Networks, proximities and inter-firm knowledge exchanges

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Abstract
Building on previous literature that provides extensive evidence concerning flows of knowledge generated by inter-firm agreements, in this paper, we aim to analyze how the occurrence of such collaborations is driven by multi-dimensional proximity among participants and by their position within firms' networks. More specifically, we assess how the likelihood that two firms set up a partnership is influenced by their bilateral geographical, technological, organizational, institutional and social proximity and by their position within networks in terms of centrality and closeness. Our analysis is based on agreements in the form of joint ventures or strategic alliances, announced over the period 2005-2012, in which at least one partner is localized in Italy. We consider the full range of economic activities, which allows us to offer a general scenario and to specifically investigate the role of technological relatedness across different sectors. The econometric analysis, based on the logistic framework for rare events, provided three noteworthy results. First, all five dimensions of proximity jointly exert a positive and relevant effect in determining the probability of inter-firm knowledge exchanges, signaling that they are complementary rather than substitute channels. Second, the higher impact on probability is due to technological proximity, followed by the geographical proximity, while the other proximities (social, institutional and organizational) have a limited effect. Third, we find evidence concerning the positive role played by networks, through preferential attachment and transitivity effects, in enhancing the probability of inter-firm agreements.

Keywords: knowledge flows, strategic alliances, joint ventures, proximities, networks

JEL: L14, O31, O33, R12

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1. Introduction

The exchange of knowledge among firms is facilitated by their geographical proximity, given that knowledge has, in part, a tacit nature that tends to bind the spatial scope of spillovers (Jaffe et al., 1993; Audretsch and Feldman, 1996). Notwithstanding the much-investigated role of geography, the most recent literature has highlighted that inter-firm exchanges can also be mediated by other dimensions of closeness, which may have an a-spatial nature, such as technological, institutional or organizational proximity (Torre and Gilly, 2000; Boschma, 2005). Moreover, interactions among economic agents create social links that, over time, tend to evolve into wider networks, which are likely to facilitate the future exchanges of knowledge and moderate the adverse effects of other distances (Boschma and Frenken, 2009).

A growing body of empirical research has extensively analyzed the characteristics of networks that are expected to prompt innovation diffusion by considering various forms of connections among agents. These include participation in research programs (Autant-Bernard et al., 2007; Maggioni et al., 2007; Balland 2012), co-patenting (Cantner and Meder, 2007; Maggioni et al., 2007; Cassi and Plunket, 2012), citations (Maurseth and Verspagen, 2002; Paci and Usai, 2009), co-publications (Ponds et al., 2007), applicant-inventor relationships (Maggioni et al., 2011; Picci, 2010) and human capital mobility (Miguelez and Moreno, 2011; Breschi and Lissoni, 2009).

In this paper, we intend to follow a novel route by investigating the knowledge exchanges generated by two particular modes of agreements among firms: joint ventures and strategic alliances. The management literature (Kogut, 1988; Inkpen, 2000; Oxley and Sampson, 2004, Phelps et al., 2012) has remarked how such inter-firm agreements, regardless of their specific nature and motivations, create the conditions for knowledge sharing and thus represent an important channel of knowledge exchange among the companies involved. Indeed, firms perform several activities before, during and after the agreements that allow partners to access and share knowledge-based resources, often embedded within the organizations and thus restricted to their members (Muthusamy and White, 2005; Janowicz-Panjaitan and Noorderhaven, 2008; García-Canal et al., 2008). Beginning during the preliminary stages of the agreement, such activities involve information flows among managers and employees, which may entail access to new technologies and organizational competencies, integration, sharing or transfer of capabilities, human and organizational resources, and, finally, formal and informal inter-organizational learning processes.

The aim of this paper is to analyze how the occurrence of inter-firm collaborations and the consequent knowledge exchanges among partners are driven by different dimensions of proximity among participants and by the features of the networks in which they are involved. More specifically, we assess the likelihood that any two firms choose to activate a bilateral partnership (or take part in a multi-participant agreement) in relation to their reciprocal geographical, technological, organizational, institutional and social proximities. Moreover, on the basis of the past experience of each firm within networks, we assess whether the preferential attachment and transitivity characteristics have an additional effect on the occurrence of inter-firm agreements.

We base our empirical analysis on announced agreements over the period from 2005 to 2012, in which at least one firm is localized in Italy, including both domestic and international collaborations. In total, we examine 631 agreements involving 1078 firms. An original feature of our study is that we consider agreements covering all economic activities, which allows us to offer a wide-ranging scenario with respect to previous contributions on the role of proximity based on individual data. To the best of our knowledge, previous studies limit their investigations to a single industry, such as footwear (Boschma and Ter Wal, 2007), nanotechnology (Autant-Bernard et al., 2007), aviation (Broekel and Boschma, 2012), biotechnology (Fornahl et al., 2011), global navigation satellite systems (Balland, 2012), wine (Giuliani, 2010) and genomics (Cassi and Plunket, 2012). Other studies give a global picture of the role of proximity with respect to the whole economy but are conducted on data aggregated at a regional level (Marrocu et al., 2013; Maggioni et al., 2013). Our study represents a novel contribution in investigating five dimensions of proximity within a multi-sector framework and in testing whether they act as substitutes or complements in today's complex economic systems.

Given the large sample dimensionality difficulties that arise when analyzing firm partnerships across different countries – the network structure becomes virtually worldwide, reaching high degrees of complexity – we chose to restrict our sample to the set of agreements with at least one firm located in Italy. This allows us to obtain a manageable dataset and computationally less demanding proximity and network indicators for each pair of firms. It is worth noting that our choice is unlikely to alter the general validity of the results because, as noted by Narula and Hagedoorn (1999), firms' propensities to initiate an agreement are much more influenced by sectoral determinants than by country features. This is confirmed by examining the distribution of agreements by the number of partners: in our sample, 90% of them involve only two partners; such proportions are very similar to the one (88%) reported by García-Canal et al. (2008) for 15 countries of the European Union. Additionally, the geographical distribution of the deals does not show any relevant country-specific features: for the Italian case, only 15% of the firm pairs involved in the agreements are domestic (i.e., both firms located in Italy), which is very similar to what is recorded for France (11%) or Germany (12%).

The econometric analysis, based on the logistic framework for rare events, provided three main results. First, all five dimensions of proximity jointly exert a positive and relevant effect in determining the probability of inter-firm knowledge exchanges, signaling that they are complementary rather than substitute channels. Second, technological proximity exhibits a higher impact on probability, followed by the geographical one, while the other proximities (social, institutional and organizational) have a limited effect. Third, firms' network positioning, in terms of both preferential attachment and transitivity, significantly enhances the probability of inter-firm agreements.

The remainder of the paper is organized as follows. In the second section, a detailed description of the data on inter-firm agreements is offered. In the third section, we present the empirical model and describe how we operationalize the proximity and network measures. In the fourth section, we address some econometric issues and present our estimation strategy. The econometric results are discussed in section 5, while concluding remarks are provided in section 6.

2. Inter-firm agreements

In this section, we describe the data on inter-firm agreements, which we propose as an indicator apt to account for knowledge exchanges occurring among companies. Data on announced agreements over the period 2005-2012 are collected from the SDC Platinum database (Thomson Financial) and include all the deals involving at least one partner located in Italy. Our data on inter-firm agreements comprise both joint ventures and strategic alliances. A joint venture is defined as a cooperative business activity formed by two or more firms that creates an independent organization and allocates the ownership, operational responsibilities and financial risks and rewards to each partner while preserving their separate identities. A strategic alliance is a cooperative activity formed by two or more organizations for a wide range of strategic purposes (manufacturing, licensing, marketing, supply, technology transfer, etc.) that does not create an independent entity but establishes a contractual agreement among the partners, which remain independent organizations.

From Table 1, we see that the total number of agreements is 631, which involved 1078 different organizations, of which 511 are Italian. Agreements can be simple or complex depending on the number of potential partners involved. Table 1 clearly shows that most of the partnerships (570) do not go beyond the simplest form, a single pair of firms. Only 10% of total exchanges involve more than two partners, with a maximum of seven organizations engaged. Given the presence of deals among multiple partners, the number of actual pairs – 887 – is higher than the number of agreements, as shown in Table 1. The firm dyads are formed either in joint ventures (607) or in strategic alliances (280).

Table 1 also offers interesting information on the quota of announced agreements that were completed (382, equal to 43% of the total). The agreements aggregated in the uncompleted category can take on a different status, such as pending, letter of interest or renegotiated. It is important to remark that because we are using the agreements as a proxy of knowledge exchanges among partners and given that these exchanges also take place in the preliminary and earlier stages of the contract, independently from their successive progress, we prefer to consider all the announced agreements in our analysis. In the robustness analysis, we test whether there are significant differences between completed and uncompleted deals. Another interesting aspect concerns the localization of partners, that is, the place where the headquarters are located. Table 1 shows that most pairs are formed by an Italian and a foreign partner (72%), with both partners located in Italy in only 15% of cases, and both partners being foreign in 14% of cases.[1]

Given our interest in spatial proximity, in Table 2, we report the geographical location of the participants, which are located in 61 different countries all over the world. Most partners (47%) are obviously firms located in Italy, followed by those situated in other EU countries (13%); as expected, EU firms represent the most frequent partners for the Italian companies due to their closeness in terms of geography and other proximity dimensions. Widespread exchanges are also recorded, with almost 12% of the partners located in the United States. Interestingly, among the most common partners, we also find firms located in emerging countries, such as India (7%), China (4%) and Russia (4%).

Finally, in Table 3, we report the distribution of the 631 agreements (first two columns) and of the 1078 participants (last two columns) across economic sectors, according to the Standard Industrial Classification (SIC) divisions. As expected, most agreements refer to manufacturing (almost 50%), while another large proportion (42.5%) refers to service sectors, such as Personal and Business, Finance Insurance and Trade and Transportation, Energy and Sanitary services. Nearly the same shares can be found for the distribution of participants, except for the fact that the manufacturing sector has a lower quota (around one third).

3. The empirical model

As stated in the introduction, we focus on the case of cooperation agreements as an indicator of knowledge flows because they imply a complex and lengthy process of interactions involving two or more partners. The purpose of our analysis is to model the probability that any two firms exchange knowledge by means of taking part in an agreement as a function of the bilateral

[1] Given the selection criteria of our sample, the pairs with both foreign participants are necessarily part of a larger agreement where at least one Italian firm is also included.

geographical, technological, organizational, institutional and social measures of proximity and of the individual firm's network positions. The general form of our empirical model is:

Prob (agreement between any two firms) = f (proximities, firms' network positions, firms' controls) (1)

In this section we discuss the rationale for including the five dimensions of proximity and the two network indicators, and we describe in detail how they are measured. The list of variables is reported in the Appendix.

3.1 The dependent variable

The observational unit in our model is represented by pairs of firms, and the dependent variable is constructed as a binary variable that takes value 1 when an agreement was announced between any two companies over the period 2005 – 2012 and 0 when a pair of firms could have set up a deal but did not. We refer to the latter as "potential" pairs. To identify the potential firm dyads, we apply the approach followed, among others, by Autant-Bernard et al. (2007) and Cassi and Plunket (2012). This requires pairing the 1078 firms involved in the 631 agreements included in our sample to obtain the number of all possible pairs, which is 580,503.[2] Of this total, 887 pairs were involved in actual agreements, while the remaining 579,616 were not; therefore, they are considered as potential pairs. Thus in our sample, the number of firm pairs involved in agreements is equal to 0.15% of total possible dyads: setting up partnerships is clearly a sporadic event (Table 1). Therefore, we apply the methodology for rare events proposed by King and Zeng (2001), discussed in detail in section 4, where we address some relevant estimation issues.

3.2 Proximity dimensions

Geographical proximity. The ability of a firm to use ideas and technologies created and developed by other firms is a crucial mechanism for knowledge accumulation and economic growth at both the micro and macro levels (Rallet and Torre, 1999; Romer, 1986). Such diffusion can be facilitated when knowledge, especially in its tacit form, can be transmitted among agents that are physically proximate (Von Hippel, 1994). Consequently, spatial proximity has been the most thoroughly investigated dimension in the wide literature on knowledge flows and spillovers (Jaffe, 1986; Jaffe et al., 1993; Anselin et al., 1997). We measure geographical proximity by the inverse of distance (*Inv_dist*) between the locations of the partners (in kilometers).[3] As an alternative, spatial

[2] Because actual agreements are set up by firms that may operate in different productive sectors, we do not impose any restriction on the potential pairs on the basis of firms' productive relatedness.
[3] For the case of extra-European companies, given the difficulties of finding the exact location of the firms, we have used the location of the country capital as a proxy.

closeness between partners is also measured by means of a more specific binary variable (*ID_intra_reg*) that takes the value of 1 when both partners are located in the same Italian region.

Technological or cognitive proximity. It is a commonly accepted idea that knowledge transfer is not an easy, smooth or generally accessible (Cohen and Levinthal, 1990). It may require specific and appropriate absorptive capacity, which entails a homogenous cognitive base to understand and effectively process the available knowledge (Nooteboom, 2000). We expect that firms having a similar cognitive base will exchange knowledge more easily and efficiently. We account for the technological relatedness between partners with a set of five mutually exclusive technological interaction dummies ordered by increasing technological similarity (Ellwanger and Boschma, 2012). These dummies are based on the primary economic activity, which is reported in the SDC database at the 4-digit SIC code for each participant.[4] The first interaction dummy (*ID_intra_SIC4*) takes the value of 1 when the partners operate in the same 4-digit SIC Industry and the value of 0 when the two firms operate in different Industries. It is interesting to note that this strong sectoral affinity is not unusual, as it occurs in almost 28% of the firm pairs involved in the actual agreements. The dummy *ID_intra_SIC3* takes the value of 1 when the highest degree of industrial relatedness is at the 3-digit SIC Industry Group and 0 when the two firms operate in different industry groups or are related at a finer industrial disaggregation.[5] Using the same methodology, we compute the next dummies for the 2-digit SIC Major group (*ID_intra_SIC2*), for the 1-digit SIC Division (*ID_intra_SIC1*) and, finally, for the case (*ID_inter_SIC1*) when the partners operate in different divisions (conglomerate agreements). This last dummy is not included in the regressions so that firms operating in different divisions – the least proximate ones – represent the reference group; this final case is the most recurrent one as it is observed in 316 out of 887 cases (approximately 35%).

Organizational proximity. The exchange of information and knowledge can be influenced by the membership of individuals in the same club, group or organization, which generates strategic interdependence. The common membership implies the sharing of a set of rules and practices, based on organizational arrangements, which are crucial in reducing uncertainty and opportunistic behavior (Kirat and Lung, 1999). Such arrangements can be either within or among firms and may take different forms, ranging from informal relations among companies to formally organized firms. In our empirical analysis, as in Balland et al. (2013), we measure organizational proximity with a dummy variable (*ID_intra_group*) equal to 1 if the two participants involved in a partnership have

[4] The Standard Industrial Classification is organized in 10 Divisions (1-digit classification), 83 Major groups (2-digit), 410 Industry groups (3-digit) and 965 Industries (4-digit).

[5] Note that these first two dummy variables indicate that the two participants in the agreement operate in very similar economic activities; thus, the two dummies also proxy the direct competition among partners (García-Canal et al., 2008).

the same ultimate parent company, that is, they belong to the same corporate group, and 0 otherwise.

Institutional proximity. The exchange of ideas among economic agents may be easier and more effective if such agents share the same institutional framework. Formal and informal institutions such as laws, rules and norms can provide a set of standard procedures and routines that are shared by firms and, therefore, taken for granted. This common institutional background is crucial in reducing uncertainty and lowering transaction costs and, thus, favors pro-cooperative attitudes. These, in turn, enhance the possibility of an agreement and the exchange of knowledge (Maskell and Malmberg, 1999; Gertler, 2003). Following previous studies (Ponds et al., 2007; Cassi and Plunket, 2012), institutional similarity is measured by means of a dummy variable based on the status of the two partners. More specifically, the dummy (*ID_status*) takes the value of 1 if the two firms share the same institutional status (both listed on a stock exchange, or private, or subsidiaries, or government bodies). In our data, for 38% of pairs involved in actual agreements, the two partners are institutionally similar. As an alternative measure, we also compute another dummy (*ID_indep*) taking the value of 1 if the partners are both independent entities. This is a very frequent case in our sample as it involves almost half of the firm pairs (47.8%).

Social proximity. The existence of social ties among individuals is another important catalyst for the exchange of ideas and knowledge (Granovetter, 1985). The analysis of social networks is therefore vital to understanding the phenomena of knowledge creation and diffusion. Social proximity refers mainly to reputation and trust effects created by the experience of past collaborations and repeated contacts between partners. Previous experience, which breeds reputation and trust, contributes to informal knowledge flows, which in turn lead organizations with a common partner to be more likely to interact and collaborate, especially within a risky and uncertain environment such as that of technological change and innovation. We measure social proximity by means of social network analysis using pre-sample information on agreements announced in the past, starting from the year 2000. We assume that past direct and indirect relationships provide a facilitating environment for sharing knowledge in the future. Consequently, as in Autant-Bernard et al. (2007) and Balland (2012), we assume that the degree of social proximity decreases with geodesic distance, which measures the shortest path between two nodes (i.e., firms). Therefore, our social proximity indicator is the inverse of the geodesic distance, which ranges from zero (when two nodes are virtually infinitely distant and neither they nor any of their direct and indirect partners ever met in the past) to one (when two nodes are directly linked because they have been partners in the past). To extract as much information as possible from our data, we compute the inverse of the recursive measure of geodesic distance (*Inv_geod_rec*) between firm *i* and firm *j* in all available previous years.[6] A robustness test is also performed by using the inverse of the geodesic distance computed considering only the previous five years (*Inv_geod_5y*).

3.3 Individual network characteristics

Social ties may be the result of an individual attitude or customary behavior and thus have to be examined from two complementary perspectives: the single node and the entire system perspective (Bramanti and Maggioni, 1997). This is why we introduce two additional measures that take into account each firm's single social position within the network of potential ties. Such measures supplement the information on the bilateral notion of social proximity, discussed above. The theoretical literature has shown how networks' architectures may impact knowledge growth and diffusion (Cowan and Jonard, 2004, Cowan et al., 2004 and Ter Wal and Boschma, 2009). Consequently, several empirical studies (Balland et al., 2013, Autant-Bernard et al., 2007, Cassi and Plunkett, 2012, Giuliani, 2010) have investigated to what extent the position of firms within the network influences knowledge diffusion. We follow this research path by introducing two measures related to the network characteristics featured by each firm over the previous years, starting from the year 2000. These indicators are expected to account for firms' past experiences in partnering.

Preferential attachment hypothesis. According to this hypothesis, actors are more inclined to link to the most connected individuals. Agents with a large number of relations are more attractive because they are supposed to be more productive or more trustworthy (Barabasi and Albert, 1999). A firm's preferential attachment is usually measured in terms of the number of its previous partnerships. Therefore, for each firm, we count the relations in which it was involved in the past, and this provides its degree of centrality (*P_deg*).

Transitivity hypothesis. This hypothesis states that some agents are more reachable than others because of their relative position in the network. Some nodes are relatively closer to all other nodes, and therefore, they represent a more effective route to connect to potential nodes to obtain information and acquire knowledge. It is important to note that the literature usually refers to transitivity when organizations that have a partner in common are more likely to partner themselves, thereby effectuating triadic closures. In our work, we prefer to employ a more general concept and indicator because triadic closures are very rare in our sample. We thus measure the transitivity property by referring to the notion of closeness centrality (*P_clo*); that is, the inverse of the sum of the distances of a node to all other nodes. This indicator can be regarded as a measure of either how long it takes to spread information from one node to all other nodes sequentially or how long it takes to retrieve information from all other nodes.

[6] This implies that the reference period for 2005 is the five-year period from 2000 to 2004, whereas the reference period for the 2012 observations is the period from 2000 to 2011.

The expected sign for both indicators – preferential attachment and transitivity – is positive because firms are supposed to be willing to maximize the opportunity to obtain knowledge from the whole network, thus connecting to the most joined and central firms. However, it may also be possible to observe a negative effect if firms are worried that linking to a central and highly connected partner may jeopardize the appropriability of their knowledge (Autant-Bernard et al., 2007).

3.4 Individual firms' characteristics

In our empirical model, we also control for various characteristics at the firm level. More specifically, we include information on each firm's status, organization, ownership nationality, geographical location and principal sector of activity. Regarding the status, we have computed two dummies (*PD_listed* and *PD_private*) for the most recurrent actual cases that account for the firm being publicly traded on a stock exchange market or being a private company; in other words, a company owned either by non-governmental organizations or by a relatively small number of shareholders, often a family in Italy.[7] We have also included a dummy (*PD_indep*) taking the value of 1 when the participant is an independent firm (i.e., when the ultimate parent company corresponds with the partner itself) and a dummy (*PD_fo*) taking the value of 1 for foreign-owned companies. The categorical variables such as economic activity and spatial location have been transformed into dummy variables defined for each of their categories. In this way, we have computed ten mutually exclusive dummies for the 1-digit SIC divisions of economic activity. Five mutually exclusive dummies have been created for the firm's spatial localization, which can be in one of the three Italian macro regions - North, Center and South - or in one of the European Union countries or in an extra-EU country.

4. Estimation issues for rare event logit models

The analysis of the effects of networks and proximities on the probability that two firms exchange knowledge through an agreement is performed within the logistic framework for rare events. As stated above, this entails creating the dependent variable (*Y*) taking value 1 for pairs of firms (887) which actually established a cooperative link during the period 2005-2012 and 0 for dyads of firms (579,616) that could have set up an agreement but did not.

By comparing the high number of potential pairs with the one related to actual deals (0.15% of all possible pairs), it is evident that setting up a cooperative agreement can be considered a rare event. In this case, given the disproportionate number of 0 observations, the logit model estimated

[7] In addition to the main institutional status represented by these two dummy variables, firms can also be subsidiaries, joint ventures or governmental organizations.

on the total number of firm pairs would severely underestimate the probability of occurrences. Following King and Zeng (2001, 2002), we apply the choice-based or endogenous stratified sampling approach, which requires selecting all the observations for which Y=1 (the "cases") and randomly (independently from the explanatory variables) selecting the observations for which Y=0 ("controls"). It is important to note that selecting on the zeros also allows for more efficient data collection because only a small part of these observations contribute to the information content of the explanatory variables. As is well known, data selection based on Y induces bias, and it is therefore necessary to apply the appropriate statistical corrections to obtain consistent and efficient estimators. The most applied ones are based on prior correction and on the weighting method, both of which require prior knowledge of the population proportion of one observations.[8]

It is worth noting that we have also to face another issue related to sample selection because the decision to set up an agreement - rather than consider other forms of collaboration - might be driven by the fact that a firm knows its proximate potential partners. To attenuate the possible selection bias, we apply the independence-in-conditional-mean approach by including in our models a wide range of firms' characteristics, which are jointly likely to affect firms' collaboration modes. Such characteristics, described in Section 3, are related to firms' statuses, organization, ownership nationality, operating divisions and geographic locations. Once we control for these individual firm features, we expect that the decision to select a particular partner to carry out a specific agreement is independent of higher-level collaboration or acquisition decisions.[9]

The empirical specification for the probability of observing an agreement is formalized on the basis of the following cumulative logistic distribution:

$$Prob\left(Y_{ij}=1 \middle| X_{ij}, N_i, N_j, W_i, W_j\right) = \frac{1}{1+e^{-\left(X_{ij}\beta_1+N_i\beta_2+N_j\beta_3+W_i\beta_4+W_j\beta_5\right)}} \qquad (2)$$

where Y_{ij} takes the value of 1 when an agreement process involves firm i and firm j and 0 otherwise; the matrix X_{ij} includes the interaction terms that allow us to assess to what extent the agreements are driven by inter-firm proximity, measured along the various dimensions – spatial, technological, organizational, institutional and social – described in detail in the previous section. Each of the N_i

[8] For a comprehensive discussion of rare event logit models, see King and Zeng (2001). As far as the correction methods are concerned, we recall that the prior correction method is less computationally demanding because it entails only correcting the constant estimate on the basis of the population proportion of ones; the maximum likelihood estimators for the coefficients associated with the explanatory variables do not need any correction because they maintain their unbiasedness and consistency properties. The weighting method entails weighting the sample observations so that the weighted proportions of ones and zeros in the sample equal the corresponding population proportions. The weighting method is robust to potential misspecification (Manski and Lerman, 1977), but it requires further corrections because the MLE for the variance-covariance matrix is severely biased.

[9] The same approach is adopted by Chakrabarti and Mitchell (2013) for the case of M&A determinants.

and N_j matrices includes the two network indicators for firm *i* and *j*, respectively, whereas each of the matrices W_i and W_j comprise the individual firm's control variables.

We estimate model (2) by performing the sequential procedure suggested by King and Zeng (2001) for selecting the zero observations.[10] More specifically, we considered several random samples by starting with the proportion of ones/zeros observations equal to 0.5 (each actual pair matched with just one random control) and stopping when we obtained no further efficiency gains, signaled by a reduction in the magnitude of standard errors. This occurred for the 0.1 proportion (1 actual pair matched with 10 other randomly drawn potential pairs) sample for both the prior correction and the weighting method. Comparing the alternative correction approaches, we found that overall, the estimated coefficients did not differ substantially, thus signaling the absence of any clear misspecification problem. We interpret this result in favor of our highly parameterized specification, which simultaneously accounts for five different proximity dimensions, network features and a wide range of firm characteristics to control for possible sources of heterogeneity.[11] For these reasons, in the next section, we focus the discussion on the evidence provided by models based on the prior correction method.

5. Empirical results

The estimated models are presented in Table 4. The first model includes only the geographical proximity, while the second one comprises the five proximity dimensions. Model 1 can be seen as a sort of benchmark, which allows us to investigate to what extent the different kinds of inter-firm proximity act as substitutes or complements and to assess whether the almost undisputed effect of geographical closeness is maintained when the role of other proximities is taken into account. The subsequent models (3-5) address the robustness of our results across specifications that include alternative indicators for some proximity measures.

5.1 The baseline model

In column 1, we report the benchmark model, according to which knowledge flows are affected by geographical proximity and by the network characteristics of each partner; controls at the individual firm level are also included to account for firm heterogeneity. The results show that geographical nearness is a crucial determinant of such flows and also that preferential attachment (degree of centrality) significantly influences the cooperation decisions among firms. At the same time, closeness centrality has the right sign but is only marginally significant. Most importantly, this

[10] All estimations are carried out by using the ReLogit software by Tomz et al. (1999).

[11] Results on model comparisons for different sample sizes and correction methods are not reported to save space but are available from the authors upon request.

model estimates the probability that any two firms start an agreement process (see last row in column 1) at 2.7%, which is eighteen times the basic random probability of 0.15%. We can interpret such an increase in probability as evidence of the predictive power of our model, even in its underspecified form with only the spatial proximity.

The second model, presented in column 2, is our baseline specification where the effect of proximity is assessed with respect to all the additional dimensions - technological, organizational, institutional and social - discussed in section 3. The results show that geographical closeness remains relevant even when all other dimensions are controlled for; its estimated coefficient does not change or changes negligibly (from 0.254 to 0.256). This evidence is in line with the findings from Paci et al. (2013) that geography and the other dimensions of proximity are not substitutes but rather complements. As a matter of fact, the results in column 2 show that all dimensions of proximity exhibit a positive and significant coefficient, which is expected to imply an increased probability of knowledge exchange through inter-firm agreements.[12] As a matter of fact, the estimated probability for this model rises to 3.8%, which implies that, thanks to the introduction of all proximities, cooperation becomes 40% more likely than when only geographical proximity is taken into account, indicating that our baseline model has a high predictive power. This result thus highlights the importance of simultaneously accounting for the whole set of relevant proximities within a comprehensive empirical specification, as suggested by the French School of Proximity (Kirat and Lung, 1999; Torre and Gilly, 2000).

Another noteworthy aspect is that the coefficients of technological proximity are not only positive and significant, but that their magnitude increases with the degree of similarity of firms' productive and knowledge bases. With respect to the reference group that comprises the most unrelated firms, the smallest coefficient (0.94) is found when the highest level of technological relatedness is the SIC1 division, whereas the largest (3.97) one is associated with the case when both firms operate in the same SIC4 industry. This result confirms recent findings by Boschma et al. (2013) on the relevant role played by industrial relatedness in favoring mergers and acquisitions partnering. Firms operating in the same economic activity are more likely to set up a cooperation agreement to exploit the potential synergies in terms of products and services and to benefit from economies of scale and scope. Moreover, information asymmetries between firms that are highly technologically related are lower, which favors their exchange of knowledge (Hussinger, 2010).

As far as social proximity is concerned, the probability that two firms announce an agreement is a positive and significant function of the inverse of the geodesic distance, as in Autant-Bernard et al. (2007). Moreover, the fact that two firms share the same ownership status, that is, that

[12] Basile et al. (2012) provide evidence on the positive and synergic effects of different kinds of proximities (spatial, social and relational) on the productivity growth of European NUTS2 regions.

they are institutionally proximate, is also a favoring factor for collaborative agreements, as in Cassi and Plunket (2012). Finally, we find a positive and significant effect of organizational proximity, measured in terms of membership to the same group, confirming the results from Balland (2012) and Balland et al. (2013).

We also find evidence supporting the relevant role of network characteristics, as the two indicators of centrality have a positive sign and are significant for both partners. Regarding the preferential attachment hypothesis (degree of centrality), we confirm previous findings (Balland et al., 2013, Balland, 2012, Cassi and Plunket, 2012) that agents prefer to interact and exchange knowledge with those that have former agreement experiences. Such a preference induces a self-reinforcing process of collaboration around the most connected firms that may lead to an increase in the degree of concentration within the network. This process has its rationale in the belief that firms that have already experienced knowledge exchanges possess more information as a result of those exchanges. Previous experience is also interpreted as an indirect signal of the potential value of a firm as a partner. Moreover, we find that the closeness centrality of firms within the network is an additional facilitating factor for knowledge exchanges, thus supporting the transitivity hypothesis. Our findings confirm that firms are selected as partners because their positions within the network make them potentially more able to connect to all other nodes and to cooperate to acquire external knowledge.

It is important to note that the positive and significant signs exclude that the occurrence and prevalence of another contrasting effect, that related to appropriability. Firms may face a trade-off between the necessity to increase the probability of getting effective information through cooperation and the concurrent necessity to control the dissemination of their own knowledge (Antonelli et al., 2011). In our case, firms are not wary of coming into contact with firms that are in the best position, not only for collecting knowledge, but also for spreading it.

5.2 Robustness tests

In the last three columns of Table 4, we test the robustness of our results across specifications that include alternative indicators for the proximity measures.

In column 3, we find that spatial proximity also affects knowledge exchanges when we refer to the sharing of the same regional location by partners. All other regressors keep their signs and significance; however, the average estimated probability declines to 2.8%, which is definitely lower than the one obtained from model 2, which remains the preferred one.

In column 4, we include an alternative measure for institutional proximity, i.e., the fact that both partners are independent entities; however, it is not significant, while leaving the coefficients of the other regressors almost unchanged. In column 5, we also test the robustness of our results with respect to a different proxy for social proximity; more precisely, we now calculate the inverse of the geodesic distance, limiting the time span to the previous five-year period to consider the same time span for all observations. We find that this variable is only partially significant (10%), even though the average estimated probability remains almost constant.

Finally, it is worth mentioning that we also carried out a sub-sample analysis to investigate whether relevant differences emerged when splitting the sample according to some features of the agreements, such as completed vs. uncompleted agreements, joint ventures vs. strategic alliances and manufacturing vs. service sectors. This analysis is rather preliminary because the limited number of actual agreements prevents us from estimating all the sub-samples, and thus further research is required. In any case, no significant differences were found across subsamples, thus confirming the main findings discussed above for the whole sample.

5.3 Effects on probability

In this final section, unlike previous contributions in the literature on proximity, we take a step forward in assessing how changes in proximity or network features affect the likelihood that any two firms exchange knowledge thanks to inter-firm collaborations. Therefore, we measure the increase in the estimated conditional probability for a given change in each explanatory variable in turn. Unless otherwise stated, such a change is considered with respect to the median value and is equal to one standard deviation.

Table 5 reports the results obtained with respect to our preferred model 2 in Table 4. We recall that model 2 yielded an estimated probability of an agreement equal to 3.8% when median values are attributed to all variables.

The first and most interesting result is that, as in Paci et al. (2013) and Montobbio and Sterzi (2013), the highest impact on probability is found when the technological proximity measured by sharing the same industry increases by one standard deviation with respect to the median. The probability goes up to approximately 7.4%, with an increase of 98% with respect to the baseline estimation. Increases of approximately 50% are also registered for all other measures of technological proximity.

Regarding geographical proximity, one standard deviation change makes the estimated probability increase by 23% (from 3.8% to 4.6%), which is around one quarter of the effect produced by a change in the same-industry dummy. As a matter of fact, the same effect induced by an increase in the highest degree of technological relatedness would be obtained with a reduction in the geographical distance as remarkable as moving from the median value (1728 km) to a distance of only 100 kilometers.

As for the other proximities, the effect on the estimated probability is always positive but smaller: a change in the organizational proximity induces a change of 12.2%, while 9.3% and 0.8% are the increases in probability due to increases in institutional proximity and social proximity, respectively. Despite the modest influence of social proximity, we find that a firm's own social relations are much more effective. Considering the partners average effects, preferential attachment raises the probability of observing an agreement by 31.1%, while 8.1% is the increase due to the transitivity property.

Overall, our findings offer further support to the composite role played by proximities and network features in driving the complex diffusion of knowledge. Although they may have reciprocal moderate effects, proximities and social links are by no means interchangeable; they supplement each other by contributing to favoring the transmission of knowledge among firms.

6. Conclusions

In this paper, we analyze the determinants of knowledge exchanges among firms originating from inter-firm agreements, such as joint ventures and strategic alliances. The management literature has provided extensive evidence on the existence of knowledge flows generated during the various stages of inter-firm agreement processes, when partners share knowledge-based resources, often embedded within organizations and accessible only by members. The knowledge flows occur in the form of transfers of new technologies and organizational capabilities and also in active participation in formal and informal organizational learning processes.

More specifically, we assess the effects exerted by different types of proximity and by the position of participants within the network of previous ties on the probability that any two firms engage in a cooperation agreement and therefore exchange knowledge. We analyze the case of announced agreements over the period 2005-2012 in which at least one firm is localized in Italy, considering a total of 631 agreements, which involve 1078 unique firms and give rise to 887 pairs of actual partners. The analysis is performed within a logistic framework for rare events given the large number of potential firm pairs; that is, any two firms that could have set up an agreement but did not. Our preferred model simultaneously accounts for five different proximity measures (geographical, technological, organizational, institutional and social), two network effects and a wide set of covariates to control for firm heterogeneity such as status, organization, ownership nationality, principal sector of activity and geographic location.

The results show that all dimensions of proximity exhibit a positive and significant effect, thus providing further and compelling evidence that knowledge exchanges are facilitated not only by spatial proximity, as argued traditionally, but also by other dimensions of inter-firm closeness, such as sharing a common cognitive base and the same institutional background, being a part of the same organization and belonging the same network.

Most importantly, we find that the highest impact on the probability of generating inter-firm knowledge exchanges is found when we consider the technological proximity between firms rather than geographical proximity. The latter, however, remains much more effective than the other proximities in driving the agreement process. Organizational, institutional and social proximities facilitate the exchange of knowledge to a significant but smaller degree. Despite the modest influence of social proximity, the relevance of network links is supported by significant preferential attachment and transitivity effects. There is robust evidence that the degree of centrality, that is, firms' previous experiences within the existing networks, positively affects the probability that companies set up cooperation agreements and thus give rise to a knowledge exchange. At the same time, firms are attracted by those partners that are on average closer to all other firms, as they are perceived as more capable of obtaining and processing information within the network. The concurrent effect of different proximities and firms' network positions makes the probability of observing an inter-firm agreement as high as 3.8%, which is 25 times higher than the random probability.

Thus, our findings highlight the importance of analyzing inter-firm knowledge flows by simultaneously accounting for the whole set of relevant proximities and network features within a comprehensive empirical model.

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Appendix. Variable definitions

Dependent variable		
	Y	dummy: = 1 if the two participants have an agreement; = 0 otherwise
Interaction variables for proximity dimensions between each partner in a pair		
Spatial proximity		
	Inv_dist	inverse of the distance in km between partners cities (log)
or	ID_intra_reg	dummy = 1 if partners are located in the same Italian region
Technological proximity		
	ID_intra_SIC4	dummy = 1 if the highest degree of industrial relatedness is at SIC4
	ID_intra_SIC3	dummy = 1 if the highest degree of industrial relatedness is at SIC3
	ID_intra_SIC2	dummy = 1 if the highest degree of industrial relatedness is at SIC2
	ID_intra_SIC1	dummy = 1 if the highest degree of industrial relatedness is at SIC1
Organisational proximity		
	ID_intra_group	dummy =1 if partners belong to the same group
Institutional proximity		
	ID_status	dummy = 1 if partners have the same insitutional status
or	ID_indep	dummy = 1 if both partners are independent companies
Social proximity		
	Inv_geod_rec	inverse of geodesic distance with recursive window (log)
or	Inv_geod_5y	inverse of geodesic distance with 5-year window (log)
Network characteristics for each partner		
Preferential attachment		
	P_deg	degree centrality, number of links incident upon a node
Transitivity		
	P_clo	closeness centrality, inverse of the sum of its distances to all other nodes
Control dummies for individual characteristics of each partner		
	PD_listed	partner is publicly traded on a stock exchange
	PD_private	partner status is private
	PD_indep	partner is independent, it is not part of a group
	PD_fo	partner is owned by a foreign ultimate parent company
	PD_north	partner location in northern Italy
	PD_centre	partner location in central Italy
	PD_south	partner location in southern Italy
	PD-EU	partner location in another EU countries
	PD_div_1-10	partner economic activity in 10 SIC divisions (ten dummies)

Table 1. Inter-firm agreements with at least an Italian participant, 2005-2012

Announced agreements	**631**
with 2 participants	*570*
with 3 participants	*43*
with 4 participants	*6*
with 5 participants	*8*
with 6 participants	*2*
with 7 participants	*2*
Participants	**1078**
Italian	*511*
foreign	*567*
Actual participant pairs	**887**
joint ventures	607
strategic alliances	280
completed	382
uncompleted	505
with both partners in Italy	*130*
with one partner in Italy	*636*
with both partners not in Italy	*121*
Total possibile pairs	580503
Proportion of actual pairs on population (%)	0.15

Table 2. Participants per country of origin, 2005-2011

	Number	%
Italy	511	47.4
EU countries	141	13.1
United States	127	11.8
India	72	6.7
China	44	4.1
Russian Fed.	40	3.7
Utd Arab Em.	16	1.5
Canada	13	1.2
Turkey	13	1.2
Japan	11	1.0
Rest of the World	90	8.3
Total	1078	100.0

Table 3. Agreements and participants per SIC division, 2005-2012

	Agreements		**Participants**	
	Number	%	Number	%
A Agriculture	1	0.2	2	0.2
B Mining	20	3.2	34	3.2
C Construction	12	1.6	17	1.9
D Manufacturing	213	46.8	504	33.8
E Transp., Comm., Energy, Sanitary Serv.	91	14.8	160	14.4
F Wholesale Trade	58	2.4	26	9.2
G Retail Trade	30	2.4	26	4.8
H Finance, Insurance, Real Estate	90	15.1	163	14.3
I Services (personal and business)	114	12.6	136	18.1
J Public Administration	2	0.9	10	0.3
Total	631	100.0	1078	100.0

Table 4. Logit models for the probability of inter-firm agreements

Prior correction model for rare events

	1	2	3	4	5
Spatial proximity					
inverse geographic distance	0.254 ***	0.256 ***		0.257 ***	0.254 ***
	(0.024)	*(0.026)*		*(0.026)*	*(0.026)*
same region			1.495 ***		
			(0.261)		
Technological proximity					
same division (SIC1)		0.939 ***	0.931 ***	0.939 ***	0.945 ***
		(0.112)	*(0.118)*	*(0.119)*	*(0.119)*
same major group (SIC2)		2.733 ***	2.720 ***	2.732 ***	2.731 ***
		(0.167)	*(0.166)*	*(0.166)*	*(0.166)*
same industry group (SIC3)		3.174 ***	3.123 ***	3.167 ***	3.209 ***
		(0.205)	*(0.207)*	*(0.205)*	*(0.205)*
same industry (SIC4)		3.972 ***	3.984 ***	3.969 ***	3.966 ***
		(0.166)	*(0.167)*	*(0.165)*	*(0.166)*
Organisational proximity					
same group		3.073 ***	3.279 ***	3.128 ***	3.046 ***
		(0.719)	*(0.775)*	*(0.719)*	*(0.720)*
Institutional proximity					
same status		0.199 **	0.208 **		0.223 **
		(0.094)	*(0.093)*		*(0.093)*
both partners independent				0.205	
				(0.193)	
Social proximity					
inverse geodesic distance		0.175 ***	0.169 ***	0.178 ***	
		(0.059)	*(0.058)*	*(0.060)*	
inverse geodesic distance (previous 5 years)					0.120 *
					(0.064)
Network characteristics					
preferential attachment - partner 1	0.076 ***	0.068 ***	0.069 ***	0.068 ***	0.069 ***
	(0.007)	*(0.008)*	*(0.008)*	*(0.008)*	*(0.008)*
preferential attachment - partner 2	0.065 ***	0.063 ***	0.064 ***	0.063 ***	0.065 ***
	(0.009)	*(0.009)*	*(0.010)*	*(0.009)*	*(0.010)*
transititvity - partner 1	9.117	13.453 **	14.362 **	13.330 **	13.661 **
	(5.957)	*(6.889)*	*(6.817)*	*(6.859)*	*(6.894)*
transititvity - partner 2	12.705 *	17.127 **	17.695 **	16.928 **	17.732 **
	(6.761)	*(8.198)*	*(8.055)*	*(8.184)*	*(8.272)*
Estimated probability Y=1|X at median values (%)	2.69	3.77	2.78	3.13	3.88

See Appendix for variables' definitions

Numbers of observations: 9757. Proportion of ones:zeros observations equal to 1:10

All models include individual firm controls for status (listed, private), organization (independent, subsidiary), ownership nationality (Italian, foreign), SIC1 division, geographic location (North, Centre, South Italy, another EU country, rest of the world)

Geodesic and geographic distance are log-transformed

Robust standard errors in parenthesis. Significance level *** 1%, ** 5%, *10%

Table 5. Effects of proximities and networks on the probability of inter-firm agreements

All changes are equal to one standard deviation and are measured with respect to the median values

From Model 2 Table 4: Prob (Y=1|X)=0.038	**Standard deviation**	**Absolute difference**	**Percentage Increase**
Spatial proximity			
geographic distance	3321.7	0.0087	23.1
Technological proximity			
same division (SIC1)	0.424	0.0173	45.9
same major group (SIC2)	0.168	0.0204	54.1
same industry group (SIC3)	0.122	0.0167	44.4
same industry (SIC4)	0.184	0.0371	98.4
Organisational proximity			
same group	0.039	0.0046	12.2
Institutional proximity			
same status	0.470	0.0035	9.3
Social proximity			
geodesic distance	0.036	0.0003	0.8
Network characteristics			
preferential attachment (partners average)	4.353	0.0117	31.1
transititvity (partners average)	0.005	0.0031	8.1

All effects are calculated by the Bayesian method and are significant at the 5% significance level