

The partner next door? The effect of micro-geographical proximity on intra-cluster inter-organizational relationships

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Abstract: Substantial research has focused on how innovation is influenced by geography from a macro perspective (e.g., at the country, state, or metropolitan level). However, less attention has been paid to how innovation is configured within a cluster from a micro perspective (e.g., at the district or firm level within a city), i.e., the “micro-geographical proximity” within a cluster. With this paper, we aim to “zoom into” a technology cluster to study the role of the inter-organizational micro-geographical proximity for the establishment of knowledge transfer relationships. Specifically, we analyse whether and how the micro-geographical proximity is related to the formation of three different types of inter-organizational relationships: venture capital (VC) deals, intellectual property (IP) transfer agreements, and R&D strategic alliances. We take empirical evidence from the biopharma cluster in the Greater Boston Area. Our findings suggest the importance of micro-geographical proximity for the establishment of VC deals and IP transfer agreements, which emphasizes the importance of adopting a micro-geographical perspective to highlight this “neighbourhood effect”, which would not be possible when considering spatial proximity at the macro level.

Keywords: inter-organizational relationships; knowledge transfer; venture capital deals; high-tech clusters; micro-geographical distance.

1. Introduction

“There is more learning and science within the circumference of ten miles from where we now sit than in all the rest of the world”; this was the affirmation pronounced by Samuel Johnson in London during the first Industrial Revolution. Since then, although globalization and digital communication technologies have significantly facilitated the interactions among geographically distant actors (Broekel and Boschma 2011; Cassi and Plunket 2014; Geldes et al. 2015), geographical proximity has preserved its importance as a catalyst for knowledge transfer, especially when such transfer occurs among partners with different knowledge bases (Broekel and Boshma 2012; Forman and van Zeebroeck 2019). The importance of geographical proximity for the establishment of knowledge transfer relationships is well explained by scholars who study technology clusters that are defined as agglomerations of knowledge-based firms (Storper 1992; Cesaroni and Piccaluga 2003) localized in distinctive regions where technological externalities, low communication costs, and social capital are especially conducive to raise innovation (Antonelli 2000; Kaasa 2009). Nevertheless, these latter studies have implicitly intended the geographical proximity from a macro perspective as a mere co-location of actors in the same institutional borders (i.e., same nation, region or city), while what appears to be a cluster at the macro level may refer to several geographically (and often technologically) distinct clusters at the micro level, which have different social relationships and unique needs (Feldman 2015). This because agglomeration benefits derived from the geographical proximity are not always equally distributed in the cluster (Boix et al. 2015; Andersson et al. 2019) and the quality and quantity of knowledge flows among cluster members are subject to distance decay (Jaffe et al. 1993; Breschi and Lissoni 2009; Bonaccorsi et al. 2014).

Consequently, an important characteristic in a technology cluster is its micro-geography because a specific micro-location inside a cluster enables firms to participate in and benefit from localized and highly specialized knowledge exchanges that only occur through face-to-face interactions and unanticipated encounters (Storper and Venables 2004; Messeni Petruzzelli et al. 2007; Broström 2010; Balland 2012; Cassi and Plunket 2015; Steinmo and Erasmussen 2016; Delgado et al. 2020). These latter considerations are supported by empirical evidences: considering most successful high-tech clusters, such as Silicon Valley in the U.S. or the biotech cluster in Cambridge in the U.K., the main actors are not only located in the same region but often confined to the same street or even the same building (Guzman and Stern 2016). Therefore, it is necessary to adopt a micro-geographical approach to analyse technology clusters to obtain a more realistic picture of the intra-cluster locational (and relational) advantages, which can sometimes “be traced to a very small neighbourhood” (Mudambi et al. 2018). Embracing a micro-geographical perspective implies identifying how close the actors must be to establish a relationship and benefit from the agglomeration economies of a cluster (Lublinski 2003).

Moving from these premises, our paper attempts to “zoom into” a technology cluster to provide more precise indications about the desirable levels of geographical proximity to establish inter-organizational knowledge transfer relationships. In other words, we evaluate whether being geographically located in the same technology cluster (macro-geography) causes actors to be equally likely to establish inter-organizational relationships, or, on the contrary, whether geographical proximity matters at a smaller scale (micro-geography). Accordingly, our paper seeks to answer to the following research question: RQ1) Does the micro-geographical proximity affect the probability of establishing an inter-organizational knowledge transfer relationship among two organizations in the same cluster?

Moreover, the issue of whether the micro-geographical proximity affects the probability of establishing inter-organizational relationships within a cluster is complicated by the fact that innovation-driven processes involve different types of organizations, which leads to the implementation of a broader spectrum of cooperation practices that link firms to firms, universities to firms, and venture capital investors to firms. These organizations vary in terms of the exchanged knowledge and phase of innovation development (Broström 2010; D’Este et al. 2012; Cassi and Plunket 2015; Steinmo and Erasmussen 2016; Crescenzi et al. 2016). The establishment of the different types of intra-cluster relationships can be affected in different manners by the micro-geographical proximity due to the differential role played by proximity-related determinants such as the type of knowledge exchanged, information asymmetries, and trust mechanisms. Our paper aims to coherently explore this latter aspect to answer the following research question: RQ2) Does the effect of micro-geographical proximity vary according to the type of inter-organizational relationship?

To answer to our research questions, we take empirical evidence from the biopharma cluster in the Greater Boston Area (GBA) by analysing the role of micro-geographical proximity in explaining the probability of tie formation among clusters’ members considering three types of inter-organizational relationships: venture capital (VC) deals, joint R&D partnerships and intellectual property (IP) transfer agreements. To build our sample, first, we identified different types of organizations (firms, universities and VC investors)– located in the GBA and belonging to the biopharma industry. Then, we mapped the realized inter-organizational collaborative ties among these organizations occurred during the 2012-2017 period by distinguishing among VC deals, R&D alliances and IP transfer agreements (i.e., 277 realized ties, including 175 VC deals, 56 R&D alliances and 46 IP transfer agreements). Using the dyad as the unit of analysis (Diestre and Rajagopalan 2012), we built three subsamples for each deal type, which consider both realized and

potential but unrealized ties. Then, we ran probit models, where the dependent variable was the probability that two organizations of the dyad have established a collaborative tie.

Our findings show that micro-geographical proximity is positively related to the establishment of IP transfer agreements and VC deals within the GBA biopharma cluster, while no significant association with R&D alliances is observed. These results suggest the importance of geographical proximity at a micro scale for specific cooperation dynamics such as VC deals and IP transfer agreements. This result emphasizes the importance of adopting a micro-geographical perspective to highlight this “neighbourhood effect”, which would not be possible when considering geographical proximity at the macro level.

We believe that this work contributes to the literature on technology clusters because it reveals the reasons behind the establishment of different types of knowledge transfer relationships among cluster members and emphasizes the role of micro-geographical proximity, which was almost neglected by previous studies. From an empirical standpoint, most empirical studies on technology clusters tend to consider geography in terms of the general co-localization of partners within the same institutional borders (at the national or regional level) and overlook the implications derived from its operationalization at smaller scales from a micro perspective. This study reduces the ambiguity in the notion of geographical proximity by demonstrating the presence of intra-cluster locational advantages for the establishment of certain types of inter-organizational relationships between two organizations. Moreover, our study contributes to the literature on innovation collaborations and open innovation, which often studies the geographical variables by simply distinguishing between local and international cooperation neglecting the effect of geographical proximity at the micro level (Kapetaniou and Lee 2019).

The paper is structured as follows. Section 2 reviews the literature on clusters and the role of geographical proximity in inter-organizational collaborations. Section 3 develops the research hypotheses. Section 4 presents the empirical setting, the data sources and the methodology. Section 5 reports the results of the econometric estimates. Section 6 compares our findings with those of related studies, while section 7 concludes the paper by discussing directions for future research and policy implications.

2. Theoretical Background

The clustering of firms in a geographical area has been the object of growing attention in the economic analysis from different scientific fields, such as regional economics and strategic management. Porter (1998) defines clusters as geographic concentrations of interconnected firms, suppliers, service providers, and associated institutions in a particular industry, where the firms both

compete and cooperate with one another. Then, co-localization, competition, and cooperation are considered the main features of clusters, as also emphasized by other authors (Piore and Sabel 1984; Beccatini 1989; Takeda et al. 2008).

In the literature, different types of clusters have been distinguished (Markusen 1996). In particular, technology clusters are considered an evolution of industrial districts, based on a set of more knowledge-based firms (Storper 1992), localized in distinctive regions where technological externalities, low communication costs, and social capital are especially conducive to raise innovation (Antonelli 2000; Kaasa 2009). Central to this argument is the traditional assumption in economics and geography that knowledge spillovers are geographically localized and locally bounded (Krugman 1991; Jaffe et al. 1993; Alcacer and Chung 2007; Arikan 2009). In other words, stocks and flows of knowledge tend to be spatially concentrated and only available to the co-located actors (Harrison 1994; Audretsch and Feldman 1996; Uzzi 1997; Bathelt et al. 2004; Agrawal et al. 2003; Moulaert and Sekia 2003; McCann 2004; Lagendijk and Oinas 2005; Dyer and Hatch 2006; Bell et al. 2009).

In this context, innovation can be understood as a joint action among neighbours (Camison and Villar-Lopez 2012) by assuming the importance of the geographical proximity in favouring the development of the relationships among different actors to facilitate the inter-organizational knowledge transfer (Freeman 1987; Lundvall and Johnson 1994; De la Mothe and Paquet 1998; Etzkowitz and Leyedsdorff 2000; Cooke 2001, 2004; Asheim and Coenen 2005). Empirical studies confirm that spatially concentrated actors benefit from knowledge externalities engendered by short distances, which literally bring people together, favour contacts for information exchange, and facilitate reciprocal exchanges of tacit knowledge (Maskell 2001; Gordon and McCann 2005; Waxell and Malmberg 2007; Balland 2012). This does not imply that knowledge transfer cannot be realized among distant actors, but the lack of geographical proximity must be necessarily compensated by other forms of proximity, e.g., institutional, organizational, social and cognitive (Boschma 2005; Lagendijk and Oinas 2005; Torre and Rallet 2005; Lagendijk and Lorentzen 2007; Crescenzi et al. 2016).

There is abundant literature in the areas of both knowledge management and economic geography that analyses the positive effects of geographical proximity among cluster members (e.g., Messeni Petruzzelli et al. 2007; Broström 2010; Cassi and Plunket 2015; Bøllingtoft 2012; Steinmo and Erasmussen 2016). However, most studies tend to measure it as the general co-localization of partners within the same institutional borders and overlook the implications that derive from its operationalization in terms of geographical distance on smaller scales. Indeed, the analysis of large geographical units masks cross-border activity, and it is likely to obscure proximate considerations

that are important for innovative activity. What appears to be a cluster at the country level may in fact refer to several geographically (and often technologically) distinct clusters, each with different social relationships and unique needs (Feldman 2015). In this light, some authors have begun to analyse clusters from a micro perspective (e.g., at the district- or firm-level within a city), i.e., the so-called “micro-geography of innovation” (Liu and Marx 2020). The micro-geography of innovation involves detailing the spatial delimitation of clusters based on firm-based micro-data (Boix et al. 2015) and addresses the effect of the micro-location of firms within industrial clusters (Arbia et al. 2015).

Many studies from this recent literary stream fall within the scope of economic geography and are aimed at identifying the boundaries of the micro-clusters that are part of a larger cluster area using statistical mapping tools (e.g., Boix et al. 2015; Jang et al. 2017; Delgado et al. 2020). Only a few authors focus on single clusters to understand the effect of micro-geographical proximity on inter-organizational relationships, which is the perspective that we adopt in the current study. However, within this latter perspective, a lack of general agreement emerges regarding the effect of geographical proximity on the emergence of inter-organizational ties at the micro-geographical level. This is also due to the fact that although many studies focus their attention on a single cluster, most authors limit their comparison to the efficacy and frequency of internal- versus external cluster relationships (e.g., Biggerio and Sammarra, 2010; Belussi et al. 2010; Molina Morales 2015), without considering what happens among co-located partners. Moreover, although some scholars suggest that the impact of geographical proximity varies significantly across diverse types of knowledge flows (Huggins et al. 2012; Grillitsch et al. 2015; Quatraro and Usai 2017; Lazzeretti and Capone 2016; Balland et al. 2016), too few empirical efforts have been devoted to the analysis of the differential role of micro-geographical proximity in different types of relationships at the cluster-level and to the identification of implications for innovation activities. In addition, scholars who have focused on different types of R&D collaborations have analysed such relationships at the organizational level and adopted a macro-perspective (for example, Almeida 1996; Ponds et al. 2007; Hoekman et al. 2009; Waltman et al. 2011; Plotnikova and Rake 2014), neglecting the consideration of the role of micro-geographical proximity.

Starting from these limitations, our paper analyses the effect of the micro-geographical proximity on the establishment of the knowledge transfer relationships among organizations that are co-located in a technology cluster while also considering the heterogeneity of cooperation practices.

3. Geographical proximity and inter-organizational cooperation: Research hypotheses

To understand the effect of micro-geographical proximity on the establishment of inter-

organizational relationships within a technology cluster, the different natures of such relationships must be considered. The relationships within a technology cluster are indeed characterized by different cooperation practices depending on the resources that must be transferred during the innovation process (e.g., financial capital, knowledge, and human resources) and the organizations in the process (e.g., universities, large and small firms, and VC investors). Traditionally, scholars have considered R&D alliances (Hagedoorn and Schankenraad 1994; Shan et al. 1994; Walker et al. 1997; Ahuja et al. 2008), IP agreements (such as licensing agreements) as the main knowledge transfer relationships within a technology cluster (Powell et al. 1996; Ahuja 2000). These types of inter-organizational relationships enhance the knowledge exchange, enable labour mobility among partner organizations and enable access to extra knowledge through informal ties among individuals engaged in technology development. Furthermore, they involve tighter, more proprietary conduits that are more effective in sustaining the sources of competitive advantage derived from networks over time (compared to more loosened forms of ties) (Owen-Smith and Powell 2004).

Near R&D alliances and IP transfer agreements that generally involve universities and companies, recent studies have recognized the key role undertaken in a cluster by VC investors (Kenney and Florida 2000; Lee et al. 2000; Martin et al. 2005; Zhang 2007; Lerner 2009). Many studies argue that VC deals are important sources for both financial capital and knowledge exchange (Ferrary and Granovetter 2009).

These three types of inter-organizational relationship (VC deals, joint R&D partnerships and IP transfer agreements) differ in terms of the actors involved and other variables such as the type of knowledge exchanged, information asymmetries, and trust mechanisms. These latter variables are particularly important for our discussion because micro-geographical proximity can positively affect them by encouraging face-to-face interactions, which stimulate the establishment of personal networks across organizational boundaries (Feldman 1994; Uzzi 1997), facilitate the exchange of tacit knowledge (Bathelt et al. 2004; Agrawal et al. 2006), enhance the development of idiosyncratic language and collaboration routines (Uzzi 1997; Dyer and Hatch 2006), stimulate the processes of collective learning (Lundvall and Johnson 1994; Lundvall 2010; Audretsch and Feldman 1996) and ultimately enhance mutual trust mechanisms (Moulaert and Sekia, 2003; McCann 2004). Consequently, to explore the effect of micro-geography, it is necessary to examine the characteristics of each type of inter-organizational relationship and to consider how these relationships differ in terms of type of knowledge exchanged, information asymmetries and trust mechanisms.

Regarding VC deals, in accordance with the studies that analyse the effect of geography at the macro level (e.g., Sorenson and Stuart 2001; Fritsch and Schilder 2008; Makela and Maula 2008;

Cumming and Dai 2010; Tian 2011; Dai et al. 2012; Lutz et al. 2013), the micro-geographical proximity can also play an important role. A preliminary explanation for this assumption is grounded on the relevance of the tacit knowledge in this type of relationship. The *identification and evaluation of investment opportunities* are based on tacit knowledge that is facilitated by personal contacts between the VC investor and its local business community (Florida and Smith 1993; Thompson 1989; Powell et al. 2002). The criteria upon which the VC investor assesses the risks of an investment are based on different factors such as the entrepreneur's skills and experience, the product and the market and the financial conditions surrounding the venture (Kollmann and Kuckertz 2010). The spatial diffusion of this information around the target investee can be affected by distance-related constraints (Green 1991; Doran and Bannock 2000; Zook 2002). Moreover, geographic proximity can also facilitate a final investment decision that will often demand a close, on-site inspection of the target investee (Sorensen and Stuart 2001). A second argument that supports the important role of micro-geographical proximity in VC deals is related to the amount of *transactional costs required to mitigate the information asymmetries* between the two parties (Gompers 1995; Kaplan and Strömberg 2001; Lutz et al. 2013). These costs are expected to be necessary for monitoring and supervising the financed firm (Mason and Harrison 2002; Sorensen and Stuart 2001), especially for young firms that are at the earliest stages of their innovation process (often run by engineers or natural scientists who lack management skills) and carry high levels of uncertainty about the project's technical and economic success (Sapienza et al. 1996). Monitoring mechanisms such as deal screening, due diligence, participation in the board of directors, voting rights, special control or reporting obligations (Kaplan and Strömberg 2001) require face-to-face contact. Therefore, short travel times (e.g., the "20 minutes rule") between VC investors and potential investment targets will make these monitoring activities less expensive and less time-consuming (Cumming and Dai 2010; Dai et al 2012). A third argument that supports the importance of micro-geographical proximity for VC deals relates to *the role of trust and social relationships* between investor and investee to increase mutual commitment and cooperative behaviour in the relationship (Sapienza and Korsgaard 1996; De Clercq and Sapienza 2001). Stable social relationships develop in an evolutionary process based on interactions that are not based on contractual agreements but rather on trust, reciprocity and reputation (Blau, 1964). Social relationships are more likely to arise when the parties are located in close proximity because it increases the chance of casual and first encounters and decreases the effort and expenses of face-to-face interactions, which are important for initiating and maintaining the relationship between the VC investor and the investee (McPherson et al. 2001), especially when the intensity of managerial advice is high.

Therefore, we can formulate the following hypothesis:

Hypothesis 1. The micro-geographical proximity between two organizations within a technology cluster is positively associated with the probability that these organizations establish a VC deal.

The effect of micro-geographical proximity may not as straightforward for the establishment of joint R&D alliances that are defined as partnerships where parties co-develop an innovation on the basis of complementary skills and where knowledge transfer is involved (Pisano 1990; Mowery et al. 1996).

R&D alliances are generally established at the earliest stages of the process of innovation. At these stages, organizations are typically committed to the development of new and *complex knowledge* (Blanc and Sierra 1999; Nooteboom 1999; Narula and Santangelo 2008). The complex nature of knowledge has implications for the location of R&D alliances' parties on several fronts. First, complex knowledge tends to be produced - for the most part - in tacit forms (Zucker et al. 1996). Tacit knowledge tends to be embedded in the experience accumulated by individuals and therefore cannot be appropriately articulated by verbal means or in code (Polanyi 1967). This means that complex knowledge is mostly transmitted through face-to-face interactions, which are encouraged by short spatial distance between partners (Hippel 1994; Feldman and Lichtenberg 2000). Second, in cases of R&D alliances focused on organizations' core knowledge areas, partners are sensitive to the establishment of *trust relationships* to avoid knowledge leakage of critical information to competitors and to reduce costly monitoring activities against opportunistic behaviour - such as misappropriation hazards - during the collaboration process (e.g., Li et al. 2008). Consequently, partners benefit from the relational trust (Boschma 2005; Ponds et al. 2007) that emerges from dense interpersonal networks stimulated by micro-geographical proximity (Feldman 1994; Kale et al. 2000; Capaldo 2007). Third, micro-geographical proximity allows firms to reduce *information asymmetries* because it facilitates the evaluation of partners' technological resources and localized information, which can be relevant for identifying and evaluating attractive alliance partners (Reuer and Lahiri 2014). This latter aspect is particularly important in cases of university-industry R&D alliances where informative asymmetries are more relevant (Zucker and Darby 1996; Abramovsky et al. 2011). Fourth, for the establishment of collaborative routines (Galunic and Rodan 1998) and the development of idiosyncratic language (Uzzi 1997), it is essential to overcome knowledge-related differences among the parties (Ponds et al. 2009) and to ensure the mutual understanding of both partners' technologies (Singh et al. 2016). This, in turn, requires frequent interactions among the partners that increase as a function of the partners' micro-geographical proximity (Bignami et al. 2020).

Hence, we can formulate the following hypothesis:

Hypothesis 2a. The micro-geographical proximity between two organizations within a technology

cluster is positively associated with the probability that these organizations establish an R&D alliance.

On the other hand, micro-geographical proximity can even be detrimental for the knowledge production and knowledge transfer mechanisms that are at the core of the R&D alliance (e.g., Broekel and Boschma 2011; Ponds et al. 2009; Hermann et al. 2012; Autant-Bernard et al. 2007). First, some scholars argue that organizations prefer distant partners because local R&D alliances can prevent partners from gaining access to new knowledge from distant collaboration with interregional and international actors and thereby lead to spatial knowledge lock-in (Bathelt et al. 2004; Owen-Smith and Powell 2004; Moodysson et al. 2008). A second argument supporting the detrimental effect of micro-geographical proximity for the establishment of R&D alliances is based on the idea that organizations fear that unintended knowledge outflows can become a source of competitive advantage for direct competitors located in proximity (Cantwell and Santangelo 2002; Alcácer 2006). This is particularly true for companies operating and eventually competing in the same R&D-intensive industry of the collaborative partner. Third, the extant literature argues that the probability of establishing a R&D alliance depends more on other types of proximity such as social proximity (e.g., the existence of prior links among the partners) or cognitive proximity (e.g., the degree of similarity between their knowledge bases), which can provide the typical advantages of geographical proximity in the transfer of knowledge and the establishment of trust mechanisms. For example, Cantner and Meder (2007) found that the technological overlap between two actors (cognitive proximity) positively affected the likelihood of those actors to engage in an R&D cooperation. In addition, past cooperation experience leads to a decrease in the social distance between the two partners, which positively impacts future cooperation. Finally, some authors affirm that R&D alliances do not require geographical proximity among partners because they are usually characterized by detailed and complex contracts that regulate how knowledge flows are managed and the expectations of parties when entering the alliance. Not only this prevent partners from showing opportunistic behaviour (thus reducing the need for trust-based mechanisms typical of spatial proximity), but complex contracting will also serve as a coordination tool (Teece 2008) that allows for the avoidance of miscommunication between partners that are geographically separated (Kim and Globerman 2017).

On this basis, we formulate the following alternative hypothesis:

Hypothesis 2b. The micro-geographical proximity between two organizations within a technology cluster is negatively associated with the probability that these organizations establish an R&D alliance.

As a third category of relationship, we analyse IP transfer agreements that include contract-based forms of collaboration to commercialize the results of scientific research, i.e., patents and licensing agreements, which are generally established at the later stages of the innovation process. At these stages, organizations are typically committed to the commercialization of new and complex knowledge. The empirical research at the macro geographical level has demonstrated that geographical proximity plays an important role in market channels of interaction and knowledge trade (Audretsch and Stephan 1996; Zucker et al. 1998; Agrawal 2001; Belenzon and Schankerman 2013), since it is deemed crucial for addressing various challenges related to IP transfer relationships.

The first argument for the importance of micro-geographical proximity in IP transfer agreements is that there is a significant amount of *tacit knowledge* that marks the relationship between the inventor and the potential licensee (Shane 2002; Siegel et al. 2003; Lowe 2004). In most cases, licensed inventions are frequently far from being readily marketable (Jensen and Thursby 2001), and the knowledge embedded in the original inventor may not be codified and easy to transfer (Agrawal 2006). Indeed, at the licensing stage, many inventions are only in the form of a proof of concept or a lab-scale prototype (Buenstorf and Schacht 2013), and licensees must make significant additional R&D efforts to achieve a marketable product from the licensed innovation that highly depends on the continued engagement of the original IP inventor (Jensen and Thursby 2001; Thursby and Thursby 2004; Agrawal, 2006). This is due to the fact that licensees' own knowledge base may be far from the complex knowledge underlying licensed inventions (Arora 1995; Agrawal 2006), and their absorptive capacities (Cohen and Levinthal 1990) may not be sufficient to completely understand all relevant information. By way of illustration, academic inventions are frequently developed after long rounds of experiments. Failures and mistakes in the research process are usually unreported and remain tacit. Nevertheless, information about past errors and failures could be beneficial for licensees in their additional R&D efforts to ensure that the licensed invention is ready to be marketed. This non-codified tacit knowledge can only be appreciated through direct face-to-face interactions (Von Hippel 1994), which may also lead to higher costs for the engagement of more distant licensees in the post-agreement commercialization stage due to higher travel costs and time losses. This would make licensing less profitable for licensees located far from the inventors, especially in the case of top-level inventors/scientists with high opportunity costs in terms of time (Stephan 1996; Beise and Stahl 1999; Santoro and Gopalakrishnan 2001). The second argument for the importance of micro-geographical proximity in IP transfer agreements is that the market for licensed inventions is characterized by a high level of *information asymmetry* between the licensor and the potential licensee (Shane 2002; Siegel et al. 2003; Lowe 2006) with

special regard to the quality and reliability of the invention. Therefore, it is important for licensors to have access to information about an invention and its inventors before the license agreement is entered into. Therefore, being in geographic proximity would increase a potential licensee's opportunity to overcome issues of information asymmetry by allowing her to pre-establish contacts in the same inventor's social network. This would allow easier access to information about the invention's quality as well as about the inventor's local reputation (Elfenbein 2007). Finally, micro-geographical proximity can provide firms with privileged access to information about local inventions available for licensing due to personal and informal communication, e.g., with the technology licensing office staff (Bercovitz and Feldmann 2006).

Hence, we hypothesize the following:

Hypothesis 3. The micro-geographical proximity between two organizations within a technology cluster is positively associated with the probability that these organizations establish an IP transfer agreement.

4. Research strategy

4.1 The biopharma cluster in the GBA

To test our hypotheses, this work analyses the case of the biopharma cluster in the GBA (MA, USA) for the period 2012-2017. Due to its high-ranking position in the U.S. Biotech Clusters rankings (JIL U.S. Life Science 2016), the biopharma cluster in the GBA is considered a successful case study. The biotech cluster in the GBA is, along with that of Silicon Valley, one of the oldest, best-known and most successful high-tech clusters in the U.S. Moreover, it is, together with San Francisco, one of the two key geographical clusters that currently dominate the biopharma landscape due to a unique blend of science, entrepreneurship skills, risk-taking culture and spatial concentration, especially in the city of Cambridge, where most biotechnology-related companies are clustered around Kendall Square, which hosts, among others, the Massachusetts Institute of Technology (Saxenian 1994; Breznits and Anderson 2005; Owen-Smith and Powell 2004). The GBA covers approximately 8042.7 square metres.

The rise of the biotech industry in the GBA traces back to the 1970s with the development of genetic engineering and the establishment of Biogen through the endorsement of the Cambridge City Council, after the potential of this new field has been recognized when molecular biology was predominant. However, it was not until more recent years that the cluster achieved its greatest growth. In 2008, the governor of Massachusetts promoted the *Massachusetts Life Sciences Act*, which promised an investment of \$1 billion for the development of the biotech industry. This led to a tremendous increase in jobs, capital flows and buildings that contributed to turning the area into

one of the leading U.S. life sciences clusters with regard to the amount of patent ownership per capita, VC funding and number of IPOs (JJL U.S. Life Science 2016). The region is home to many of the leaders in tech and life sciences (eighteen out of the top twenty drug companies have a major presence in the GBA) as well as world-class academic and research institutions such as Harvard and MIT. The area hosts approximately 250,000 students across 52 higher education institutions and has the largest concentration of life science researchers in the country, as well as world-class medical facilities including the top three NIH-funded hospitals. As a result of direct access to top talent, the biotech cluster in the GBA has attracted a dynamic community of investors. More precisely, VC funding is 2,580 million dollars in the GBA, which represents 38% of the total funding in the U.S., which makes the area particularly attractive to innovative entrepreneurs (JJL U.S. Life Science 2016).

4.2. Data

We test our hypotheses using a sample of realized and potential but unrealized collaborative ties (see section 4.3 for details on how we defined unrealized ties) among organizations located in the GBA biopharma cluster. These organizations have been involved in at least one of the inter-organizational relationships under investigation during the 2012-2017 period. To identify these organizations and their collaborations, we rely on secondary sources of information.

First, we identified organizations that were part of the GBA biopharma cluster. We used MassBio, which is the freely available membership directory of the Massachusetts Biotechnology Council, to identify an initial list of organizations of the cluster. MassBio includes more than 975 members dedicated to advancing cutting-edge research in the life sciences industry in Massachusetts and provides information on their location, typology and area of specialization. Members range from academic hospitals and non-profit organizations to pharmaceutical biotech companies and capital providers. We selected those organizations with headquarters or branch offices with mailing addresses in the GBA. Additionally, we considered only those members belonging to the biopharma industry mainly specialized in drug development. According to the criteria defined above, we were able to identify an initial list of 450 organizations belonging to the biotech cluster in the GBA including hospitals, universities, research institutes, government agencies, incubators, capital risk providers, and firms operating in the biotech and pharmaceutical industries.

Second, we identified the formal collaborative relationships among the 450 organizations obtained from MassBio in the previous step. It is worth mentioning that previous studies found that organizations within the GBA tend to rely more on “standard contracts” compared to those located in the Bay Area where weaker hierarchical contractual governance structures prevail (Kim and

Globerman 2017). On this basis, we decided to focus our analysis on formal relationships, specifically, VC deals, R&D alliances and IP transfer agreements. To obtain information on the three types of formal relationships, we relied on two sources of relational data. The data on VC deals come from Preqin (Preqin Ltd. 2017), which is a comprehensive and historical database on the private equity industry, offering detailed information and analytics on firms, funds, deals and portfolio companies dating back to 1999 on over 5,000 funds and 11,000 hedge funds. We selected VC deals (i.e., series A-E/round 1-5, grants, seeds, PIPE, add-ons, and venture debt) between portfolio companies and investors located in Massachusetts, completed within the period 2012-2017 in the biotech and pharmaceutical industries. We then matched the information on VC deals with the initial list of 450 organizations identified in MassBio. To gather information on R&D alliances and IP transfer agreements, we collected data from the Strategic Transactions Database (Pharma & MedTech Business Intelligence), which summarizes deals by type, industry and sector from 1995 to the present. We collected this information within the 2012-2017 timeframe and matched it with the initial list of 450 organizations from MassBio.

Overall, we identified 164 organizations of the biopharma cluster in the GBA that established 277 inter-organizational ties (175 VC deals, 56 R&D alliances and 46 IP transfer agreements) during the 2012-2017 period.

4.3 Method

We relied on the dyad as the unit of analysis to estimate the likelihood of inter-organizational tie formation (for a similar approach, see, e.g., Dushnitsky and Shaver 2009; Diestre and Rajagopalan 2012; Colombo and Shafi 2016). The underlying assumption is that the formation of a tie between two organizations in a cluster is the result of a matching process in which an organization looking for a collaborative partner evaluates the characteristics of other organizations that are located in the cluster (including micro-geographical proximity). To model this matching process, we analysed our data at the dyad level and compared the realized ties relative to unrealized dyads that could have formed (but did not).

More specifically, we considered the realized and potential but unrealized ties for each deal type, specifically, VC deals, R&D alliances and IP transfer agreements. Regarding VC deals, we began with the 175 ties, which involved 61 firms that received VC and 63 investors in the reference period. Then, we considered all possible combinations of the 61 firms that received VC and 63 investors with which the focal firms could potentially have established a VC tie, which resulted in 3,843 potential VC ties. Regarding R&D alliances, we began with 56 R&D alliances that included 49 organizations in the reference period. Then, we considered all possible combinations of these 49

organizations and the remaining 48 organizations with which the focal organizations could potentially have established an R&D alliance. After the elimination of duplicated ties, we had 1,176 (i.e., $49 \times 48 / 2$) potential R&D alliance ties¹. For IP transfer agreements, we used a similar approach. Starting with the 44 organizations in one of 46 IP transfer agreements in the reference period, we considered all $44 \times 43 / 2 = 946$ potential ties. Table 1 shows the details of the composition of the three final samples (VC deals, R&D alliances or IP transfer agreements).

Table 1. Final sample for each deal type				
	N. of organizations	N. of realized ties	N. of unrealized ties	Total n. of ties
VC deals	124	175	3,668	3,843
R&D alliances	49	56	1,120	1,176
IP transfer agreements	44	46	900	946

For each of the three samples of potential ties, we separately estimated the role of micro-geographical proximity in the inter-organizational tie formation according to the following econometric model:

$$Realized_{i,j} = \alpha + \beta D_{i,j} + \gamma X_{i,j} + \varepsilon_{i,j}. \quad (1)$$

In each sample, the dependent variable is *Realized*, which is a dummy that is equal to 1 if organization i had established a tie with organization j and zero otherwise. The intercept term is denoted by α . Because the dependent variable *Realized* is binary in nature, we estimated the likelihood of tie formation using probit models² (for an application in the context of alliance formation, see, e.g., Ghosh et al. 2016).

When estimating equation (1), we implemented different regressions for each sample considering for each mode alternative measures of geographical distance, which is used as an inverse proxy for the geographical proximity and denoted by $D_{i,j}$. We used alternative measures to increase the robustness of our results given that there are different possible approaches to measure geographical distance in the economic geography literature. All these distance measures have been calculated starting with information about the geographic location (i.e., latitude and longitude retrieved from Google Maps) of each organization's address in the GBA. First, we used the kilometric distance between the two organizations (*Distance*) expressed in absolute value. Second, in accordance with the study of Broekel and Boshma (2012), we considered the logarithm of the kilometric distance (*Distance (log)*) among two organizations to limit the disturbance of outliers. Third, we used pre-

¹ An example could be of help to clarify our approach. Let us consider 4 organizations, namely, A, B, C and D. In this case, the total number of potential ties is $4 \times 3 / 2 = 6$, namely, A-B, A-C, A-D, B-C, B-D and C-D. According to our approach, the tie is bidirectional, implying that A-B = B-A.

² The results are qualitatively similar when using logistic regressions, and they are available from the authors upon request.

defined distance intervals (for a similar approach see, e.g., Bottazzi and Peri 2003; Rosenthal and Strange 2003). We thus included in the regressions two dummy variables that equal 1 if the two organizations are located within a radius of 10 km (*Distance 0-10 km*) or between 10 and 20 km (*Distance 10-20 km*) from each other, respectively. Finally, we used Google API to obtain the travel times between the different locations in our samples (*Distance (time)*) to take into account nonlinearities in the accessibility of certain locations (Andersson and Ejermo 2005; Ejermo and Karlsson 2006). For each sample, we ran four probit regressions using distance in km (model 1), its logarithm (model 2), the two distance thresholds (model 3) or travel time (model 4) as the main independent variables.

To limit the risk of omitted variable biases, the vector $X_{i,j}$ includes a number of control variables that are likely to influence the likelihood of tie formation. Specifically, we considered measures for social, cognitive and institutional proximity.

Social proximity refers to the presence of socially embedded, trust-based, relationships at the micro-level (Boschma 2005, p. 66), which can favour the establishment of a collaborative tie (e.g., Hong and Su 2013). We measured social proximity as a dummy variable (*Social proximity*) that equals 1 if the two entities are both located in the GBA for more than five years. Informal ties, trust and mutual understanding built among individuals after years of colocation in the same area can indeed generate social proximities among the organizations to whom they belong (Agrawal et al. 2006; Miguelez 2019). Consequently, organizations that have been co-located for a longer time span have a higher level of social proximity than those organizations that located to the area more recently. To obtain information on the year of location in the GBA, we used the Orbis and Crunchbase databases, and if the information was not available, we relied on other secondary data (e.g., firms' websites and public statements). Furthermore, for organizations that are younger than 5 years (i.e., start-ups), *Social proximity* equals 1 if at least one of the start-up founders had prior work experience in the other organization of the dyad or whether the start-up had received a previous VC investment from the other organization of the dyad. In doing so, we took into account for the existence of prior social relationships between organizations based on shared experience (Broekel and Boschma 2012). To obtain information on the prior work experience of a start-up's founders, we checked all organizations that were mentioned in "education" and "previous experience" from the professional LinkedIn page of each start-up's founder while information on prior VC deals was obtained from Thomson-Eikon.

Cognitive proximity refers to the degree of similarity between the knowledge bases of two organizations (Boschma 2005, p. 63). The decision to establish a collaborative tie is likely to depend on the specific competencies and the level of expected mutual understanding of the two

organizations potentially involved in the relationship (e.g., Nooteboom 1999; Cantner and Meder 2007; Broekel and Boschma 2012), which is higher if the two organizations are cognitively proximate. We followed Breschi et al. (2003) and Broekel and Boschma (2012) to build our cognitive proximity measure³. Specifically, we first obtained from Orbis the primary and secondary NAICS codes at the 3-digit level for all organizations in our sample. We then calculated a *cosine similarity index* between all the NAICS codes that appear in our sample on the basis of their co-occurrence at the level of the organization. Finally, we considered the most similar pair of NAICS codes in the organizations' NAICS code vectors to define the degree of similarity at the organizational level. The resulting variable *Cognitive proximity* is an indicator ranging from 0 to 100, with the highest values representing higher levels of cognitive proximity between the two organizations. In all regressions, we also considered a quadratic term of *Cognitive proximity* to check for non-linear effects.

Institutional proximity includes both the idea of economic actors sharing the same institutional rules of the game and a set of cultural habits and values (Boshma 2005, p. 68). Thus, we classified organizations considering their institutional nature and identified five classes: (i) corporate, (ii) SME, (iii) research and non-profit, (iv) government, and (v) risk capital provider. We considered a dummy variable (*Institutional proximity*) of 1 if both organizations fall within the same category (, which is with the approach of Ponds et al., 2007).

Finally, we controlled for the number of metro stations (*T-stops*) within each city of the GBA in which the organization is located as an indicator of location connectivity and reachability. In all estimates, we also included other controlling variables as the industry and organization type dummy variables that take into account differences in the frequencies and the spatial scale of collaborations among large corporations, SMEs and start-ups.

Table 2 shows the description of all variables included in the regressions. Table 3 reports the summary statistics and the correlation matrix for all variables used in regression models, disaggregated by the three samples used in the empirical analyses (Panel A: VC deals; Panel B: R&D alliances; Panel C: IP transfer agreements).

³ For the sake of synthesis, we do not report here the detailed procedure used to build the cognitive proximity variables. For the full description, please see the abovementioned papers.

Table 2. Variable descriptions

Variable	Description
<i>Dependent variable</i>	
Realized	Dummy that equals 1 if the two organizations in the dyad have been involved in a VC deal, an R&D alliance or an IP transfer agreement.
<i>Independent variables</i>	
Distance	Distance in km between the two organizations.
Distance (log)	Logarithm of the distance in km between the two organizations.
Distance 0-10 km	Dummy variable that equals 1 if the two organizations are located within a radius of 10 km from each other.
Distance 10-20 km	Dummy variable that equals 1 if the two organizations are located at more than 10 km but less than 20 km from each other.
Distance (time)	Travel time by car between the two organizations.
<i>Controls</i>	
Social proximity	Dummy variable that equals 1 if the two organizations are both located in the GBA for more than five years. For organizations incorporated after 2011 (i.e., start-ups), the variable equals 1 if at least one of the start-up founders has had prior work experience in the other organization of the dyad or whether the start-up has received a previous VC investment from the other organization of the dyad.
Cognitive proximity	Indicator ranging from 0 to 100, with highest values representing higher levels of cognitive proximity between the two organizations, based on the cosine similarity index of the 3-digit NAICS codes associated to the two organizations (Breschi et al. 2003; Broekel and Boschma 2012).
Institutional proximity	Dummy variable that equals 1 if the two organizations fall in the same category (corporate, SMEs, research and non-profit organizations; government; and risk capital providers).
T-stops	Sum of the total number of T-stops in the cities in which the two organizations are located.

Table 3. Summary statistics and correlations

Panel A. VC deals															
	Variable	N	Mean	SD	Min	Max	1	2	3	4	5	6	7	8	9
1	Realized	3,843	0.05	0.21	0	1	1.00								
2	Distance	3,843	6.99	9.17	0.00	60.28	-0.03	1.00							
3	Distance (log)	3,843	1.25	1.28	-5.94	4.10	-0.03	0.76	1.00						
4	Distance 0-10 km	3,843	0.76	0.43	0	1	0.01	-0.77	-0.72	1.00					
5	Distance 10-20 km	3,843	0.21	0.41	0	1	0.00	0.47	0.59	-0.91	1.00				
6	Distance (time)	3,843	15.09	9.62	1	59	-0.02	0.92	0.88	-0.75	0.51	1.00			
7	Social proximity	3,843	0.43	0.50	0	1	0.02	0.07	0.14	-0.13	0.14	0.11	1.00		
8	Cognitive proximity	3,843	41.66	33.19	0	100	-0.02	0.06	-0.03	0.00	-0.04	0.01	-0.01	1.00	
9	Institutional proximity	3,843	0.16	0.37	0	1	-0.01	-0.02	0.01	-0.02	0.03	-0.01	-0.03	-0.02	1.00
10	T-stops	3,843	49.63	36.43	0	148	0.02	-0.08	0.11	0.10	-0.05	0.01	0.10	-0.35	0.04

Panel B. R&D alliances															
	Variable	N	Mean	SD	Min	Max	1	2	3	4	5	6	7	8	9
1	Realized	1,176	0.05	0.21	0	1	1.00								
2	Distance	1,176	6.45	11.47	0.01	60.06	0.03	1.00							
3	Distance (log)	1,176	0.79	1.50	-5.15	4.10	0.00	0.75	1.00						
4	Distance 0-10 km	1,176	0.80	0.40	0	1	-0.02	-0.76	-0.74	1.00					
5	Distance 10-20 km	1,176	0.16	0.37	0	1	0.00	0.35	0.57	-0.87	1.00				
6	Distance (time)	1,176	13.55	12.57	1	60	0.03	0.94	0.90	-0.79	0.48	1.00			
7	Social proximity	1,176	0.42	0.49	0	1	0.10	-0.11	0.01	0.00	0.09	-0.03	1.00		
8	Cognitive proximity	1,176	68.71	33.52	0	100	-0.01	0.07	-0.05	-0.11	0.09	0.01	-0.06	1.00	
9	Institutional proximity	1,176	0.40	0.49	0	1	-0.03	-0.12	-0.07	0.03	0.06	-0.11	0.01	0.24	1.00
10	T-stops	1,176	24.31	29.22	0	148	0.07	-0.09	0.06	0.17	-0.14	0.02	0.21	-0.40	-0.15

Panel C. IP transfer agreements															
	Variable	N	Mean	SD	Min	Max	1	2	3	4	5	6	7	8	9
1	Realized	946	0.05	0.22	0	1	1.00								
2	Distance	946	8.48	15.61	0.00	60.12	-0.05	1.00							
3	Distance (log)	946	0.88	1.58	-5.61	4.10	-0.05	0.80	1.00						
4	Distance 0-10 km	946	0.79	0.41	0	1	0.06	-0.81	-0.79	1.00					
5	Distance 10-20 km	946	0.12	0.32	0	1	-0.04	0.18	0.44	-0.71	1.00				
6	Distance (time)	946	14.95	14.96	1	60	-0.05	0.96	0.90	-0.84	0.30	1.00			
7	Social proximity	946	0.47	0.50	0	1	0.11	-0.11	-0.12	0.17	-0.15	-0.12	1.00		
8	Cognitive proximity	946	68.86	29.40	2	100	-0.03	0.06	0.00	-0.08	0.07	0.03	-0.23	1.00	
9	Institutional proximity	946	0.38	0.48	0	1	0.02	-0.08	-0.11	0.04	0.04	-0.10	0.02	0.29	1.00
10	T-stops	946	26.09	30.63	0	148	0.02	-0.13	0.00	0.19	-0.13	-0.04	0.23	-0.34	-0.14

5. Findings

5.1 Main results

We first performed a univariate analysis to verify whether there are statistically significant differences in the average distance in km when considering realized and potential unrealized ties for the three types of inter-organizational ties considered in this study. The results from this analysis are shown in Table 4.

Table 4. Average distance in km of realized and potential unrealized ties				
	Realized ties (A)	Unrealized ties (B)	Difference (A-B)	t-test (p-value)
<i>VC deals</i>				
N. of observations	175	3,668	-	-
Average distance (km)	5.92	7.04	-1.12	0.057
<i>R&D alliances</i>				
N. of observations	56	1,123	-	-
Average distance (km)	7.92	6.38	1.54	0.163
<i>IP transfer agreements</i>				
N. of observations	46	900	-	-
Average distance (km)	5.06	8.65	-3.59	0.064

The results from Table 4 suggest that micro-geographical proximity is positively associated with the formation of VC deals and IP transfer agreements. The average geographical distance of realized ties is indeed lower than the corresponding figure in the case of potential unrealized ties for these two types of inter-organizational relationships. These differences are statistically significant at the 10% level. In contrast, we do not observe statistically significant differences in the average distance when focusing on R&D alliances. This preliminary evidence is therefore in line with hypothesis 1 and hypothesis 3 while we do not find any supporting evidence for either hypothesis 2a or hypothesis 2b.

Next, we consider the results from the multivariate analysis on the probability of tie formation. Table 5, Table 6 and Table 7 show the results of VC deals, R&D alliances and IP transfer agreements, respectively. Each table shows the coefficients from the probit regressions, using distance in km (model 1), its logarithm (model 2), the two distance thresholds (model 3) or travel time (model 4) as the main independent variables.

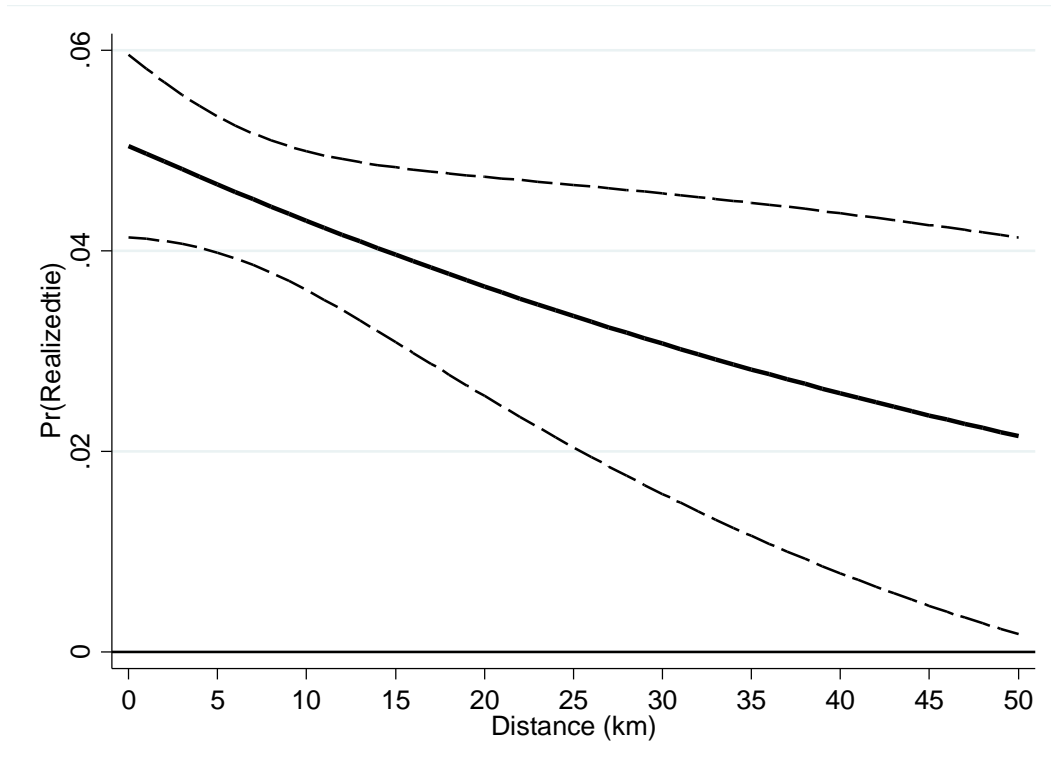
Table 5. Results from probit regressions – VC deals

	Model 1	Model 2	Model 3	Model 4
Distance	-0.007 * (0.004)			
Distance (log)		-0.054 * (0.030)		
Distance 0-10 km			0.695 * (0.366)	
Distance 10-20 km			0.658 * (0.369)	
Distance (time)				-0.007 * (0.004)
Social proximity	0.028 (0.077)	0.029 (0.077)	0.022 (0.076)	0.027 (0.077)
Cognitive proximity	0.011 ** (0.005)	0.011 ** (0.005)	0.011 ** (0.005)	0.011 ** (0.005)
Cognitive proximity ²	-0.000 ** (0.000)	-0.000 ** (0.000)	-0.000 ** (0.000)	-0.000 ** (0.000)
Institutional proximity	-0.076 (0.096)	-0.075 (0.096)	-0.087 (0.097)	-0.074 (0.096)
T-stops	-0.000 (0.001)	-0.000 (0.001)	-0.000 (0.001)	-0.000 (0.001)
Entity type dummies	YES	YES	YES	YES
Industry dummies	YES	YES	YES	YES
Constant	-1.954 *** (0.335)	-1.957 *** (0.335)	-2.652 *** (0.500)	-1.912 *** (0.336)
N. observations	3,843	3,843	3,843	3,843
Log-likelihood	-697.380	-696.914	-695.950	-697.338
Pseudo R ²	0.020	0.021	0.022	0.020

***, **, and * indicate significance at the 1%, 5% and 10% levels, respectively. Robust standard errors are in parentheses.

The results from Table 5 are still in line with hypothesis 1. We find that when considering VC deals, the geographical proximity (distance) is positively (negatively) associated with the likelihood of tie formation. The coefficients of the distance variable in model 1 are negative and statistically significant at the 10% level. The results from models 2-4 in Table 5 are qualitatively similar to those of model 1. In terms of magnitude, it is worth noting that the average marginal effect of distance on the probability of tie formation, calculated on the basis of the coefficients of model 1, is -0.001 (p-value = 0.082). The estimated probability of tie formation for VC deals as distance varies is shown in Figure 1 (the solid line). The dashed lines show the corresponding 95% confidence intervals. The likelihood of tie formation is 0.050 when the distance between the two organizations is less than 1 km. When the distance is 20 km, this probability is 0.036, and then it tends to zero as the distance increases. Therefore, the geographical proximity is relevant for VC deals at the micro-level.

Figure 1. Probability of tie formation as distance varies – VC deals



Conversely, we do not detect any significant association between geographical proximity and probability of tie formation when considering R&D alliances (Table 6). All the coefficients associated with the distance variables are indeed not statistically significant at the conventional confidence levels.⁴ Hence, our results do not support either hypothesis 2a or hypothesis 2b. This result might be driven by a combination of the positive and negative effects associated with geographical proximity in R&D alliances.

Let us now focus on IP transfer agreements. The evidence in Table 7 is consistent with hypothesis 3. All coefficients of the distance variables are indeed negative and statistically significant at least at the 5% level. The geographical proximity (distance) appears to be even more beneficial (detrimental) for the establishment of IP transfer agreements than VC deals. According to the coefficient of the distance variable of model 1 in Table 7, the average marginal effect of distance on the probability of tie formation is -0.003 (p-value = 0.001). The probability of tie formation as distance varies is shown in Figure 2, which shows that the likelihood of tie formation is 0.080 when the distance between the two organizations is less than 1 km. When the distance is 20 km, the probability of tie formation becomes 0.029, and then it tends to zero as distance increases (and not significantly different from 0 after 45 km).

⁴ The average marginal effect of distance (model 1) on the probability of tie formation is indeed 0.000 (p-value = 0.542).

Table 6. Results from probit regressions – R&D alliances

	Model 1			Model 2			Model 3			Model 4		
Distance	-0.006											
	(0.009)											
Distance (log)				-0.046								
				(0.053)								
Distance 0-10 km							0.487					
							(0.589)					
Distance 10-20 km							0.543					
							(0.607)					
Distance (time)										-0.003		
										(0.007)		
Social proximity	0.435	***		0.452	***		0.411	**		0.438	***	
	(0.162)			(0.162)			(0.162)			(0.162)		
Cognitive proximity	0.036	***		0.033	***		0.039	**		0.034	***	
	(0.014)			(0.011)			(0.015)			(0.012)		
Cognitive proximity ²	-0.000	***		-0.000	***		-0.000	***		-0.000	***	
	(0.000)			(0.000)			(0.000)			(0.000)		
Institutional proximity	-0.257			-0.263	*		-0.252			-0.257		
	(0.161)			(0.158)			(0.160)			(0.160)		
T-stops	0.005	**		0.005	**		0.005	**		0.005	**	
	(0.003)			(0.003)			(0.003)			(0.003)		
Entity type dummies	YES			YES			YES			YES		
Industry dummies	YES			YES			YES			YES		
Constant	-1.772	**		-1.799	**		-2.178	***		-1.822	**	
	(0.880)			(0.839)			(0.833)			(0.880)		
N. observations	1,176			1,176			1,176			1,176		
Log-likelihood	-200.260			-200.001			-200.049			-200.333		
Pseudo R ²	0.111			0.112			0.112			0.111		

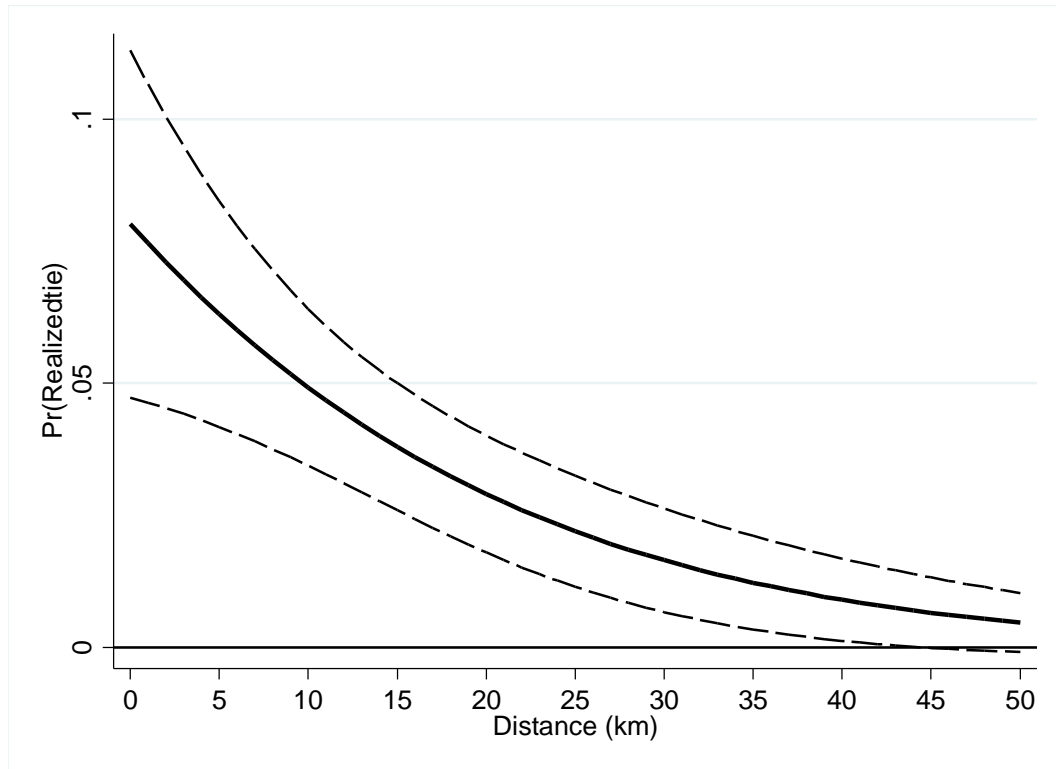
***, **, and * indicate significance at the 1%, 5% and 10% levels, respectively. Robust standard errors are in parentheses.

Table 7. Results from probit regressions – IP transfer agreements

	Model 1			Model 2			Model 3			Model 4		
Distance	-0.030											
	(0.011)											
Distance (log)				-0.093								
				(0.043)								
Distance 0-10 km							6.275					
							(0.539)					
Distance 10-20 km							6.090					
							(0.607)					
Distance (time)										-0.018		
										(0.007)		
Social proximity	0.496	***		0.487	***		0.511	***		0.492	***	
	(0.170)			(0.168)			(0.170)			(0.169)		
Cognitive proximity	0.000			-0.002			0.001			-0.001		
	(0.017)			(0.017)			(0.017)			(0.017)		
Cognitive proximity ²	-0.000			0.000			-0.000			-0.000		
	(0.000)			(0.000)			(0.000)			(0.000)		
Institutional proximity	-0.023			-0.044			-0.010			-0.033		
	(0.170)			(0.167)			(0.169)			(0.169)		
T-stops	-0.001			-0.000			-0.001			0.000		
	(0.003)			(0.003)			(0.003)			(0.003)		
Entity type dummies	YES			YES			YES			YES		
Industry dummies	YES			YES			YES			YES		
Constant	-5.109	***		-5.127	***		-11.756	***		-5.253	***	
	(0.696)			(0.711)			(0.751)			(0.715)		
N. observations	946			946			946			946		
Log-likelihood	-167.871			-171.061			-166.956			-169.513		
Pseudo R ²	0.087			0.070			0.092			0.078		

***, **, and * indicate significance at the 1%, 5% and 10% levels, respectively. Robust standard errors are in parentheses.

Figure 2. Probability of tie formation as distance varies – IP transfer agreements



Finally, although this study focuses on the importance of micro-geography within a cluster, the above results suggest a differential of other types of proximity for the establishment of different types of inter-organizational ties. Social proximity appears irrelevant for VC deals but is positively associated with the probability of forming an R&D alliance and an IP transfer agreement with a partnering organization within the cluster. Indeed, the average marginal effect of *Social proximity* is 0.038 (p-value = 0.008; Table 6, model 1) and 0.046 (p-value = 0.005; Table 7, model 1) for R&D alliances and IP transfer agreements, respectively.

Furthermore, we find an inverse U-shaped relationship of cognitive proximity with both VC deals and R&D alliances. For VC deals, the average marginal effect of *Cognitive proximity* reaches its maximum for very low levels: 0.001 when *Cognitive proximity* = 10 (p-value = 0.024; Table 5, model 1). For R&D alliances, the average marginal effect of *Cognitive proximity* is 0.002 (p-value = 0.009; Table 6, model 1) at its maximum, when *Cognitive proximity* = 30. On the contrary, we do not detect any significant association between the cognitive proximity and the probability that an organization establishes an IP transfer agreement (Table 7) with another organization in the cluster.

For institutional proximity, the above results do not provide any evidence of the role of this form of proximity for the formation of the three types of inter-organizational relationships under investigation among the organizations of a cluster.

5.2 Additional evidence and robustness checks

To assess the differential role of micro-geography in different types of inter-organizational relationships under investigation, we ran additional regressions using the entire sample of potential realized and unrealized ties, i.e., jointly considering all three subsamples in this study (VC deals, R&D alliances and IP transfer agreements). In the econometric specification, we then included the dummy variables *Sample R&D* and *Sample IP*, which equal 1 if the subsample refers to R&D alliances and IP transfer agreements, respectively, and their interactions with the distance variable. When both dummies (and interaction terms with distance) are included, the coefficient of the distance variable (without interactions) refers to the subsample of VC deals, which is the baseline category, while the coefficients of the interaction terms measure the difference in the distance's coefficients with respect to the baseline category. The results from these additional regressions are shown in the Appendix (Table A1). The coefficient of distance is negative (-0.010) and statistically significant (p-value = 0.033), which confirms the positive role of geographical proximity in the formation of VC deals. Quite interestingly, the coefficient of the interaction term between the distance variable and *Sample R&D* is positive (0.014) and significant (p-value = 0.065), while the interaction term between distance and *Sample IP* is very close to zero in magnitude (0.000) and not significant (p-value = 0.949). In other words, these results appear to suggest that the geographical proximity similarly positively affects the establishment of VC deals and IP transfer agreements in a cluster.

We also performed three additional analyses to model the probability of tie formation for VC deals. In our main analysis, we decided to keep the same variables in the econometric specification for comparison purposes. Nevertheless, it could be argued that additional investor- and firm-level characteristics can explain the matching process between these two categories.

First, we replaced our variable on cognitive proximity to take into account that professional VC investors can be cognitively proximate to investee firms regardless of whether they are coded as financial intermediaries according to the NAICS classification. We therefore ran additional estimates by including the dummy variable *Investor focus*, which equals 1 i) for professional VC investors whose industry focus is on pharma/biotech industries and ii) if the investor and the investee firm share the same NAICS code at the 3-digit level in the case of non-professional VC firms (e.g., corporate investors). The information on investor's industry focus was obtained from the VC firm's website. The results are shown in Table A2 in the Appendix. The industry focus variable is not statistically significant in all model specifications while the results concerning the distance variables are in line with the main estimates.

Second, we included a measure for the VC investor's reputation to take into account that more

reputable investors are more attractive for firms looking for VC (Table A3 in the Appendix). The variable *VC reputation* is a dummy variable that equals 1 if the investor appears in the list of reputable VC investors according to the Lee-Pollock-Jin VC Reputation Index (Lee et al. 2011)⁵. The results when including *VC reputation* suggest that investors' reputation is positively related to the probability of tie formation. The coefficient of *VC reputation* is indeed statistically significant in all model specifications at the 5% level. More importantly, the results concerning the distance variables are qualitatively similar to those presented in Table 5.

Third, we checked whether the relevance of geographical proximity is higher when focusing the analysis on start-ups, i.e., organizations incorporated after 2011 (Table A4 in the Appendix). We indeed observe an overall increase in the magnitude of all the negative coefficients associated with the distance variables. Quite interestingly, the role of social proximity seems relevant for a start-up. The coefficient of *Social proximity* is indeed positive and statistically significant at the 1% level.

6. Discussion

This paper aims to explore the role of micro-geographical proximity in shaping the formation of (multiple types of) inter-organizational relationships within a technology cluster. The results from our empirical analysis suggest that micro-geographical proximity is relevant to the formation of VC deals and IP transfer agreements, while we do not find any significant association with the formation of R&D alliances.

In particular, our findings show that the micro-geographical proximity is positively associated with the probability that two organizations in the cluster establish a VC deal, which confirms hypothesis 1. According to our estimates, for a company looking for finance, the probability of establishing a tie with an investor is 0.036 if the two organizations are located 20 km away from each other. The same probability is 0.050 if the distance is 1 km, with a 39% increase in probability. This result is probably due to the fact that micro-geographical proximity, apart from increasing the likelihood of first encounters, reduces information asymmetry and monitoring costs. The effect of micro-geographical proximity is indeed stronger for start-ups (see Table A4 in the Appendix). Start-ups are young companies that are at the earliest stages of their innovation process (often run by engineers or natural scientists who lack management skills) and have a high level of uncertainty about the project's technical and economic success (Sapienza et al. 1996). Consequently, they are considered very risky by VC investors. For these firms, the role of geographical proximity in facilitating intensive monitoring by VC investors is likely to be even more relevant (20-minute

⁵ The list is available at http://www.timothypollock.com/vc_reputation.htm.

rule). This aspect is also coherent with our results in terms of social proximity whose coefficient is positive and statistically significant in the VC deals that involve start-ups (at the 1% level). This result seems to suggest that a VC investor is more inclined to invest in a start-up when previous social relationships exist. For IP transfer agreements, our findings show that micro-geographical proximity is positively related to the establishment of this inter-organizational relationship (hypothesis 3 is confirmed). According to our main estimates, the probability of establishing an IP transfer agreement is 0.029 if the two organizations are located 20 km away from each other. The same probability is 0.080 if the distance is 1 km with a 175% increase in probability. IP transfer agreements typically require high inventor's engagement, especially when the technology is not readily marketable, and the required knowledge to use it is difficult to codify, and a higher frequency of interactions is necessary (Audretsch and Stephan 1996; Zucker et al. 1998; Agrawal 2006; Belenzon and Schankerman 2013). In this case, being in geographical proximity would increase a potential licensee's opportunity to overcome issues of information asymmetry by allowing contacts to be pre-established in the same inventor's social network. This would allow easier access to information with regard to invention quality as well as the inventor's local reputation (Elfenbein 2007). Quite interestingly, social proximity is also relevant to IP transfer agreements. This may be explained by the fact that when the knowledge that is the object of the exchange is more difficult to transfer or embodied in the inventor due to a low degree of codification, a greater level of personal communication is needed and previous relationships are of help as they reduce the risk of opportunistic **behaviour** enhanced by the information asymmetries between inventor and licensor (Agrawal 2006).

Finally, we do not detect any statistically significant association between the micro-geographical proximity and the probability that two organizations in the cluster establish an R&D alliance (both hypothesis 2a and hypothesis 2b are not confirmed). We can only suggest that this null effect may be due to a "compensation effect" of the risks of too much proximity, such as lock-in phenomena and a lack of novel information (Broekel and Boshma 2011; Weiss and Minshall 2014) versus the advantages related to relational trust (Boschma 2005; Ponds et al. 2007) and reduction of information asymmetries (Reuer and Lahiri 2014), which emerge from dense interpersonal networks stimulated by geographic proximity (Feldman 1994; Kale et al. 2000; Capaldo 2007). In addition, the geographical proximity may exert a secondary role in the case of long-term R&D alliances with a high degree of contractualization. In these cases, the division of tasks and competencies among the parties is generally defined in detail in the contract, and the modalities of information exchange are usually formalized in protocols (especially in the biopharmaceutical industry, thus making frequent face-to-face interactions no longer needed). Moreover, we find a positive and significant effect of social proximity. This result is consistent with studies on R&D

alliances showing that the role of social proximity appears to be more significant (Mora-Valentin et al. 2004; Messeni Petruzzelli 2011) than the geographical one in R&D alliance formation. We also find a non-linear effect of cognitive proximity in R&D alliance formation. This result is in line with the view that organizations are not attracted by potential R&D partners that are too cognitively proximate, as excessive levels of cognitive proximity generate fewer learning opportunities, cognitive lock-in and higher risks of knowledge spillovers (Noteboom 1999; Boschma 2005).

To summarize, complementary to the findings of previous studies that analyse the effect of geographical proximity by adopting a macro-level perspective, our study shows that the micro-geographical proximity within a technology cluster is relevant, especially for particular types of intra-cluster relationships. In general, we observed that the probability of tie formation significantly decreases with distance for both IP transfer and VC deals, especially when comparing the likelihood of tie formation among the organizations that are closer than 1 km with those located 20 km or more away. This result suggests the importance of geographical proximity at a very small scale for cooperation dynamics.

7. Conclusions

The importance of the geographical proximity for the establishment of knowledge transfer relationships is well explained by scholars who study technology clusters, but the latter studies analyse it at the macro-level as the general co-localization of partners within the same institutional borders and overlook the implications that derive from its operationalization in terms of the geographical distance on smaller scales. However, if we consider well-known technology clusters, it is easy to observe that partners are not only co-localized in the same territory but are often situated very close to each other. Our study empirically demonstrates this. In fact, we find that the likelihood of cooperation is significantly higher when the organizations are located in close proximity despite belonging to the same high-tech cluster. Moreover, our study confirms the necessity of considering the complex nature of high-tech clusters as we show that the effect of geographical distance varies across different types of cooperation practices and, more specifically, that it has a negative effect on the formation of VC deals and IP transfer agreements. Conversely, no significant effect of micro-geographical distance has been found for the establishment of R&D alliances for which other types of proximity are more relevant than social proximity.

We believe that this work contributes to the literature on technology clusters since it enables a more comprehensive analysis of the role of micro-geographical proximity by considering its complexity nature as a network of different types of relationships. Moreover, our study contributes to the literature on inter-organizational cooperation and open innovation by explaining how different

kinds of the relationships are affected by the micro-geographical proximity, while existing studies have neglected to consider the geographical variable or have operationalized it in terms of co-location within a cluster. From an empirical standpoint, this study contributes to a reduction of the ambiguity of the notion of geographical proximity, by demonstrating the presence of intra-cluster locational advantages for the establishment of certain types of inter-organizational relationships between two organizations. From a methodological perspective, our paper provides different alternative measures of geographical proximity considering their effects.

Moreover, we believe that the results of this study have important implications for both managers and policy makers. In general, our results may orient managers by providing a framework that can guide their delocalization decisions for R&D operations and their tie selection processes. Many studies indeed affirm that being localized in a high-tech cluster has many benefits. However, to obtain these benefits, it is important to choose the right location within the cluster itself. For example, for a start-up looking for VC or for a company willing to establish an IP transfer agreement, it is important to be localized in close proximity to their potential partners. These findings are also important for universities that seek to exploit their third mission, suggesting that these universities, for instance, should choose the right place to localize their departments or technology transfer offices if they want to enhance their cooperation with companies. For example, our paper provides theoretical support to the recent choice of the University of Leeds (UK) that has modified the geography of the campus creating a new gate that is closer to the city centre to ensure the most convenient location for its new business incubator.

Additionally, our paper has interesting policy implications. In many emerging regions, the creation of a technology cluster is a top-down process, generally led by the government (Ferretti and Parmentola 2015) through the establishment of, for example, a public research centre or a business incubator. In some cases, the government defines a specific geographical area where the companies could be localized to gain particular incentives (as in the case of special economic zones). Our paper can be used as a guideline for such initiatives, helping policy makers to identify the exact location to obtain the best business opportunities. In other words, our paper shows that it is not convenient to localize an incubator or a public research centre on the city's periphery when universities and VC investors are located in the city centre.

Finally, by showing the importance of micro-geographical proximity, we suggest that policy makers also include the micro-geographical variable in their innovation-driven policies. For example, if a government aims to enhance VC investments in start-ups located in a particular area, it is important that it also plans proximity incentives that push the VC investors to open an office in delimited areas and that such office is not too far from potential clients.

However, we acknowledge that our results may suffer from some limitations. First, the sample can be expanded to include more inter-organizational practices (including informal ties) within the cluster to more deeply explore the role of the micro-geographical proximity on different patterns of cooperation. Second, the accuracy of the measures for other forms of non-geographical proximity is limited by data availability. For example, we assumed that all organizations that were located in the GBA for more than 5 years were socially proximate (while for start-ups, i.e., organizations that were less than 5 years old, we could directly check the prior work experience of their founders and their track record of previous VC deals). This aspect limits the validity of the social proximity measure as we do not effectively know if the individuals of more established organizations have actually developed previous relationships. A possible way to circumvent this limitation is to conduct a survey-based study by directly obtaining this information from the personnel of such organizations. Furthermore, we do not consider the interaction of different forms of proximity, for example, geographical proximity can affect social proximity and vice-versa. More broadly, more control variables can be included (e.g., measures for organizational revenues)⁶, while some moderation and mediating effects among the variables can be considered to improve the explanatory power of our model. Finally, we acknowledge that geographical proximity might be endogenous because of potential reverse causality. Firms may decide to move to a specific location to be near the partnering organizations (e.g., academic spin-offs near the university; a pharma company that sets up an incubator and subsequently buys IP from the tenants).

However, these limitations open interesting avenues for future research based on further advancements of this first exploratory study, which provides a better understanding of the causes and consequences of the micro-geographical proximity on different forms of inter-organizational relationships.

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⁶ As our sample is mainly based on US organizations, where the disclosure of accounting information is not mandatory for unlisted firms, accessing this type of information is difficult.

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Appendix

Table A1. Results from probit regressions – testing for differences across subsamples

	Model 1		Model 2	
	Baseline: VC deals		Baseline: VC deals + IP transfer agreements	
Distance	-0.010	**	-0.009	***
	(0.005)		(0.004)	
Distance × Sample R&D	0.014	*	0.014	**
	(0.008)		(0.007)	
Distance × Sample IP	0.000			
	(0.007)			
Sample R&D	0.034		-0.020	
	(0.118)		(0.095)	
Sample IP	0.096			
	(0.126)			
Social proximity	0.167	***	0.162	***
	(0.062)		(0.061)	
Cognitive proximity	0.007	*	0.007	*
	(0.004)		(0.004)	
Cognitive proximity ²	-0.000	**	-0.000	**
	(0.000)		(0.000)	
Institutional proximity	0.025		0.031	
	(0.090)		(0.088)	
T-stops	0.001		0.001	
	(0.001)		(0.001)	
Entity type dummies	YES		YES	
Industry dummies	YES		YES	
Constant	-2.578	***	-2.538	***
	(0.544)		(0.544)	
N. observations	5,968		5,968	
Log-likelihood	-1,096.775		-1,097.115	
Pseudo R ²	0.022		0.021	

***, **, and * indicate significance at the 1%, 5% and 10% levels, respectively. Robust standard errors are in parentheses.

Table A2. Results from probit regressions – VC deals – alternative measure for cognitive proximity

	Model 1		Model 2		Model 3		Model 4
Distance	-0.009 (0.004)	**					
Distance (log)			-0.058 (0.030)	*			
Distance 0-10 km					0.755 (0.366)	**	
Distance 10-20 km					0.717 (0.370)	*	
Distance (time)							-0.008 (0.004)
Social proximity	0.053 (0.077)		0.053 (0.078)		0.045 (0.076)		0.052 (0.078)
Investor focus	-0.095 (0.078)		-0.089 (0.079)		-0.100 (0.078)		-0.096 (0.078)
Institutional proximity	-0.095 (0.095)		-0.094 (0.095)		-0.106 (0.096)		-0.093 (0.095)
T-stops	-0.000 (0.001)		-0.000 (0.001)		-0.001 (0.001)		-0.000 (0.001)
Entity type dummies	YES		YES		YES		YES
Industry dummies	YES		YES		YES		YES
Constant	-1.765 (0.331)	***	-1.769 (0.330)	***	-2.526 (0.490)	***	-1.718 (0.332)
N. observations	3,843		3,843		3,843		3,843
Log-likelihood	-698.876		-698.435		-697.285		-698.840
Pseudo R ²	0.018		0.018		0.020		0.018

***, **, and * indicate significance at the 1%, 5% and 10% levels, respectively. Robust standard errors are in parentheses.

Table A3. Results from probit regressions – VC deals – control for investor's reputation

	Model 1	Model 2	Model 3	Model 4
Distance	-0.007 * (0.004)			
Distance (log)		-0.049 (0.030)		
Distance 0-10 km			0.678 * (0.370)	
Distance 10-20 km			0.650 * (0.373)	
Distance (time)				-0.006 (0.004)
Social proximity	0.008 (0.077)	0.010 (0.078)	0.002 (0.076)	0.008 (0.078)
Cognitive proximity	0.009 (0.006)	0.009 (0.006)	0.009 (0.006)	0.009 (0.006)
Cognitive proximity ²	-0.000 (0.000)	-0.000 (0.000)	-0.000 (0.000)	-0.000 (0.000)
Institutional proximity	-0.079 (0.097)	-0.078 (0.097)	-0.089 (0.098)	-0.077 (0.097)
T-stops	-0.000 (0.001)	0.000 (0.001)	-0.000 (0.001)	-0.000 (0.001)
VC reputation	0.204 ** (0.088)	0.201 ** (0.087)	0.206 ** (0.088)	0.206 ** (0.088)
Entity type dummies	YES	YES	YES	YES
Industry dummies	YES	YES	YES	YES
Constant	-1.993 *** (0.335)	-1.994 *** (0.335)	-2.672 *** (0.502)	-1.953 *** (0.336)
N. observations	3,843	3,843	3,843	3,843
Log-likelihood	-694.695	-694.334	-693.220	-694.605
Pseudo R ²	0.024	0.024	0.026	0.024

***, **, and * indicate significance at the 1%, 5% and 10% levels, respectively. Robust standard errors are in parentheses.

Table A4. Results from probit regressions – VC deals – start-ups

	Model 1		Model 2		Model 3		Model 4	
Distance	-0.026							
	(0.020)							
Distance (log)			-0.160 ***					
			(0.055)					
Distance 0-10 km					3.164 ***			
					(0.287)			
Distance 10-20 km					2.663 ***			
					(0.335)			
Distance (time)							-0.028 **	
							(0.012)	
Social proximity	1.657 ***		1.614 ***		1.663 ***		1.661 ***	
	(0.314)		(0.333)		(0.350)		(0.333)	
Cognitive proximity	0.011		0.010		0.011		0.010	
	(0.010)		(0.010)		(0.010)		(0.010)	
Cognitive proximity ²	-0.000		-0.000		-0.000		-0.000	
	(0.000)		(0.000)		(0.000)		(0.000)	
Institutional proximity	-0.204		-0.204		-0.189		-0.215	
	(0.227)		(0.220)		(0.216)		(0.221)	
T-stops	-0.000		0.002		-0.001		0.001	
	(0.002)		(0.002)		(0.002)		(0.002)	
VC reputation								
Entity type dummies	YES		YES		YES		YES	
Industry dummies	YES		YES		YES		YES	
Constant	-1.797 ***		-1.852 ***		-4.991 ***		-1.639 ***	
	(0.204)		(0.369)		(0.500)		(0.366)	
N. observations	1,512		1,512		1,512		1,512	
Log-likelihood	-240.925		-238.191		-240.388		-239.090	
Pseudo R ²	0.069		0.079		0.071		0.076	

***, **, and * indicate significance at the 1%, 5% and 10% levels, respectively. Robust standard errors are in parentheses.