close*; (4) interactions *Internal* to the organization and geographically *Distant*. In this paper we focus on interactions with individuals external to the inventor's organization, and we leave (3) and (4) above for future research.[3] We therefore record the importance of:

- *Close* interactions: interactions with people not in the inventor's organization and geographically close, i.e. it takes less than an hour to reach their office or location.

- *Distant* interactions: interactions with people not in the inventor's organization and geographically distant, i.e. it takes more than an hour to reach their office or location.

Close and *Distant* interactions differ only for their geographical extent. The former implies geographical proximity between the inventor and the interacting people, while the latter does not. We use the answer to this question to understand the frequency with which inventors interact on informal basis with people external to their own organization, and we investigate whether the probability to interact is influenced by geographical proximity.[4]

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[3] This is like excluding self-citations in studies that use patent citations.

[4] We explicitly asked the inventors to exclude interactions with co-inventors. We did not ask explicitly to exclude other forms of collaborations. By using information from the survey we controlled for the extent to which inventors use external interactions (*Close* or *Distant*) and inter-firm collaborations ("collaborative" patents) together to develop a patent. The share of "non collaborative" patents invented with external interactions (*Close* or *Distant* >0) is 40.5%. The average importance of external interactions is 2.6 for

We deliberately defined geographical proximity in terms of the time that it takes to reach the location of the interacting person: interactions with geographically close people are those that typically take less than an hour to reach; interactions with geographically distant people are those that take more than an hour. This is a particularly useful feature of our data that, by measuring distance in terms of the effort required to reach the other party, limits problems associated with other measures of geographical distance. For example, if distance is measured in kilometers, locations might be similar in terms of kilometric distance, but extremely different in terms of effort/time required to be reached. To simplify, suppose that a researcher is employed in a company located in the periphery of a large town, and that he interacts with two individuals who are both in a ray of 50 kilometers from his office. However, one of them is 50 kilometers towards the countryside, where roads are in good conditions and there is no traffic. The other one is 50 kilometers downtown with tremendous traffic jam. Same distance, but big difference in the effort required to reach the interacting party: in the former case it takes 15 minutes to meet; in the latter case it takes more than an hour to reach. Therefore, while traditional measures based on kilometric distance would consider them as similar locations for the researcher, our measure considers them as being different, i.e. *Close* and *Distant* respectively. Compared to measures of geographical proximity based on administrative boundaries, our definition solves cases in which locations are practically contiguous, but are considered distant because they belong to different administrative regions, or cases in which locations are considered to be close because they are in the same administrative region, but that, actually, are located far away.

How often are knowledge interactions with people external to the inventor's organization used in developing inventions? Figure 1 shows the share of patents invented by using *Close* and *Distant* interactions (*y*-axis) in each score class (*x*-axis: 0, not used; 5, very important). Up-right in the graph we also report the average importance and standard deviations of *Close* and *Distant* interactions across all inventors.

[FIGURE 1]

We compute the maximum score assigned by the inventors to either *Close* or *Distant* interactions, and report it in the dashed line in Figure 1. Over half of the patents in our sample (54.4%) are developed without any form of interaction with people external to the inventor's organization (i.e.

"collaborative" patents, while it is 1.1 for "non-collaborative" patents and the difference is statistically significant. The idea that we make from the data is that there are patents that are developed with an "open" approach: the inventors use extensively sources of knowledge external to their own organization (co-inventorship, collaborations and informal interactions). There are other patents, instead, for which the role of external knowledge is limited.

the scores of *Close* and *Distant* are both 0). When external interactions (either *Close* or *Distant*) occur during the inventive process, in 16.5% of the patents their importance is small (score 1 or 2). Their role is higher in 29.1% of the patents (score 3 and higher). This suggests that external interactions, being them with geographically close or distant people, are not a major input in the inventive process. If we take our knowledge interactions as an indicator of knowledge spillovers, this suggests that the latter are not as diffused as one might think according to the numerous contributions that emphasize them, as only one third of the inventions benefited significantly during the inventive process from informal interactions with people affiliated to other organizations.[5]

The second issue that we investigate is whether geographical proximity matters for establishing external interactions. The continuous lines in Figure 1 report the share of patents invented either with *Close* or *Distant* interactions. The two distributions in Figure 1 overlap to a great extent, even though for low values of the score (0-1-2) the *Close* distribution dominates the *Distant* distribution; for high values (3-5) the *Distant* distribution dominates the *Close* distribution. This indicates that patents that benefited from *Close* interactions are fewer than those invented with *Distant* interactions: in 69.2% of the patents the inventors indicated that they were not exposed to any interactions with *Close* individuals, compared to 59.3% of patents with no *Distant* links. This is confirmed by the average importance of *Close* across all patents (conditional on the score being higher than 0): this is 2.30 compared to 2.88 of *Distant*.

All this casts doubts about the importance of external knowledge interactions in general and, more specifically, about the importance of geographical proximity in fostering communication and informal contacts among people in the invention process. Rather, local ties are less frequent and less important than interactions across regions and countries. Figure 2 confirms these results. We compute for each patent the difference between the scores of *Close* and *Distant*. Figure 2 shows that *Close* and *Distant* interactions are equally important in 71.30% of the patents (in 54.4% of the patents they are both 0). *Distant* interactions are more important than *Close* interactions in 20.65% of the patents, while *Close* interactions benefited the invention process more than *Distant* interactions only in 8.05% of the cases.

[FIGURE 2]

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[5] We compared these data with the importance of interactions *Internal* to the inventor's organization. Only 19.5% of the patents are invented with no *Internal* interactions (excluding co-inventors), and the share of patents for which *Internal* interactions (*Close* or *Distant*) are important (score 3 to 5) is 68.3%. This suggests that knowledge spillovers in the form of discussions, meetings, etc. are more likely to occur with individuals affiliated to the same organization, i.e. spillovers are internalized within the firm/institution of the inventor.

The next Section provides an explanation for these results that, although unexpected given the many contributions on the role of geographically localized knowledge spillovers for producing innovations, are consistent with other work. For example, Audretsch and Stephan (1996) find that local links between scientists and private biotechnology companies in the USA are anything, but overwhelming. By means of case studies, Davenport (2005) shows that, for a sample of SMEs located in New Zealand, non local interactions are relevant for innovation more than local links. Hendry et al. (2000) describes how, in the opto-electronic sector, national and international networks of firms are more important than local ones for the growth of firms (see also Staber, 1996).

We also checked whether there are differences across technological classes, countries and type of applicant organization in the relative importance of *Close* vs. *Distant* interactions. For each applicant organization, the histograms in Figure 3 reports the difference between the shares of patents invented with *Close* and *Distant* interactions in each score category. Positive (negative) differences, i.e. those in the upper (lower) part of the graph, indicate that the share of patents invented with *Close* interactions is higher (lower) than the share of patents invented with *Distant* interactions in the selected category.

[FIGURE 3]

Consistently with Figure 1, the graph shows that the share of patents that do not use *Close* interactions is higher than the share of patents with no *Distant* interactions (score = 0). The same applies when the importance of external interactions is small (score = 1 or 2). When the score is 3 and higher, *Close* interactions are less frequent than *Distant* interactions. These results suggest that, independently of the type of employer organization, geographical localized knowledge interactions are less frequent and less important than those with distant people.[6] This pattern is confirmed across countries and technologies (Results available from the authors).

3. Is there a Silicon Valley effect?

Up to now we know that the majority of patents are developed with no interactions with people external to the inventor's organization. Moreover, both the frequency and the average importance of

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[6] The share of patents invented by Large Firms that do not use any *Close* interaction is 70.1%, similar to Medium and Small firms (68.9% and 68.8%) and higher than Universities (60.2%). The share of patents developed by no means of *Distant* interactions is 59.2%, 62.5%, 63.0%, and 47.1% respectively for the four types of organizations. For high scores (3 to 5) of *Close* interactions, the share of patents developed by Large Firms is 11.4%. It is 13.2% for Medium Firms, 15.1% for Small Firms and 16.2% for Universities.

Close interactions are lower than those of *Distant* interactions, suggesting that geographical proximity does not play a major role in fostering such links.

This is true unconditionally. There might be, however, variation across regions in the extent to which geographical proximity matters for establishing local ties. In other words, knowledge spillovers, if they exist, are not uniformly distributed across regions and the exchange of knowledge is stimulated in some regions more than in others according to their local technological endowment. This is also suggested by studies like Almeida and Kogut (1999) who show that the localization of knowledge varies across US regions with Silicon Valley, New York and Southern California at the top of the list for semiconductors. Thompson (2006) shows that knowledge spillovers are stronger in California, Texas and Massachusetts than elsewhere (see also Audretsch and Feldman, 1996).

This part of our research will therefore shed some light on two questions concerning the geographical extent of knowledge interactions that inventors set up during the inventive process:

1. Is there a "Silicon Valley effect"? We test the hypothesis that local interactions are more likely to take place in technological active and richer regions (i.e. the technological clusters) to a greater extent than elsewhere. In other words, we expect that the inter-regional variation is reflected in the extent to which people take advantage of localized knowledge spillovers. Therefore, after controlling for other factors, we expect *Close* interactions to be more important than *Distant* interactions in the cluster regions.

2. Is the spatial dimension of interactions shaped by the characteristics of the inventors who set them up? Studies like Audretsch and Stephan (1996) on the role of scientists on the geographical dimension of research links between universities and private companies in biotechnology suggest that these might be key factors also in our analysis. This would be also consistent with other contributions like Almeida and Kogut (1999), Breschi and Lissoni (2001), Singh (2005), Sorenson and Singh (2007), and Fleming et al. (2007) on the role played by the individual ("social") networks in explaining knowledge flows and regional co-location.

To explore these issues we perform a multiple correlation analysis followed by a number of robustness checks. We discuss in the following sub sections the reduced form model that we test.

3.1. Construction and interpretation of the dependent variables: levels and pairwise differences

The importance of *Close* interactions (score 0 to 5) and the importance of *Distant* interactions (score 0 to 5) are the two dependent variables of our Ordered Probit regressions. Each of these two dependent variables, however, measures two simultaneous decisions by the inventor: the institutional setting in which interaction takes place (*Internal* vs. *External*) and its geographical breadth (*Close* vs. *Distant*). By reading the estimated coefficients of the two equations it is not possible to isolate the effect of the regressors on each decision separately. Therefore, for example, the results to the *Close* equation would speak about the factors that affect the importance of interactions that are geographically close and institutionally external to the inventor's organization. Similarly, the estimated coefficients of the *Distant* equation would show the correlates with the importance of interactions that are both geographically distant and external to the inventor's organization.

As a possible solution to separate the two effects we propose to perform a third regression whereby the dependent variable is the pairwise difference between the score assigned by the inventor to *Close* and *Distant* interactions to develop the specific patent. This is because, for the single patent, *Close* and *Distant* interactions share the same institutional setting (i.e. *External*) while they differ in the geographical extent of the links. The estimated coefficient of this regression would show the net effect of each variable on the relative importance of *Close* vs. *Distant* interactions, given that they take place with individuals external to the inventor's organization. Moreover, by running a third equation on the difference between *Close* and *Distant* scores, we limit a potential problem that we would have with other statistical tests when there is correlation between the error terms of the two equations (because, for example, of common omitted variables).

This variable ranges from -5 to +5. A negative difference indicates that *Distant* interactions are more important than *Close* interactions to develop the patent, while a positive difference indicates that *Close* interactions are more important than *Distant* interactions. A difference of 0 implies that *Close* and *Distant* interactions are equally important during the inventive process.

3.2. Discussion of explanatory variables

Let us assume that the importance of an interaction depends on the probability to find a "matching" individual with complementary competencies needed in the inventive process. The pool of potential matching people, in turn, is located in the inventor's region (*Close*) and in other regions (*Distant*).

The data shown in Section 2, where, on average, *Distant* interactions are more important than *Close* interactions, are consistent with the following view. Suppose that there are r regions that an inventor can reach, and that the pool of potential matching individuals is evenly distributed across them. The inventor is located in one region where he can set up *Close* interactions; he can develop *Distant* interactions with individuals located in all the other $r-1$ regions. As r increases, the probability to find a perfect match in the *r-1* regions increases as well. The higher *r* is, the higher the probability to find the perfect match in one of the *r-1* regions compared to find it at home. In our study, the own region is the one in one-hour reach of the inventor, while the number of outside regions is very large, suggesting that, on average, the probability to find a good *Distant* match is high compared to have it *Close*.

Given a fixed number of *Distant* regions (as it is in our study and in general), two additional regional factors contribute to explain the relative importance of *Close* and *Distant* interactions: one is the geographical distribution of the pool of potential matching individuals; the other one is the existence of geographically bounded knowledge spillovers. Specifically, suppose that knowledge spillovers are not geographically bounded. Then, the probability to develop *Close* and *Distant* interactions simply mirrors the geographical distribution of the matching individuals: knowledge interactions are more likely to take place in regions where the potential pool of interacting individuals concentrates.[7] Differently, if knowledge spillovers arise in the technological clusters, the expectation is that the positive impact on *Close* interactions is higher than the negative effect on *Distant* interactions due to some increasing returns process. In other words, the propensity to engage in local relationships does not simply follow the local pool of potential matching individuals: when we move to the technological clusters, local knowledge flows increase more than proportionally compared to the local availability of intellectual resources.[8]

In order to take these forces into account, we include a set of variables that describe the technological environment in which the inventor works. We first measure the importance of the general technological setting outside the inventor's organization in all technological disciplines. Since we do not have an indicator of the number of individuals with whom the inventor might match, we consider, as a proxy for it, the 1994-1996 average number of patents applied in all sectors in the NUTS3 region where the inventor was located at the time of the invention (REGPATS) (source: Regio Eurostat).[9] Moreover, in order to distinguish between private and public sources of knowledge, we downloaded from the *European R&D database* (1996) a stock of

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[7] To simplify suppose that 100% of the research is performed in the region of the inventor. In this case he will develop no *Distant* interactions. If this is the case, however, rather than the effect of localized knowledge spillovers*, Close* and *Distant* interactions would result from the uneven geographical distribution of inventive activities (Jaffe et al., 1993), which we need to control for if the aim of the study is to understand the additional role played by geographical proximity.

[8] Other factors may affect the probability to set up *Close* and *Distant* interactions like the different cost to reach nearby people compared to distant individuals. We capture these factors by controlling for firm and inventor's characteristics. As a further check we also run separate regressions for the two sub-samples of arge and small firms, for which, typically, resource constrains are different.

[9] The list of European regions used in this paper is available from the authors and from the website http://ec.europa.eu/comm/eurostat/ramon/nuts/codelist_en.cfm?list=nuts

about 20,000 R&D laboratories located in Europe as for December 1995, and classified them as private laboratories, universities and government laboratories. In place of REGPATS we then included the 1995 stock of private research laboratories (LABS_PRIVATE), public research laboratories (LABS_PUBLIC) and higher education laboratories (LABS_UNI) located in the NUTS3 region.[10]

Second, since knowledge interactions might be more likely to occur between people sharing common research interests and complementary competencies within a technological field, we include a set of variables that proxy for the technological endowment of the region that is specific to the technology of the surveyed patent. To do this we collected from the Regio Eurostat database the 1994-1996 number of regional patents applied at the EPO in each of the 30 ISI-INPI-OST technological classes in which the patents in our sample are also classified (see Appendix 1 for the list). The breadth of the 30 technological classes is such that each of them includes inter-connected micro fields, without being too narrow to capture only research in the very micro-specialty. For each patent in our sample we computed the share of patents invented in the region in the specific technology over the number of patents invented in all regions in the same technology (SHARE_TECH). The larger the share is, the higher the potential for setting up interactions. Moreover, to control for the fact that knowledge spillovers arise only after a “critical mass” of research located in the region, we construct a variable that indicates whether a region is top in the discipline of the patent. We ranked the regions according to SHARE_TECH and produce a dummy variable (TOP5_TECH) that is 1 for regions in the top 5% of the distribution in each technology; 0 otherwise. Similarly, the variable TOP1_TECH is for regions in the top 1% of the distribution. Regions in the top percentile have between 4% up to 15% of the patents in the technology. In order to check for higher level top regions, we introduce the variable THRESH5_TECH that takes the value 1 if more than 5% of the European patents in a specific technology is located in the region; 0 otherwise. This is intended to capture regions that develop the bulk of innovations in each technology.[11] The inclusion of these variables will also tell us whether interactions (and possibly knowledge spillovers) are not “generic” but, rather, they occur because of the research effort undertaken by others in the particular technological discipline of the inventor (see, among others, the results reported by Jaffe 1989 and Furman et al. 2006).

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[10] Jaffe (1989) provide evidence that corporate patent activity is positively affected by university research. Zucker et al. (1998) show the importance of proximity to university research for developing inventions in biotechnology. Similarly, Furman et al. (2006) find that spillovers to pharmaceutical research come from public knowledge, while private research is negatively correlated with research productivity.

[11] SHARE_TECH and TOP1_TECH are calculated at the NUTS2 regional level of aggregation because NUTS3 level data by micro technological class are not available from Regio-Eurostat.

To the technological features of the regions we add exogenous controls for their size (AREA), population (POP) and economic development (GDPPC).

Apart from the technological endowment of the external environment, other factors affect the extent to which inventors develop *Close* vs. *Distant* ties during the inventive process. For example, the attributes of the inventor and the invention that he produces, and the characteristics of the applicant organization may affect the cost and benefits of *Close* vs. *Distant* interactions.

We therefore include a set of variables that describe the applicant organization. They can affect both the decision to develop *Internal* vs. *External* interactions, and the decision to go *Close* vs. *Distant*.[12] We control for the type of organization: large (LARGE), medium (MEDIUM) and small firms (SMALL), private research organisations (PRIVATE), Universities and other public research institutions (UNIV), and independent inventors (INV). Moreover, for private firms, we have information about the size and R&D intensity of the parent company drawn from Compustat (1998) and Amadeus (2005). We use the number of employees (EMPLOYEES) to proxy for the scale of the firms, and the ratio between R&D expenditure and sales (R&DINT) for R&D intensity. By controlling for both the size and the R&D intensity of the organisation, we separate the effect of the scale of the organisation from its capacity/effort devoted to innovation, which otherwise would both be reflected by the same variable.[13] R&D intensity measures the importance of research and invention for the organization, which, in turn, might affect the extent to which inventors need to set up interactions during the invention process. Moreover, the development of inventions requires extensive resources in terms of technical equipment, research laboratories, instruments, research assistants and complementary expertise. The size and R&D intensity of the organisation also proxy for the availability of internal resources, and therefore for the extent to which inventors might want to resort to external interactions. Compared to smaller companies and to other private and public research institutions, large firms might have enough internal resources to engage in complex research projects and to ask for patent protection on a larger number of inventions. We therefore expect that, on average, they will tend to internalize spillovers and to use less external interactions compared to the other private and public types of organizations.[14] Moreover, given that one uses

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[12] This is worth keeping in mind. It will be true also for other variables like inventor and invention characteristics, and this is the driver of our decision to run the third regressions where the dependent variable is the difference *Close-Distant*.

[13] The dummy variable for the type of organization is also used to cover missing data for EMPLOYEES and R&DINT. Information on EMPLOYEES are available for 77.78% patents; data on R&DINT iare available for 41.92% patents. The sample of missing EMPLOYEES is a subsample of missing R&DINT. The share of missings for R&DINT is 45.21% for large firms; it is 99.6% for small and medium firms.

[14] See, for example, Acs, Audretsch and Feldman (1994) and Feldman (1999).

external resources, if *Distant* interactions are more expensive than *Close* interactions in terms of organizational capabilities and financial resources, small firms might suffer from this constrain more than large corporations.

A challenging opportunity provided by the PatVal-EU survey is the possibility to control for the individual characteristics of the inventor who established the interaction. This is quite useful in our analysis, as the establishment of local vs. global networks of researchers may rest, to a great extent, in the ability and experience of the individuals. For example, young researchers might tend to invest in the organization in which they work. Only later on in their career they might want to exploit the output of this investment outside the firm (Cole, 1979; Audretsch and Stephan, 1996). We therefore expect them to focus more on interactions with people internal to the firm than with external parties. However, conditionally upon the fact that they establish links outside the employer organization, we expect younger and less experienced researchers to be more likely to engage in local networks of researchers more than older and more experienced inventors (Audretsch and Stephan, 1996). Once controlling for age (AGE), the educational background of the inventors is another key factor that might influence the geographical extent of the interactions. Inventors with a long and high level curriculum of education might have had better opportunities to enter into geographically extensive networks of people who share common scientific interests. The level of education might then be a signal of the inventor's ability to rely on personal research connections to establish interactions in their working career: the higher the educational background, the larger and geographically broader is expected to be, on average, the network of individuals to interact with. We employ a dummy variable for the highest degree of education among the following: Secondary and High School (HIGH_DEGREE), University BSc or Master (UNI_DEGREE), PhD (PhD_DEGREE). Moreover, to control for the effort that, on average, male inventors can spend in doing research and in setting up interactions compared to women, we also use a dummy for their gender (MALE).

We also include a set of invention-level indicators. We first control for co-inventorship (N_INVENTORS). This variable indicates whether more formal types of interactions that end up in co-inventorship are complement or substitutes to more informal knowledge interactions. The number of inventors involved in developing a patent is also a proxy for the scale of the research project leading to the invention. If there is complementarity (substitutability) between more formal types of collaborations and our informal knowledge interactions, there will be a positive (negative) sign in both *Close* and *Distant* regressions, while the coefficient will not be statistically significant in the *Close-Distant* regression. We then control for the extent to which a patent is related to basic research. This is done by SCIENCE that measures the importance of the scientific literature as a source of knowledge for the research that led to the invention. As Gittelman (2005) suggests, the benefits of geographical proximity are expected to be less important for science-based research compared to more technological work. More scientific research would benefit less from geographically localized spillovers due to more open and spatially dispersed communities of individuals and to the communication mechanisms that are not linked to location externalities. Finally, we control for the reasons that led the inventor to patent the invention. Specifically, we control whether the inventor was moved by the desire to commercially exploit the invention (COMM_EXPLOIT), license it (LICENSING) or prevent others from imitation (IMITATION). For example, we expect inventors to be more inward-looking when they work on patents that are exploited commercially or that are produced to prevent others from imitation. Differently, interactions with external parties are expected to be more important for patents that are produced to be licensed, which would determine a positive sign of LICENSING in both regressions. We do not have priors on the effect of these variables on the importance of *Close* compared to *Distant*.

Finally, all regressions are performed with dummies for the application year and dummies for the country of the inventors to capture the effect of regional characteristics that are independent of the variation across countries. We also include dummies for the 30 micro ISI-INIPI-OST technological classes of the patents. This is because the mechanism by which knowledge is transferred might be different in different technological fields (Audretsch and Feldman, 1996; Jaffe et al. 993). Table 1 provides the definition of the variables. Table 2 shows their descriptive statistics.

[TABLES 1 and 2]

4. Results

We performed three reduced-form model regressions. The dependent variable of the first one is the importance of *Close* interactions; the second one is for the importance of *Distant* interactions; and the third regression is performed on the difference between importance of *Close* and *Distant* interactions. This set of three regressions is performed with six specifications that differ for the regional technological variables included. All the other variables are the same across all specifications. As we will discuss in Section 5, a number of robustness checks are also performed with no significant changes in the results.

Tables 3 and 4 show the results of the econometric estimates. Since the survey over-sampled “important” patents, we corrected for the stratification by computed sampling weights for the hypothetical unbiased sample. Sampling weights also control for the representativeness of the sample of patents for which we received a response with respect to the selected sample of patents/questionnaires that have been sent to inventors (for details, see Giuri and Mariani, 2006).

Cluster robust estimators on firms are included in order to take into account any unobserved correlation among the errors of the patents belonging to the same parent company.

All the variables are in logs. All regressions include dummies for missing value for EMPLOYEES and R&DINT, inventor country, year of application and technological field of the patent (30 ISI-INIPI-OST classes).

[TABLES 3 and 4]

The goal of the econometric exercise is to understand if, after controlling for other possible factors, there is a Silicon Valley effect, i.e. if knowledge interactions with close-by people are more likely to take place in technological active and rich regions compared to elsewhere. Additionally, we test the hypothesis that the inventors' personal characteristics influence the geographical breadth of their research network.

The first specification uses the variable on the general technological environment external to inventor as measured by REGPATS. Let's go through the results. Firm characteristics do not affect the geographical extent of interactions set up with individuals outside the employer organization. EMPLOYEES is not statistically significant on both *Close* and *Distant* interactions, while R&D intensity matters only for the decision to set up knowledge interactions *External* to the employer organization. The higher the R&D intensity of a firm, the higher the probability to internalize knowledge interactions: the importance of both *Close* and *Distant* interactions decreases as R&DINT gets higher, and the effect is statistically significant at 5% level. However, R&DINT is not statistically significance on the difference *Close-Distant*, suggesting that, given that the inventor interacts with people external to the organization, R&D intensity does not affect the geographical breadth of the relationship.

As expected, inventors' characteristics are correlated with the decision/ability to enter into local vs. broader networks of research. First of all, the age of the inventor (AGE) has a negative and statistically significant effect on *Close*, although it is not correlated with *Distant*. Therefore, interactions with people *Close* and *External* to the firm are less important for older inventors. However, we know that this measures the effect of AGE on the importance of both *Close* and *External* interactions, i.e. with both the geographical extent and the institutional setting in which interactions take place. To isolate the net effect of AGE on the geographical dimension of the interactions, the third regression shows that the estimated coefficient of AGE is negative and statistically significant at 5% level. This suggests that, once conditioning on *External* interactions, the older the inventor is, the more likely it is that he engages in *Distant* compared to *Close* interactions.

Second, the educational background explains a lot of the geographical dimension of knowledge interactions. Our baseline category is High School degree or lower. The estimated coefficient of both University/Master and PhD degree is statistically not significant on the importance of *Close* interactions. They are, however, both positive and statistically significant on *Distant* interactions and, as expected, they are positive and statistically significant at 5% and 1% level respectively, on the difference *Close-Distant*. This is very important as it shows that inventors with a high level of education have better opportunities to enter into broader networks of research. As we discussed earlier, this might be because prior experience gave the inventors the opportunity to set up personal relationships with people who share common interests. These relationships are then used later to get knowledge from people that they know might have the needed expertise.

From the PatVal-EU survey we also know the inventors' mobility across organizations before and after the development of the surveyed patent. We constructed a dummy variable equal to 1 if the inventor changed employer at least once in the ten years before the patent application in order to explore whether knowledge interactions are explained by human capital mobility.[15] The estimated coefficient of the mobility variable is positive and statistically significant on both *Close* and *Distant*. It is, however, statistically not significant on the difference *Close-Distant*. This holds both when the mobility variable is included in place of the educational background and when it is included in addition to it (results available from the authors), suggesting that, once we control for exogenous inventors' characteristics, the extent to which they move across organizations does not affect the geographical breadth of knowledge interactions. It says, however, that more mobile inventors have a higher probability to set up knowledge interactions with people external to their current employer organization independently of the fact that they are geographical close.

As far as the characteristics of the invention are concerned, the variable SCIENCE is positively correlated with both the importance of *Close* and *Distant* interactions. The estimated coefficient is significant at 1% level. However, this could be due to the fact that, by its own nature, more scientific work is performed by a more "open" network of researchers, and that therefore, the positive correlation is due to the tendency to link to people *External* to the employer organization. The third regression should isolate the net effect of SCIENCE on the relative importance of *Close* vs. *Distant*, given that interactions are *External* to the organization. The estimated coefficient of

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[15] We do not show the results here because mobility may be endogenous to other inventor's characteristics like the level of education that, in turn, proxies for the unobservable individual talent. Multiple correlation analysis (negative binomial regressions) with the number of moves as the dependent variable shows that mobility is highly correlated with the educational background of the inventors, though, unexpectedly, it is not correlated with the technological characteristics of the European regions.

SCIENCE is negative and statistically significant at 1% level, suggesting that more scientific work is more likely to be undertaken by a geographically broad network of people.

The other patent controls are either not correlated with any of our types of interactions, or, like LICENSING, is positively correlated with *Close* and *Distant* (significant at 1% level), but it is not correlated with *Close-Distant* in the third regression. This suggests, again, that if an invention is patented to be licensed out, the inventor will be more likely to engage in interactions with *External* parties, independently of their geographical location.

Therefore, as we expected, the nature of the invention and the individual characteristics of the inventors are important in shaping the geographical extension of knowledge interactions. We did not expect, however, that these are the only factors that matter in our regressions. In particular, we did not expect that the estimated coefficient of REGPATS, which proxies for the richness of the external technological environment, is not correlated with the importance of local ties.

However, the variable REGPATS may not capture technological aspects of the regions that are more specific to the rise of local knowledge spillovers. We therefore replaced it with the number of public, private and University research laboratories located in the NUTS3 region (columns 4-6 in Table 3). The results show that, while the scientific content of the invention and inventor characteristics are still significantly correlated with the geographical dimension of knowledge interactions, the number of research laboratories of any type does not affect it. The estimated coefficients of LABS_UNI, LABS_PUBLIC and LABS_PRIVATE are not statistically significant in any of the three regressions.[16]

Still, however, spillovers may occur because of the regional co-location of research activities specific to the technological field of the patent/inventor. Moreover, inventors may link to *Close* more than to *Distant* people if, compared to other regions, the area has a sort of technological "advantage" in the specific discipline. Patents and research laboratories in all technologies may not capture this aspect. We therefore include a set of variables that proxy for the relative importance of

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[16] An issue arises here about the potential endogeneity of firm location: the decision to locate in a region might be a function of the desire to access knowledge generated by others, or, by contrast, to avoid that knowledge produced by the own firm spills over to others. Or, still, the firm might determine to a large extent the technological characteristics of the region. This problem is limited in our case for various reasons. First, since we use data at the level of the inventor, it is unlikely that the strategic behavior of the firm with respect to competitors applies also to individuals. It is also unlikely that the specific inventor/interaction determines the technological characteristics of a region. Second, we showed in Section 2 that the importance of Close interactions is low, suggesting that they are not a major factor in shaping the technological advantage of the regions. Finally, in order to use pre-determined (and therefore more exogenous) regional variables, we employed the stock of University and public research laboratories in 1995 and patents invented in 1994-1996, which are the output of research conducted earlier.

the region in the technology of the patent. The first one is SHARE_TECH calculated as the share of patents invented in the region in the specific technology over the number of patents invented in all regions in the same technology. The third specification (columns 7-9 in Table 3) shows the results for the inclusion SHARE_TECH in addition to REGPATS. The estimated coefficient of SHARE_TECH is negative and statistically significant at 1% level on *Distant* interactions. It is positive, although not statistically significant on *Close*. It is negative and statistically significant at 1% level on *Close-Distant*. This suggests that, when the region is comparatively good at doing research in a specific technological field, than inventors will look link less to people in other regions. Or, to say it differently, when a large pool of potential matching individuals is located at home, the need to go outside it decreases. This does not produce, however, an increase in the importance of *Close* interactions. This might be because more than 90% of the regions in our sample perform a modest share (less than 4%) of the total European research in the technology of interest. Hence, in most cases, the cross-regional change in SHARE_TECH is very small and does not give rise to the "critical mass" of research activities that is probably needed to stimulate knowledge exchange locally, i.e. to let spillovers arise. Again, all the other inventor, patent and firm variables behave as in previous specifications.

The next step is to find out whether there is a threshold in the local availability of technological resources in order to give rise to local knowledge exchange. We therefore replace SHARE_TECH with a dummy variable for the top 5% and 1% regions in the discipline of the patents. Specifications 4 (columns 1-3 in Table 4) and 5 (columns 4-6 in Table 4) show the results for the inclusion of TOP5_TECH and TOP1_TECH respectively. The effect of both variables is negative and statistically significant on *Distant*. It is, as expected, positive on *Close*, even though it is not highly significant (it is almost at 10% level for TOP1_TECH).

We also go one step further, and given that the regions in the top percentile develop between 2.6% up to 15.1% of the patents in the specific technology, we restrict the sample of top regions to those that develop the bulk of innovations in each technology. The variable THRESH5_TECH serves this purpose. It takes the value 1 if more than 5% of the European patents in a specific technology are located in the region. The results (columns 7-9 in Table 4) show that the effect of this variable is negative and statistically significant at 5% level on *Distant*; it is positive and statistically significant at 10% level on *Close*. It is positive and statistically significant at 1% level on the difference *Close-Distant*. This gradual increase in the importance of *Close* interactions as we restrict the analysis to the very top regions might suggest that the importance of local knowledge interactions increases only in the very few technological clusters in the specific discipline. However, in order to control whether this is the effect of an increasing returns process or if this is the result of the geographical distribution of inventive activities (i.e. the potential pool is located at home), we computed the marginal effects of these variables (at their means) for *Close* and *Distant* interactions.[17] The elasticity for the top region variables (TOP5_TECH, TOP1_TECH and THRESH5_TECH) are almost the same on *Close* and *Distant*, though with opposite signs. This suggests that, more than increasing returns associated to local spillovers and a critical mass of research in a region, the relative increase in *Close* might follow the distribution of inventive activities: when the pool of potentially interacting people is at home, the probability to link with it increases independently of any effect of localized knowledge spillovers.

We achieved the same results as those shown in Tables 3 and 4 when we used the number of research laboratories in the three categories in place of AVGPATS, and when we define the top regions according to the total number of patents rather than patents in the specific technology: the top variables are never statistically significant (both at the NUTS3 and NUTS2 regional level). The estimated results do not change also when we run the regressions for the two sub-samples of large and medium-small firms, guided by the consideration that large firms might have a different cost to go Distant compared to small, and that this difference is not fully captured by the firm level variables included in the regressions (results are available from the authors).[18]

All in all, we can conclude as follows. First, in general, local knowledge interactions do not seem to be more important in cluster-like regions. Moreover, if a slight positive effect of being in a technological cluster exists on local knowledge interactions, it applies only to a very restrict club of top regions in Europe. Second, the most important actors that explain the geographical breadth of inter-personal knowledge interactions are the scientific content of the research and the individual characteristics of the inventors that allow them to take part in local vs. more international research networks. This holds across different specifications.

5. Conclusions

This paper provides new evidence about the role of geographical proximity in fostering knowledge interactions. To do so it uses new data collected from a large survey of European inventors (i.e. the PatVal-EU survey) and other data from complementary databases on the characteristics of the organizations in which the inventors were employed at the time of the invention, and the

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[17] We computed the marginal effects in a probit regression for *Close* and *Distant* with: 0=no interactions and 1=yes interactions, independently of their importance.

[18] We also used the number of patents in the technology invented in the region in place of the SHARE_TECH. Technological fields were measured both by using the ISI classification and the IPC3-digit. Alternatively, we computed the share and number of patents by IPC1-digit at the more disaggregated NUTS3 regions. The estimated results are similar to those shown in Table 3.

characteristics of the regions in which they were located. An important novelty of the paper is that, instead of using indirect indicators, it employs a measure of knowledge exchange as provided directly by the inventors: this is given by the importance of meetings, discussions and, more generally, circulation of ideas that inventors developed during the inventive process.

The empirical analysis consisted of two stages. First, we analyzed the importance of geographical proximity among individuals to establish knowledge interactions. The data indicated that interactions with individuals external to the inventor's organization are not common during the inventive process. On average, interactions with geographically close individuals are fewer and less important than interactions that cut across regions, suggesting that geography boundaries do not represent a real barrier to knowledge spillovers.

In the second part of the paper we tried to answer two questions on the geographical extent of knowledge interactions. The first one is whether a "Silicon Valley effect" exists, i.e. if local interactions are more likely to take place in technological active and richer regions (i.e. the technological clusters) to a greater extent than elsewhere. Second, we explore the role of inventors' personal characteristics in shaping the spatial dimension of knowledge interactions. We used ordered probit regressions to show that, once controlling for many factors, a positive environment for research does not affect significantly the importance of local interactions during the inventive process. Interestingly, however, key factors are the inventors' educational background and the scientific content of the research performed. Specifically, knowledge interactions are set up with geographically close individuals when: 1) the research project has a low scientific content; 2) the inventors are young and have a low level of education. By contrast, the higher the experience and the educational background of the inventors, the wider and more geographically dispersed are inter-personal connections.

What are the implications of all this? If spillovers are important for economic growth, we showed that inter-regional spillovers (assuming that our indicator is a proxy for them) are more important than local spillovers. Moreover, our analysis shows that, being located in a technological cluster does not increase the importance of *Close* compared to *Distant* interactions. This raises concerns about the design and effectiveness of regional policies aimed at fostering them. Moreover, we found that the real barrier to knowledge spillovers is the inventor. Inventors with a lower level of education and little experience tend to enter in local networks of research, while older and better educated inventors take part in broader networks. This suggests that, more than an opportunity, the setting up of local interactions is the result of an inventor constrain: local networks seem to be an option that the inventors play when they do not have the possibility to take part in broader networks.

This suggests that it might be beneficial to think about policies aimed at stimulating “openness” at the micro individual level.

References

Acs Z., Audretsch, D.B. and M.P. Feldman, 1994, R&D Spillovers and recipient firm size, *The Review of Economics and Statistics*, Vol 76, No. 2, pp 336-340

Alcacer, J. and Gittelman, M, 2006, Patent Citations as a Measure of Knowledge Flows: The Influence of Examiner Citations, *The Review of Economics and Statistics*, Vol. 88, No. 4, Pages 774-779

Almeida, P. and Kogut B., 1999, Localization of Knowledge and the Mobility of Engineers in Regional Networks." *Management Science, 45*(7), pp. 905-17.

Audretsch, D.B. and M.P. Feldman, 1996, R&D Spillovers and the Geography of Innovation and Production, *The American Economic Review*, Vol. 86, p. 630-640.

Audretsch D., Stephan P., 1996, Company-Scientist Locational Links: The Case of Biotechnology**,** *The American Economic Review*, Vol. 86, No. 3

Cole, S., 1979. Age and scientific performance, *American Journal of Sociology*, 84, 958-977.

Breschi S. and Lissoni F., 2001, Localised knowledge spillovers vs. innovative milieux: Knowledge 'tacitness' reconsidered", Papers in Regional Science, 80(3), 255-73.

Davenport S. (2005), Exploring the role of proximity in SME knowledge-acquisition, Research Policy, 34, 683-701.

Doring T. and Schnellenbach J., 2006, What do we know about geographical knowledge spillovers and regional growth?: A survey of the literature, *Regional Studies*, Volume 40, Number 3, May 2006, pp. 375-395(21)

Feldman M., 1999, The new economics of innovation, spillovers and agglomeration: A review of empirical studies, Economics of Innovation and New Technology, Vol.8, pp. 5-25

Fleming, Lee, C. King, and A. Juda., Small Worlds and Regional Innovation." *Organization Science,* forthcoming

Funke M., Niebuhr, A. (2005), Regional geographic research and development spillover and economic growth: Evidence from West Germany, *Regional Studies*, 39 (1), pp. 143-153.

Giuri P., Mariani M., Brusoni S., Crespi G., Francoz D., Gambardella A., Garcia-Fontes W., Geuna A., Gonzales R., Harhoff D., Hoisl K., Lebas C., Luzzi A., Magazzini L., Nesta L., Nomaler O., Palomeras N., Patel P., Romanelli M., Verspagen B., 2006. "Everything you always wanted to know about inventors (but never asked): Evidence from the PatVal-EU survey" *CEPR Working Paper 5752*.

Grossman, G. and Helpman E., 1991, *Innovation and Growth in the Global Economy*, Cambridge, MA: MIT Press.

Harhoff, D., Hoisl, K., Webb, C., 2005, *European patent citations - how to count and how to interpret them?* mimeo.

Hendry C, Brown, J. and DeFillippi, R. J. (2000), Regional Clustering of High Technology-Based Firms: Opto-Electronics in Three Countries, *Regional Studies*, 34 (2), 129-144.

Jaffe, A.B., Fogarty, M.S., Banks, B.A., 1998, Evidence from Patents and Patent Citations on the Impact of NASA and other Federal Labs on Commercial Innovation, *Journal of Industrial Economics*, 46, No. 2, pp. 183-205.

Jaffe A., Trajtenberg M. and M. Fogarty, 2000, Knowledge spillovers and Patent Citations: Evidence from a Survey of Inventors, The American Economic Review, Vol. 90, No 2, pp. 215-218

Jaffe, A., Trajtenberg M. and Henderson R., 1993, Geographic knowledge spillovers as evidenced by patent citations, *Quarterly Journal of Economics*, 108(3):577-98.

Krugman, P. R., 1991, *Geography and Trade*. Cambridge, MA: MIT Press

Marshall, A., 1920, *Principles of Economics*, 8th edition. London: Macmillan

Jaffe, A., 1989, Real Effects of Academic Research, *American Economic Review*, Vol. 79, p. 984-1001.

Maskell, P. (2001): Towards a Knowledge-based Theory of the Geographical Cluster, *Industrial and Corporate Change*, 10 (4), 919-941.

Pavitt K., 1987. On the nature of technology, University of Sussex, SPRU, Brighton

Romer, P., 1990, Endogenous technological change, *Journal of Political Economy*, **98**(5), pp.71-102

Saxenian, A.L,1994, *Regional Advantage, Culture and Competition in Silicon Valley and Route 128*, Cambridge (MA) and London.

Singh J., Collaborative Networks as Determinants of Knowledge Diffusion Patterns, 2005, *Management Science*, 51(5): 756-770.

Sorenson O., Singh J., 2007 "Science, social networks and spillovers", *Industry & Innovation*, 13: forthcoming.

Staber U., 1996, Accounting for variations in the performance of industrial districts, International Journal of Urban and Regional Research, 20, 299-316.

Swann, P., Prevezer, M., Stout D. (Eds.), 1998. *The Dynamics of Industrial Clustering. International Comparisons in Computing and Biotechnology*, Oxford University Press, Oxford UK

Thompson P., 2006, Patent Citations and the Geography of Knowledge Spillovers: Evidence from Inventor- and Examiner-added Citations, *The Review of Economics and Statistics*, MIT Press, vol. 88(2), pages 383-388, 06.

Thompson P. and Fox-Kean M., 2005, Patent Citations and the Geography of Knowledge Spillovers: A Reassessment, *American Economic Review*, vol. 95(1), pages 450-460,

Verspagen B., 1997, European Regional Clubs: Do They Exist and Where Are They Heading? On Economic and Technological Differences between European Regions, in: Adams J., Pigliaru F. (Eds.), *Economic Growth and Change: National and Regional Patterns of Convergence and Divergence*, Edward Elgar, Cheltenham

Verspagen, B., De Loo, I., 1999. Technology spillovers between sectors and over time. Technological Forecasting and Social Change 60, 215-235.

Zucker, L., Darby, M., Armstrong, J., 1998. Geographically localized knowledge: Spillovers or markets?, *Economic Inquiry,* 36, January, 65-86

Zucker L., Darby M. and Armstrong J., 1999, *Intellectual Capital and the Firm: The Technology of Geographically Localized Knowledge Spillovers*, NBER Working Papers 4946, National Bureau of Economic Research

Appendix 1. List of ISI-INPI-OST technological classes used in the paper and descriptive statistics.

	Mean	Std. Dev.
Electrical devices, engineering, energy	0.074	0.262
Audio-visual technology	0.020	0.139
Telecommunications	0.032	0.176
Information technology	0.022	0.146
Semiconductors	0.010	0.101
Optics	0.019	0.138
Analysis, measurement, control technology	0.060	0.237
Medical technology	0.024	0.153
Organic fine chemistry	0.066	0.249
Macromolecular chemistry, polymers	0.056	0.230
Pharmaceuticals, cosmetics	0.017	0.131
Biotechnology	0.009	0.093
Materials, metallurgy	0.032	0.176
Agriculture, food chemistry	0.015	0.121
Chemical&petrol, basic materials chem.	0.037	0.188
Chemical engineering	0.031	0.174
Surface technology, coating	0.015	0.121
Materials processing, textiles, paper	0.054	0.225
Thermal processes and apparatus	0.022	0.148
Environmental technology	0.018	0.135
Machine tools	0.035	0.183
Engines, pumps, turbines	0.032	0.176
Mechanical Elements	0.043	0.203
Handling, printing	0.076	0.264
Agricultural&food proc-machin-apparatus	0.021	0.144
Transport	0.066	0.248
Nuclear engineering	0.003	0.057
Space technology weapons	0.004	0.062
Consumer goods and equipment	0.047	0.212
Civil engineering, building, mining	0.039	0.195

Appendix 2. Robustness checks

This Appendix describes a part of the robustness checks that we performed in order to control the robustness of our estimated results. Other robustness checks are reported in various parts of the text.

We started by using a different formulation of the dependent variables used in the three equations. In place of the 0-5 scale for *Close* and *Distant* we employed a dichotomous variable that takes the value 0 when no interactions take place (score 0), and the value 1 when interactions occur independently of their importance (score 1 to 5). We used these variables in two probit regressions. The third regression was performed on the difference between the dichotomous *Close* and *Distant* variables. This is a new variable that ranges between -1 and 1.

Also, in order to take into account that a difference between small scores of *Close* and *Distant* [e.g. 2-1] might mean something different compared to the same distance between higher scores (e.g. 5-4), we build a third "standardized" variable for *Close-Distant*. This is: [(*Close*+1)-(*Distant*+1)] / [(*Close*+1)+(*Disant*+1)]. The correlation coefficient between the resulting variable and the -5 to +5 variable is 0.98 and it is statistically significant. We employed this as the dependent variable in an OLS regressions. The signs and statistical significance of the estimated coefficients in the regressions with each of these new formulations of the dependent variables are similar to the ones obtained by using the 0-5 dependent variables.

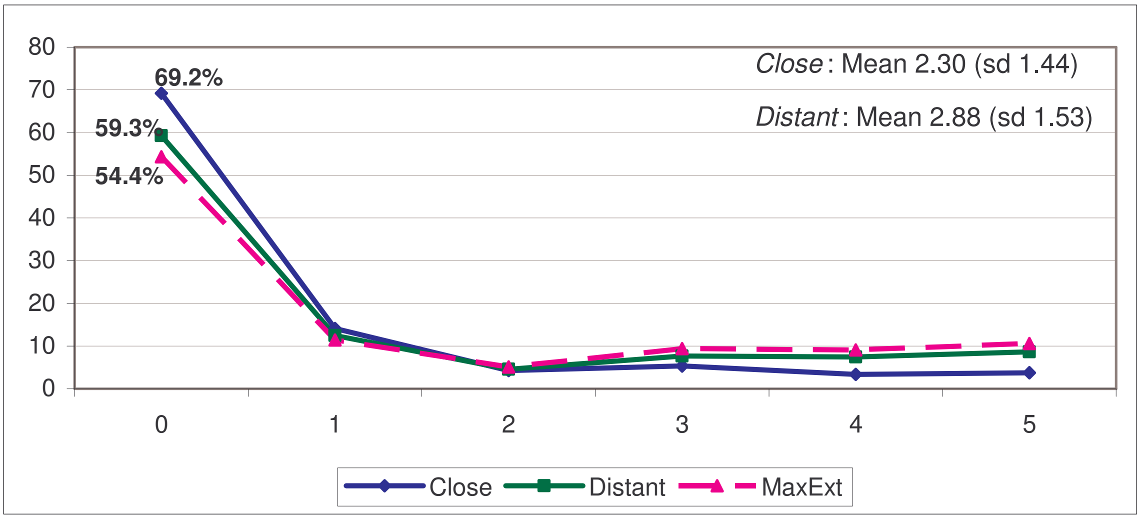
The results obtained by means of pairwise difference regressions do not change significantly also when we perform Wald tests for statistically significant differences between the estimated coefficients of the *Close* and *Distant* equations (since we estimated them separately, no correlation between the error terms of the two equations is assumed).

A concern with our estimates is multicollinearity between different regional variables like GDP, population and number of patents invented in the areas. For example, the simple correlation coefficient between the log of GDPPC and AVGPATS is 0.40. We performed our regressions by omitting alternatively GDPPC, POP and AREA, and all three together. We also run alternative specifications with TOP5_TECH, TOP1_TECH and THRESH5_TECH without controlling for the general technological environment of the region (REGPATS and LABS). In all these checks the sign and statistical significance of the variables included in the regressions do not change significantly compared to those in Tables 3 and 4.

Another possible concern with our estimates is the correlation between firm variables, i.e. R&DINT and EMPLOYEES. We perform our regressions by omitting R&DINT. The estimated coefficient of EMPLOYEES turned out to be negative and statistically significant in the *Close-Distant* regression. We also tried with different specifications for firm dummies: we omitted EMPLOYEES and used a dummy for the size of the companies while employing a dichotomous variables for missing R&DINT; we included both EMPLOYEES and R&DINT and a dichotomous variable for missing R&DINT. All the estimated coefficients are consistent with those described in Section 4. In particular, while it holds that inventors in R&D intensive firms do less *External* interactions, being them *Close* or *Distant*, when we use EMPLOYEES and R&DINT and only a dichotomous variable for missing R&DINT, inventors in smaller organizations tend to engage in *Close* interactions more than in *Distant* ones.

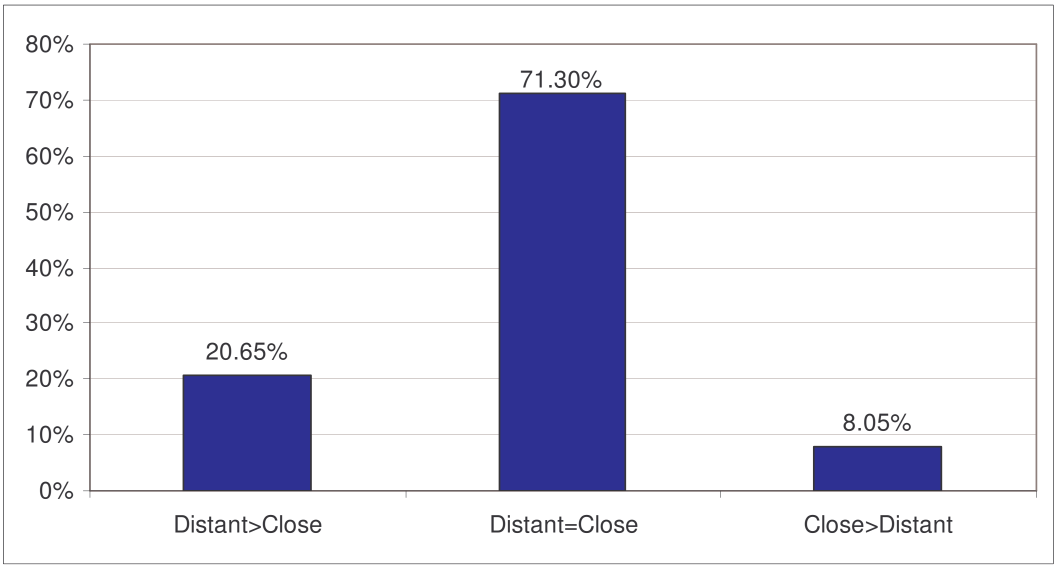
Tables and Figures

Figure 1: *Close* and *Distant* interactions: mean value and frequency distribution



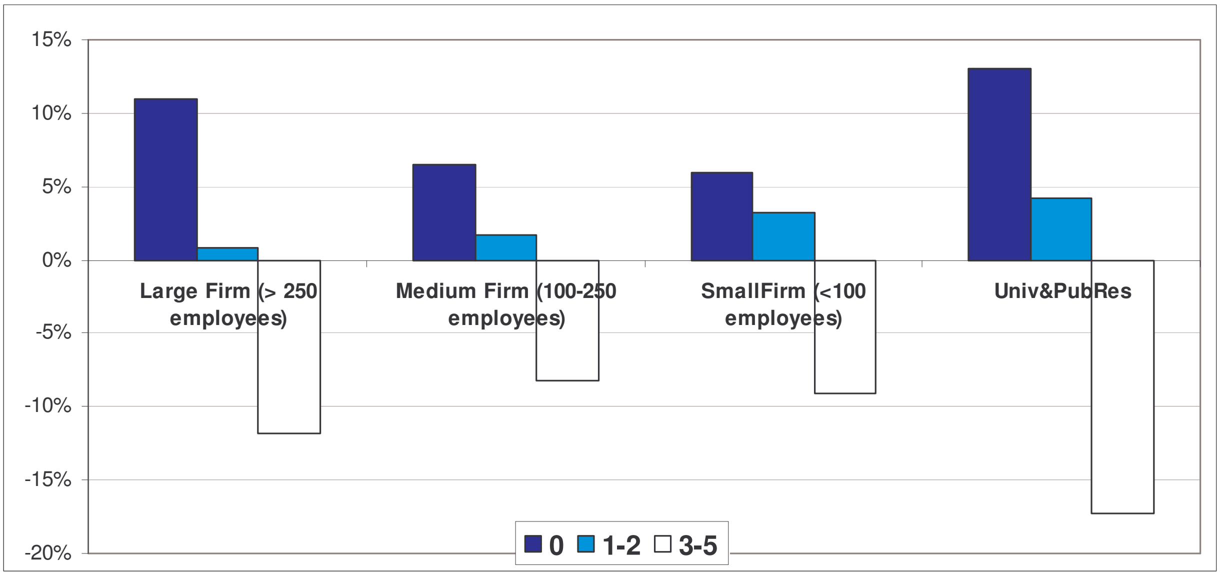
Source: PatVal-EU dataset

Figure 2: Relative importance of *Close* vs. *Distant* interactions



Source: PatVal-EU dataset

Figure 3: *Close* and *Distant* interactions by type of Applicant (Parent) Organization. Differences between shares of *Close* and *Distant* interactions by categories of importance: 0; 1-2; 3 to 5.



Source: PatVal-EU dataset

Table 1. Variables

	Dependent Variables	Source of data
Close	Importance of interactions with people belonging to unaffiliated organizations and geographically close. Scale 0 (not used) to 5 (very important)	PatVal-EU
Distant	Importance of interactions with people belonging to unaffiliated organizations and geographically distant. Scale 0 (not used) to 5 (very important)	PatVal-EU
Close-Distant	Relative importance of close vs. distant external interactions. Scale: -5 to +5 (-5 to -1: Distant more important than Close; 1-5 = Close more important than Distant).	PatVal-EU
	Employer and Inventor characteristics	
EMPLOYEES	Number of employees of the applicant parent company	Amadeus, Compustat
MISS_EMPLOYEES	SMALL, MEDIUM, LARGE applicant parent company	PatVal
R&DINT	R&D/sales ratio of the applicant parent company	Compustat
MISS_R&D	Small and Medium company: <250 empl; Medium and Large company: 251-500 empl; Large company: >500 empl; PRI: University or public research institution; Independent Inventor.	PatVal
AGE	Age of inventors: year of patent application-year of birth	PatVal
MALE	0 = Female inventor (baseline case); 1 = Male inventor	PatVal
HIGH_DEGREE	Dummy for the level of education: equal to 1 if highest Academic degree at the time of the invention is High School Degree or lower. This is the baseline case in our regressions.	PatVal
UNI_DEGREE	Dummy for the level of education: equal to 1 if highest Academic degree at the time of the invention is UNIV_MASTER.	PatVal
PhD_DEGREE	Dummy for the level of education: equal to 1 if highest Academic degree at the time of the invention is PhD.	PatVal
	Patent characteristics	
N_INVENTORS	Number of co-inventors listed in the patent	EPO
SCIENCE	Importance of scientific literature as a source of knowledge for the research that led to the invention (0 not important; 5 = very important)	PatVal
COMM_EXPLOIT	Importance of commercial exploitation as a reason to patent the invention (0 not important; 5 = very important)	PatVal
LICENSING	Importance of licensing as a reason to patent the invention (0 not important; 5 = very important)	PatVal
IMITATION	Importance of prevention from imitation as a reason to patent the invention (0 not important; 5 = very important)	PatVal
	Regional characteristics	
GDPPC	NUTS3 regional per capita Gross Domestic Product in 000 of purchasing power parity corrected for inflation (average 1994-1996)	Eurostat-Regio
POP	NUTS3 Population of the region (thousands - average 1994-1996)	Eurostat-Regio
AREA	NUTS3 Area of the region (Km2)	Eurostat-Regio
REGPATS	NUTS3 Number of patent applications in all sectors invented in the region (units - average 1994-1996)	Eurostat-Regio
LABS_UNI	NUTS3 Number of universities laboratories located in the region (stock in 1995)	European R&D database
LABS_PUBLIC	NUTS3 Number of public laboratories located in the region (stock in 1995)	European R&D database
LABS_PRIVATE	NUTS3 Number of private laboratories located in the region (stock in	European R&D

	1995)	database
SHARE_TECH	NUTS 2 Number of patent applications in the same micro technological field of the patent (ISI-INPI-OST classification in 30 technogical fields).	Eurostat-Regio
TOP5_TECH	Dummy variable: 1 for regions in the top 5% of the distribution in each technology; 0 otherwise	Eurostat-Regio
TOP1_TECH	Dummy variable: 1 for regions in the top 1% of the distribution in each technology; 0 otherwise	Eurostat-Regio
THRESH5_TECH	Dummy variable: 1 if more than 5% of the European patents in a specific technology is located in the region; 0 otherwise.	Eurostat-Regio
	Other Controls	
COUNTRY	Seven dummies for the country of inventor (IT, DE, ES, UK, DK, HU, NL). Baseline = UK.	EPO
YEAR	Dummies for the patent application year (from 1993 to 1998)	EPO
TECH_FIELD	Dummies for 30 micro technological fields in which the patent is classified (ISI-INIPI-OST classification)	EPO

Source: PatVal-EU dataset, EPO, Eurostat-Regio, *European R&D database*

Table 2. Descriptive statistics

	Mean	Std. Dev.	Min	Max
		Dependent Variables		
Close	0.710	1.331	0	5
Distant	1.175	1.722	0	5
Close-Distant	-0.465	1.772	-5	5
		Employer and Inventor characteristics		
EMPLOYEES	84260.45	114751	1	723328.6
MISS_EMPLOYEES	0.222	0.416	0	1
R&DINT	0.055	0.032	0	0.412
MISS_R&D	0.581	0.493	0	1
AGE	44.946	9.736	20	84
MALE	0.973	0.162	0	1
HIGH_DEGREE	0.195	0.396	0	1
UNI_DEGREE	0.547	0.498	0	1
PhD_DEGREE	0.258	0.438	0	1
		Patent characteristics		
N_INVENTORS	2.266	1.527	1	22
SCIENCE	2.593	1.873	0	5
COMM_EXPLOIT	3.808	1.554	0	5
LICENSING	2.059	1.543	0	5
IMITATION	3.798	1.578	0	5
		Regional characteristics		
GDPPC	22941.680	8915.593	5479.200	76910.800
POP	727.197	873.060	19.900	4634.400
AREA	1583.436	1997.538	35.600	18275.300
REGPATS	120.412	132.559	0.830	543.213
LABS_UNI	45.635	84.048	0	429
LABS_PUBLIC	12.438	36.351	0	461
LABS_PRIVATE	7.165	14.192	0	118
SHARE_TECH	0.024	0.026	0	0.151
TOP5_TECH	0.436	0.496	0	1
TOP1_TECH	0.142	0.349	0	1
THRESH5_TECH	0.146	0.353	0	1
		Other Controls		
UK	0.182	0.386	0	1
DE	0.410	0.492	0	1
IT	0.158	0.365	0	1
ES	0.027	0.161	0	1
NL	0.158	0.364	0	1
DK	0.062	0.241	0	1
HU	0.004	0.067	0	1
AppYear1993	0.027	0.162	0	1
AppYear1994	0.278	0.448	0	1
AppYear1995	0.263	0.440	0	1
AppYear1996	0.225	0.418	0	1
AppYear1997	0.157	0.363	0	1
AppYear1998	0.050	0.217	0	1

Source: PatVal-EU dataset, EPO, Eurostat-Regio, *European R&D database. # obs:* 6945.

Table 3: Ordered probit estimations. Specifications 1-3

Variable	*Close*	*Distant*	*Close-Distant*	*Close*	*Distant*	*Close-Distant*	*Close*	*Distant*	*Close-Distant*
	Specification 1			*Specification 2*			*Specification 3*		
Employer and Inventor characteristics									
EMPLOYEES	0	0.01	-0.01	0	0.01	-0.01	0	0.01	-0.01
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
R&DINT	-2.82**	-1.77**	-0.35	-2.84**	-1.82**	-0.33	-2.83**	-1.73**	-0.38
	(1.21)	(0.96)	(0.6)	(1.21)	(0.96)	(0.6)	(1.22)	(0.94)	(0.6)
AGE	-0.39***	-0.12	-0.19**	-0.39***	-0.12	-0.19**	-0.39***	-0.12	-0.2**
	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)
MALE	0.05	-0.13	0.19**	0.05	-0.13	0.19**	0.04	-0.12	0.19**
	(0.12)	(0.09)	(0.09)	(0.12)	(0.09)	(0.09)	(0.12)	(0.09)	(0.09)
UNI_DEGREE	-0.03	0.12**	-0.12**	-0.03	0.11**	-0.12**	-0.03	0.11**	-0.11**
	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)
PhD_DEGREE	0.02	0.23***	-0.21***	0.02	0.23***	-0.21***	0.02	0.24***	-0.21***
	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)
Patent characteristics									
N_INVENTORS	0.02	0.02	0	0.02	0.02	0	0.02	0.03	0
	(0.04)	(0.03)	(0.03)	(0.04)	(0.03)	(0.03)	(0.04)	(0.03)	(0.03)
SCIENCE	0.3***	0.29***	-0.07***	0.3***	0.29***	-0.07***	0.3***	0.29***	-0.06***
	(0.03)	(0.03)	(0.02)	(0.03)	(0.03)	(0.02)	(0.03)	(0.03)	(0.02)
COMM_EXPLOIT	0.03	0.04	-0.03	0.03	0.04	-0.03	0.03	0.04	-0.03
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
LICENSING	0.17***	0.16***	-0.02	0.17***	0.16***	-0.02	0.17***	0.16***	-0.02
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
IMITATION	0.08*	0.05	0.01	0.08*	0.05	0.01	0.08*	0.05	0.01
	(0.04)	(0.05)	(0.04)	(0.04)	(0.05)	(0.04)	(0.04)	(0.05)	(0.04)
Regional characteristics									
GDPPC	-0.06	-0.17*	0.12*	-0.07	-0.2**	0.13*	-0.06	-0.15*	0.1
	(0.08)	(0.09)	(0.07)	(0.07)	(0.09)	(0.07)	(0.08)	(0.09)	(0.06)
POP	0.06*	0.03	0.03	0.05	-0.02	0.05	0.06*	0.02	0.04
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.03)
AREA	-0.05***	0	-0.03*	-0.05***	0	-0.04*	-0.05***	-0.01	-0.03
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
REGPATS	0	-0.02	0.01				-0.01	0.01	-0.02
	(0.03)	(0.03)	(0.03)				(0.03)	(0.03)	(0.03)
LABS_UNI				-0.01	0.02	-0.01			
				(0.02)	(0.02)	(0.02)			
LABS_PUBLIC				0.01	-0.02	0.01			
				(0.03)	(0.02)	(0.02)			
LABS_PRIVATE				0	0.02	-0.01			
				(0.02)	(0.02)	(0.02)			
SHARE_TECH							0.54	-2.83***	3.08***
							(0.96)	(0.83)	(1.01)
N	6945	6945	6945	6945	6945	6945	6945	6945	6945
Ll	-7022.52	-8897.15	-8390.63	-7022.35	-8896.35	-8390.17	-7022.31	-8890.82	-8382.87
chi2	497.6	513.72	170.66	508.78	517.87	173.57	496.91	553.68	197.63

Note: Cluster-Robust standard errors are in parentheses. All regressions include dummies for *Missing value for EMPLOYEES and R&DINT*, *Inventor country,Year of application and Technological field (30* ISI-INIPI-OST classes). Coefficient significant at *0.1 level, ** 0.05, ***0.01

Table 4: Ordered probit estimations. Specifications 4-6

Variable	*Close*	*Distant*	*Close-Distant*	*Close*	*Distant*	*Close-Distant*	*Close*	*Distant*	*Close-Distant*
	Specification 4			*Specification 5*			*Specification 6*		
Employer and Inventor characteristics									
EMPLOYEES	0	0.01	-0.01	0	0.01	-0.01	0	0.01	-0.02
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
R&DINT	-2.82**	-1.74*	-0.37	-2.83**	-1.77*	-0.33	-2.87**	-1.74*	-0.38
	(1.22)	(0.94)	(0.6)	(1.21)	(0.96)	(0.6)	(1.21)	(0.96)	(0.6)
AGE	-0.39***	-0.12	-0.19**	-0.4***	-0.12	-0.2***	-0.4***	-0.11	-0.21***
	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)
MALE	0.05	-0.12	0.19**	0.05	-0.13	0.19**	0.04	-0.12	0.19**
	(0.12)	(0.09)	(0.09)	(0.12)	(0.09)	(0.09)	(0.12)	(0.09)	(0.09)
UNI_DEGREE	-0.03	0.12**	-0.12**	-0.03	0.11**	-0.11**	-0.03	0.11**	-0.11**
	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)
PhD_DEGREE	0.02	0.24***	-0.21***	0.02	0.24***	-0.21***	0.02	0.24***	-0.22***
	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)
Patent characteristics									
N_INVENTORS	0.02	0.02	0	0.02	0.02	0	0.02	0.02	0
	(0.04)	(0.03)	(0.03)	(0.04)	(0.03)	(0.03)	(0.04)	(0.03)	(0.03)
SCIENCE	0.3***	0.29***	-0.07***	0.3***	0.29***	-0.06***	0.3***	0.29***	-0.06***
	(0.03)	(0.03)	(0.02)	(0.03)	(0.03)	(0.02)	(0.03)	(0.03)	(0.02)
COMM_EXPLOIT	0.03	0.04	-0.03	0.03	0.04	-0.03	0.03	0.04	-0.03
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
LICENSING	0.17***	0.16***	-0.02	0.17***	0.16***	-0.03	0.17***	0.16***	-0.02
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
IMITATION	0.08*	0.05	0.02	0.07*	0.05	0.01	0.07*	0.05	0.01
	(0.04)	(0.05)	(0.04)	(0.04)	(0.05)	(0.04)	(0.04)	(0.05)	(0.04)
Regional characteristics									
GDPPC	-0.06	-0.16*	0.12*	-0.07	-0.15*	0.1	-0.07	-0.16*	0.1
	(0.08)	(0.09)	(0.07)	(0.08)	(0.09)	(0.06)	(0.08)	(0.09)	(0.06)
POP	0.06	0.02	0.03	0.07*	0.02	0.04	0.06*	0.03	0.03
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.03)	(0.04)	(0.04)	(0.03)
AREA	-0.05***	-0.01	-0.03	-0.05**	-0.01	-0.03	-0.05**	-0.01	-0.03
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
REGPATS	-0.01	0	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
TOP5_TECH	0.01	-0.09**	0.08**						
	(0.05)	(0.04)	(0.04)						
TOP1_TECH				0.09	-0.14***	0.2***			
				(0.05)	(0.05)	(0.05)			
THRESH5_TECH							0.11*	-0.13**	0.22***
							(0.06)	(0.05)	(0.06)
N	6945	6945	6945	6945	6945	6945	6945	6945	6945
ll	-7022.5	-8894.62	-8388.53	-7021.03	-8892.93	-8381.32	-7020.38	-8893.72	-8381.08
chi2	497.59	517.56	177.77	494.36	542.25	213.53	494.13	535.92	197.90

Note: Cluster-Robust standard errors are in parentheses. All regressions include dummies for *Missing value for EMPLOYEES and R&DINT*, *Inventor country,Year of application and Technological field (30* ISI-INIPI-OST classes). Coefficient significant at *0.1 level, ** 0.05, ***0.01