Tangible and intangible proximities in the access to Venture Capital: evidence from Italian innovative start-ups

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2 authors:

Francesca Ghinami
University of Cagliari

Sandro Montresor
Gran Sasso Science Institute

Tangible and intangible proximities in the access to Venture Capital: evidence from Italian innovative start-ups

Ghinami, Francesca *†
francesca.ghinami@gssi.it

Montresor, Sandro *
sandro.montresor@gssi.it

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Abstract

This paper aims to investigate the role that different forms of proximity have in the access to Venture Capital (VC) by Innovative Startup Companies (ISC). By referring to the population of Italian innovative startups, we find that tangible (spatial) proximity account for this matching, but more in functional than in geographical terms. Industrial proximity between the two actors matters too, and makes the role of functional proximity less binding for the matching. The greatest correlation emerges with respect to a relational kind of proximity, due to the closeness between partners in organisational and social terms.

Keywords: Venture Capital, Innovative Startup Companies, proximity, regional equity-gaps, rare-events

JEL classifications: G24, R12, C20

*Gran Sasso Science Institute, Social Sciences Area, L'Aquila, Italy
† Autonomous University of Barcelona, Department of Applied Economics, Bellaterra, Spain

1 Introduction

Financial capital markets are notably characterised by an uneven geography. Peripheral cities and non-central areas systematically reveal smaller flows of both debt and equity capital (Martin *et al.*, 2002), and this makes them relatively more affected by financial constraints to their firms' innovation (Lee and Luca, 2019; Lee and Brown, 2017; Donati and Sarno, 2015; Lee and Drever, 2014; Cumming and Johan, 2007).

Regional funding gaps are particularly evident with respect to Venture Capital (VC) investments (Martin *et al.*, 2005; Mason, 2007; Martin *et al.*, 2002), as the most relevant funding for newly established high-tech firms (Colombo *et al.*, 2010; Giraudo *et al.*, 2019; Caviggioli *et al.*, 2020; Alperovych *et al.*, 2020; Colombelli *et al.*, 2020), on which we focus in this paper. In general, regional disparities in VC availability have been accounted by the joint occurrence of two phenomena: a local bias, due to the tendency of financiers to invest the largest part of their portfolio where they choose to locate (Cumming and Dai, 2010; Zook, 2002; Lutz *et al.*, 2013); a clustering pattern, leading risk-capital investors to concentrate in major financial cities (Lee and Luca, 2019; Florida and Mellander, 2016; Mason, 2007). In turn, both phenomena can be explained by the importance of the spatial proximity between investor and investee, in mitigating the information asymmetries and the transaction costs entailed by their financial relationship (Van Osnabrugge, 2000; Zook, 2002).

However, the primacy of spatial proximity in accounting for the firms' access to local VC has been recently shown to have some interesting specifications, if not even contradictions. In some dedicated business surveys, for example, investors started showing a certain indifference to the investee location and an increasing engagement in deals that are apparently not local (Carlson and Chakrabarti, 2007, Martin *et al.*, 2005). Aligned with this is econometric evidence showing that VC investors overcome the boundaries of their location and target geographically distant firms, providing they can rely on networking to draw info about them (Sorenson and Stuart, 2001). Indeed, if spatial proximity was to be a major discriminant for investments to occur, firms seeking equity would locate closer to risk-capital owners and regional equity gaps would not arise. This evidence of non-location-mirroring patterns in VC investments is intriguing, and entrepreneurship studies have so far addressed it by integrating the analysis of the physical distance with that of the social ties that link the partners, mainly through their networking (Sorenson and Stuart, 2001). While this is for sure an important dimension to retain, economic geography studies have shown that other forms of proximity than the geographical one can account for the outcome of an economic transaction, especially when it involves the exchange of innovative knowledge (Balland *et al.*, 2013, Boschma, 2005). Drawing on this literature, we claim that the clash between regional equity biases and the absence of location-mirroring behaviors can be reconciled by looking at a manifold proximity between VC investor and investee and at the relationship among its different variants. Firstly, we argue that the role of spatial proximity in affecting the firms' access to VC is twofold in nature, and mainly indirect, as related to its facilitating other forms of intangible proximities. Secondly, we maintain that the same relationship is also affected by (at least) other two forms of proximity, of an industrial and relational nature, respectively. Thirdly, we posit that these intangible proximities could work in alleviating the binding role of tangible proximities for the financial relationship to take place.

We test these hypotheses with respect to the population of Italian innovative start-ups (ISCs) and their VC investors between 2014 and 2019, by adding to the scant evidence so far available on VC for this country (Grilli, 2019; Vacca, 2013; Bertoni *et al.*, 2011; Bertoni *et al.*, 2007).[1] By exploiting the legal definition of ICSs recently issued by the Italian government, we merge data for them in the Italian business registry (*Registro Italiano delle Imprese*) with Bureau Van Dijk data. We then use this novel dataset to run a set of logistic models, which estimate the conditional probability to observe the occurrence of a specific VC-ISC investment pair, and its dependence on our proximity arguments.

We find that tangible proximities account for this matching, but more in functional than in geographical terms. Industrial proximity between the two actors matters too, and makes the role of functional proximity less binding. The greatest correlation emerges with respect to a relational kind of proximity, due to the closeness between partners in organisational and social terms. Its effect grows exponentially with the level of proximity, but relational proximity does not moderate the impact of functional proximity on the matching.

The rest of the work is structure as follows. Section 2 positions the paper in the extant literature and develops our research hypotheses. Section 3 presents our dataset and the evidence about regional gaps in Italian VC investments, for then illustrating model, methodology and estimation issues of the empirical analysis. Results are discussed in Section 4 and Section 5 concludes with a discussion of their implications.

2 Proximities in the relationship between Venture Capitalists and innovative start-ups

As is well known, the monitoring and tutoring activities implemented by VC to address agency and information issues (Van Osnabrugge, 2000), require face-to-face interactions with the investee. These interactions are the more costly and the less effective, the larger their geographical distance, even in the presence of digital forms of communication (Fritsch and Schilder, 2006; Zhao and Jones-Evans, 2017). However, as we said in the previous Section, VC have been found to pair with ISC also at long geographical distance, and this creates a clash that requires explanation. In the following we will argue that this explanation can be obtained by better disentangling the twofold nature of tangible proximity between the partners, and by retaining the role of their intangible proximities.

2.1 Tangible proximities in VC investments: geographical and functional

The extant literature about VC usually refers to the distance between investors and ventures in generic terms, as a factor that facilitates both the pre-investment activities of the former – that is, the identification and appraisal of investment opportunities – and their post-investment ones – amounting to the monitoring of the identified ventures and

[1]The majority of existing studies on geography (as of other proximities) in VC investments in fact mainly refer to the U.S. (Florida and Mellander, 2016; Carlson and Chakrabarti, 2007; Cumming and Dai, 2010; Sorenson and Stuart, 2001; Zook, 2002), the UK (Lee and Drever, 2014; Mason and Pierrakis, 2013; Martin *et al.*, 2005; Mason and Harrison, 1992; Harrison and Mason, 2002) and the German (Lutz *et al.*, 2013; Bender, 2010; Fritsch and Schilder, 2006; Martin *et al.*, 2005) markets, with few world (Tykvová and Schertler, 2014) and European-wide studies (Martin *et al.*, 2002).

to the supply of value-added services to them (Sorenson and Stuart, 2001). Indeed, all of these are experiential tasks that involve the acquisition and elaboration of procedural and tacit knowledge, if not even social interactions, which become difficult to implement at a distance.

On the basis of this argument, the role of a proximity that facilitates the physical interaction between partners, or a tangible proximity, in facilitating the occurrence and the success of VC investments has been argued since long (Gupta and Sapienza, 1992). The empirical proof of this argument has also been found extensively (Martin *et al.*, 2005; Mason, 2007; Martin *et al.*, 2002), mainly by referring to the inverse of the geographical distance that separates economic actors, or as the length of space between them: in brief, to what can be more specifically defined as their tangible, *geographical proximity* (Boschma, 2005). This proximity is considered pivotal in evolutionary economic geography and regional studies, as it conditions the spatial concentration and agglomeration of agents, which permit the knowledge spillovers that conduce innovation, on which it focuses. However, when we look at financial relationships like VC investments, the production of innovative knowledge is not the focal outcome of the interaction, which is rather intended to contrast information asymmetries and to facilitate the selection, evaluation and commercial exploitation of the innovative deals. With respect to this kind of interaction, "the effort that it takes to interact", at the basis of what (Moodysson and Jonsson, 2007, p. 118) have defined "functional distance", is a different and arguably more relevant form of (inverse) tangible, *functional proximity* in accounting for VC investments.

The two variants of tangible proximity are of course connected, but not coincident. By focusing on the functional activities undertaken by agents to interact, the latter additionally accounts for the existence of infrastructures and travelling times. These are pivotal in the interaction required by a VC investment, as they increase the opportunity costs of getting info and monitoring investments. In the light of that, even two equally distant places could be heterogeneously hard to be reached. Not only are the two tangible proximities conceptually different, but their relevance can also be claimed to be different. Indeed, previous studies about other forms of equity investments, like business angel investments (Hermann *et al.*, 2016), have argued and found that the extra opportunity costs entailed by the functional one can be more preventing than the informative and transaction costs that the geographical distance also entails. In the light of that, we do expect this holds true also with respect to VC investments and that the empirical testing of this argument could help us explaining the apparently contradictory evidence on the spatial sensitivity in deals selection.[2]

2.2 Intangible proximities in VC investments: industrial and relational

While of great relevance, the tangible (geographical and functional) proximity between VC and target firms is not the only dimension along which they relate. As the seminal paper by (Sorenson and Stuart, 2001) has shown, VC partners do also relate in networks, which

[2]In business surveys, questions about functional distance, usually posed to managers by using relevant thresholds (e.g. within-two-hours travel distance) are possibly easier to be evaluated than more general questions about geographical distance (e.g. importance of location). This framework effect could also concur to explain the perceived irrelevance of the latter detected by Carlson and Chakrabarti, 2007 and Fritsch and Schilder, 2006.

they create by interacting, knowing and trusting each other, and within which they can be more or less close, attenuating the conditional role of their tangible proximity.

This study represented an important extension in the way entrepreneurship research had looked at the distance between VC investor and investee until then. Indeed, it opened up a door towards relevant studies about proximity in economic geography, which has been unfortunately seldom overcome afterwards. The main point of these studies is that, despite the 'overterritorialized' analysis of their relationships over the last two decades (Hess, 2004), economic actors are embedded in different a-spatial contexts, which create different forms of proximities between them, but not along the tangible dimension. Quite importantly, as alluded by the study of (Sorenson and Stuart, 2001), all of the proximities can be argued to interact among them, and with the tangible one in particular: typically by substituting one the lack of another.[3]

Extending this economic geography argument to the realm of entrepreneurship studies, and strengthening their combination, their two intangible proximities appear salient in affecting the financial relationship between VC and ISC that we are investigating, and requires more attention than the one they found so far. Following an "interactionist" approach to proximity (for which see Balland *et al.*, 2013), these can be considered: a "similarity" kind of proximity, represented by the industrial closeness between VC and target firm, and a "belonging" kind of proximity, emerging along the business relationships they entertain.

2.2.1 Industrial proximity

An important proximity between VC and target firms is the *industrial proximity* determined by the extent to which the former has already invested in the industry of the latter. Through its prior investments in the industry of the target company, the VC fund can in fact get more knowledge and experience of that industry and this can be expected to facilitate the deal through two channels. The first channel is represented by the enabling effect that industrial proximity has on both pre-investment and post-investment activities (Sorenson and Stuart, 2001). On the one hand, it extends the number of contacts with entrepreneurs and third investors of the focal industry, and this in turn improves the exploration of new opportunities. On the other hand, industrial proximity can make the VC more confident in its capacity to detect and interpret signs of early-stage problems and to monitor the evolution of the prospected deal in the same industry. The second channel through which the VC-ISC industrial proximity can facilitate their matching in a new deal is represented by the synergies it creates between the prospected and the existing backed companies in the VC portfolio. The presence of industry-specific knowledge in fact spurs VC firms to specialise in the industry at stake, and this provides them with coordination economies in the management of their portfolio, which could benefit the new deal too (Norton and Tenenbaum, 1993). Thinking of the operation of these two channels, we do expect industrial proximity to be positively associated with the probability of observing a VC-ISC match. However, still by mimicking and extending the arguments and the evidence obtained with respect to innovative relationships (Boschma, 2005), we also have other two expectations. On the one hand, we anticipate that also the role of industrial proximity on the matching between VC and ISC could be non-monotonic. This could descend from the fact that, as

[3]For example, more geographically distant partners, can compensate the problems in the exchange of tacit knowledge with their belonging to the same organisational culture.

some recent studies have shown (Buchner *et al.*, 2017; Patzelt *et al.*, 2009), an excessive industrial proximity, as reflected by an intensive specialisation strategy of VC investors, could deprive them of knowledge-sharing opportunities chances of risk-reduction across different industries. On the other hand, still in line with the proximity literature, we expect that the experience that VC investors can acquire through their industrial proximity to the ISC could compensate for the eventual lack of tangible proximity between them. For example, through the experience entailed by industrial proximity, the VC could increase the number of knowledge sources to be used for a deal, as well as extend and consolidate the synergies of their backed-firms portfolio, and this could compensate the loss of a few or a unique local knowledge source.

2.2.2 Relational proximity

An additional kind of proximity that can affect the matching between VC and ISC is the "belonging" one that descends from their being part of common interpersonal networks, or in brief, their *relational proximity.*

The relevance of this proximity emerges by considering that, as we have repeatedly noticed, the financial relationship we are investigating depends on information transmission and knowledge exchanges among the focal actors; and that, as diverse streams of sociological literature have shown since long (Coleman, 1994;Friedkin, 1998), interpersonal relationships are the main driver and structuring factor of information/knowledge circuits. This is particularly relevant in the VC market, in which public information about investment opportunities and early stage companies is basically missing and in which operators often lack sufficiently long histories of business performance to base their evaluations on. In such a kind of context, creating and participating to social networks becomes a crucial means for VC investors to trust and verify imperfect information. A social tie – either direct or mediated by a common link with another firm or individual – in fact involves expectations of social obligations (Uzzi, 1996), which represent a trust-based privileged information channel.

Extending an earlier research stream about the importance of close contacts in the general access to finance (Fried and Hisrich, 1994; Uzzi, 1999; Shane and Cable, 2002; Hain *et al.*, 2016), the idea that the existence and the intensity of social ties – that is, relational proximity – can affect the VC-ISC match, has been mainly investigated by focusing on the inter-firm relationships through which VC investors come to constitute their own communities. Since the seminal work by (Sorenson and Stuart, 2001), this has been mainly done by looking at the networks that VC firms form through the use of syndicated investing-facilitates[4]: not only do they enable the financial relationship at stake, but they also decrease the space-based constraints posed by tangible proximities. Drawing on this contribution, subsequent studies have found that the social embeddedness of Venture Capitalists, measured through heterogeneous social and organizational ties, crucially affect the unfolding and the performance of the investment (Meuleman *et al.*, 2017; Teten and Farmer, 2010; Milosevic, 2018) as well as the probability that VC invest in spatially (Tykvová and Schertler, 2014; Sorenson and Stuart, 2001), institutionally (Tykvová and Schertler, 2011) or technologically distant firms (Meuleman *et al.*, 2017; Tykvová and Schertler, 2014; Cumming and Dai, 2010).

[4]As is well-known, this is the case of new ventures that obtain funding from syndicates of investors, that is, from more than one VC firm.

Quite surprisingly, only few studies instead have recently addressed the personal relationships that could exist between VC and target companies (Nigam *et al.*, 2020; Hermann *et al.*, 2016; Fuchs *et al.*, 2021), and generally found that they have a positive effect on the access to financing. Given the crucial role that the interpersonal relations between the two parties of the match at stake could have in facilitating the exchange of information about the deal, and in building up trust relationship that could increase the chance of its success, this is an unfortunate gap that needs to be filled and on which we focus in our empirical application.

As we will see in the next Section, we put forward an original methodology to proxy this relational proximity between VC and ISC and empirically test if, as we do expect, this proximity facilitates their matching. Furthermore, we will also investigate if, by mimicking what has already been found with respect to the social relations between VCs, the relational proximity between VC and target companies is capable to extend the geographical coverage of their relationship.

3 Empirical analysis

Our empirical analysis focuses on the resort that innovative start-up companies (ISC) make to VC in Italy, and contributes to extend the still scanty evidence about the VC market in this country. The Italian equity market is generally considered immature with respect to countries with different models of capitalism (Della Sala, 2004; Vacca, 2013; OECD, 2017; De Socio, 2010; Bertoni *et al.*, 2007), and in fact reveals a below-average degree of attractiveness for risk-capital investments with respect to other EU countries (Groh *et al.*, 2010). The Italian financial system is in fact considered a bank-based one. Nonetheless, access to bank loans by new technology-based firms in Italy has been found to be still sparse and quite insensitive to demand-side factors (Colombo and Grilli, 2007). Accordingly, equity and personal funds represent important tools against credit constraints for young and innovative firms in this country too.

The focus on Italy is also particularly salient for our research question about proximities and the VC-ISC match. First, the nature of the Italian financial system possibly makes our focal relationship a relatively rare event to observe, and makes us expect that the market imperfections that render the proximity between investor and investee important, could be more severe than elsewhere (Whited and Zhao, 2021; Midrigan and Xu, 2014). Second, Italy is a fairly decentralized country, with relevant geographical barriers across areas and fairly unequal quality of infrastructure, that increase average transport costs and opportunity costs of potential distant partnerships. Third, the country displays below EU-average institutional quality (Adam, 2008), and this increase the importance of monitoring and referrals for risk-capital deals,[5] imposing a higher weight on transactions costs when evaluating potential risk capital investments. As a result, we expect intangible proximities, and especially relational one (Johnson *et al.*, 2002), to have an important role in this context.

[5]In particular the low degree of the judicial system's efficiency and of contract-enforcement with it are deemed to increase moral hazard and strategic behaviours of creditor firms (Schiantarelli *et al.*, 2020; Fabbri, 2010), hindering gross investments (Dejuan and Mora-Sanguinetti, 2019) and credit access both at aggregate (Moro *et al.*, 2018) and local (Giacomelli and Menon, 2016) level.

3.1 Data and descriptive evidence

Our dataset refers to the population of Italian Innovative Startup Companies (ISCs) and to the investments that Venture Capitalists (VC) have made in them over the period 2012-2019.

ISCs are identified following the definition introduced by the Italian Law 221/2012 (dedicated to their policy support), which requires two identification criteria: i) an age of less than five years; ii) at least one of the following requisites: 1) employing at least one-third of workers with a doctoral diploma, or two-thirds with a master diploma, 2) being licensee or depositor of at least one patent or other industrial property rights; 3) investing at least 15% of the value or cost of production in R&D activities. Following this definition, we have collected a panel dataset, observed over the period 2012-2019, constituted by all the 10,213 Italian ISCs that registered as such before June, 6th, 2019. With respect to this ISC population, we have merged data contained in the Italian business registry (*Registro Italiano delle Imprese*) with Bureau Van Dijk data and obtained detail information about their localization, ownership structure, investments and other balance sheet data. Among these data, information about all the investors of the identified Italian ISCs have been retrieved at the same date. Quite interestingly, out of the 38,425 detected investors, only 37 are Venture Capital funds (though, of course, each one with multiple deals): an information that we will carefully retain in the following analysis.

A preliminary investigation of these data shows that ISCs are fairly distributed across the whole Italian territory and especially present in the South, where by contrast VC actors (with at least one Italian deal) do not have any branch (Figure 1). A modified version of the Location Quotient (LQ) (see Appendix A.1 for its construction) points to the existence of large regional equity gaps in the Italian market of VC investments in ISCs. However, by confirming the inspiring motivation of this paper, VC locations do not tend to mirror that of Italian innovative startups. Regions with higher rates of VC funds location tend to exhibit above-average shares of VC-backed startups. Overall, this evidence adds to that from which we have started this paper, and seems to confirm that geographical proximity could not represent a reliable, or at least, unique predictor of VC investments in Italian ISCs.

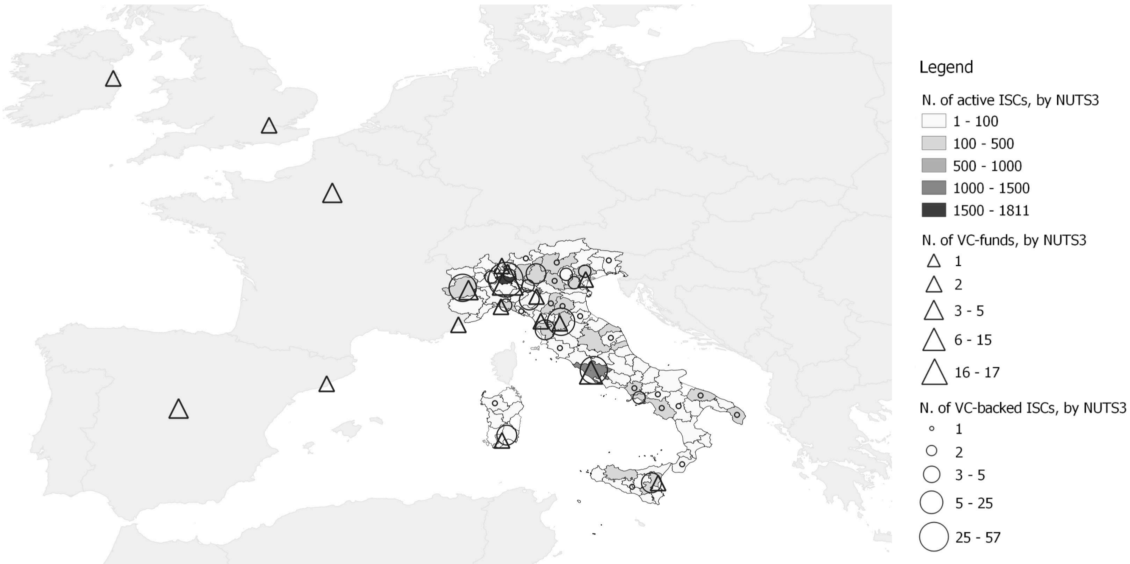
3.2 Dependent variable and econometric model

The focal variable of our empirical analysis, Y, is the probability of observing a specific VC-ISC investment pair, of which we aim to investigate the determinants and the role of proximity. To do that, following the extant literature (Sorenson and Stuart, 2001; Tykvová and Schertler, 2011), we implement an identification strategy that rules out the heterogeneity of firms' financial needs/quality by focusing on successfully financed firms and correcting for the entailed selection on the dependent variable. By retaining all of the financed start-ups and only them, we do not run the risk to have confounding effects of our focal arguments.[6].

The set of potential pairs is constructed by considering as bidders all the VC funds that completed an investment in an Italian ISC, and as targets any ISC that received a VC investment during a temporal window of 8 months (*id est* within 120 days before

[6]Together with the provision of dedicated tax and financial incentives, the Italian Law has actually instituted and closely monitored the ISC as a novel juridical form, subject to specific innovativeness requirements and to the obligation of producing publicly available data yet unexplored.

Figure 1. Distribution of Italian ISCs, of VCs and VC-backed ISCs in NUTS3 regions



or after the original bidder's date of investment): a time-frame consistent with previous evidence on the time evaluation of deals (Petty and Gruber, 2011). Given that 136 startups were backed once or multiple times by 37 different VC funds, for a total of 160 actual investments, their dyadic interaction gave raise to a sample of 8,480 dyads within the above defined time window.

The proportion of observed pairs represents only 1.89% of the whole dyadic population, lower than the share (i.e. 5%) usually retained to have a rare event bias (King and Zeng, 2002). Accordingly, we implemented a number of tests (see Appendix A.2), on the basis of which we have decided to implement a Firth's Bias-Reduced Logistic Regression (Firth, 1993) to estimate the following model:

$$P(Y = 1|W_{i,j}, X_i, X_j) = \frac{1}{1 + e^{-(W_{i,j}\beta + X_i\gamma + X_j\delta)}} \tag{1}$$

where Y denotes the occurrence of a specific VC-ISC investment pair, $W_{i,j}$ a set of dyadic proximity variables between j (VC) and i (financed ISC), while X_j and X_i contain investors specific and ISCs control variables, respectively, that will be described in the following Sections.

3.3 Proximity variables

(i) Tangible proximity(ies)

Following the arguments of Section 2.1, we build up two sets of variables of tangible proximity between VC and ISC. The first one, *geographical proximity*, refers to its territorial dimension and measures the inverse of the minimum geodetic distance between the legal and operative offices of the two parties.

As for *functional proximity*, we alternatively proxy it with: the inverse of the minimum travel time (expressed in hours) separating their respective places (by any means of transport); the minimum travel time between them being by car, within two hours, and within half an hour (by any means of transport), through three respective dummies.

Finally, we consider three mutually exclusive dummies, which indicate if at least one among the VC and ISC offices are located in the same city, province, or region.

A more detailed definition of the previous proximity variables (including their data sources), and of the other ones presented in the following, is reported in Table A.6 in the Appendix. Also in the Appendix, Table A.5 reports their descriptive statistics. For the dyadic sample used in the analysis, statistics distinguish between potential and successful pairs. Looking at these statistics, it emerges that both geographical and functional proximity exhibit higher means for successful than potential investment pairs, supporting the claim that tangible proximities do play a role in predicting the deals.

(ii) Intangible proximities

Following the arguments of Section 2.2, we measure two kinds of intangible proximities.

Industrial proximity

Following previous studies on the topic, we measure the *industrial proximity* between VC and ISC with the share of previous holdings that each VC fund reveals in the industries in which each target ISC operates. More precisely, to investigate the extent to which specific sets of industry knowledge are beneficial for the deal, we build up three proxies of industrial proximity, which compute the previous share for progressively finer levels of industry aggregation of the NAICS 2007 classification, at 2, 3, and 4 digits.[7]

As shown in Table A.5 (Appendix), successful VC-ISC pairs tend to exhibit a lower degree of industrial distance, at any industry digit, thus still confirming the role of this variable for VC investments.

Relational proximity

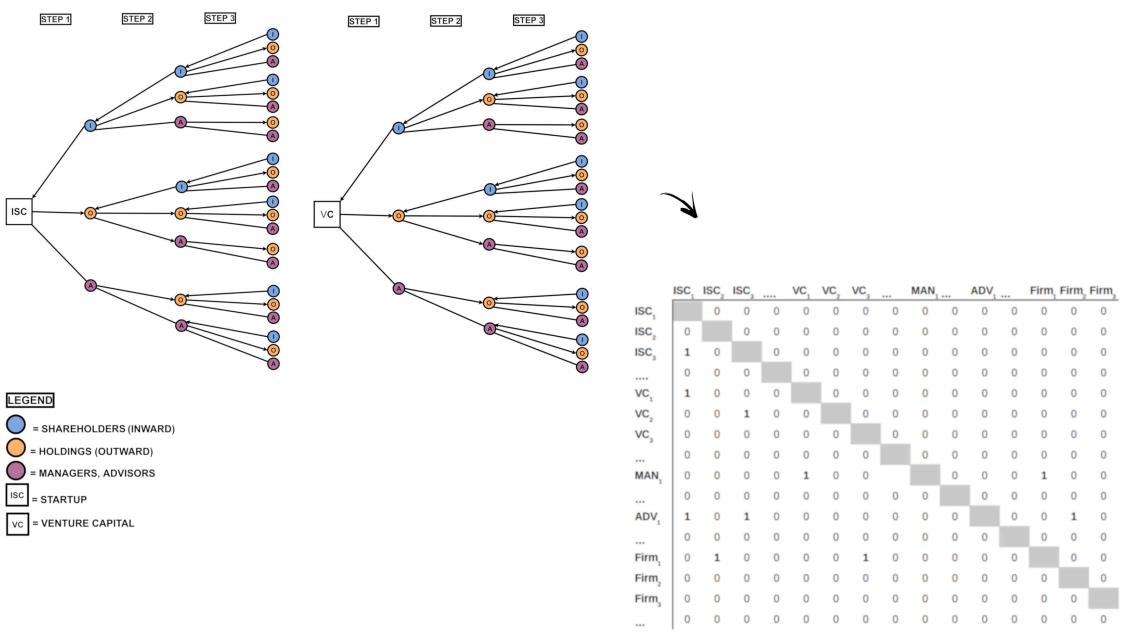
We propose an original measurement of the *relational proximity* between VC and target ISC, which refer to the (network) adjacency matrix of the professional and investment links occurred between them before the VC-backing date.

Taking these links as a proxy of the relevant personal relationships between the parties at stake, we build up this matrix in three steps. In the first step, we identify all the shareholders, holdings, and (the name of) advisors and managers of both the startups and the VC. In the second step, we proceed recursively and collect the same pieces of information for each of the firms or individuals identified in the previous step. More specifically, as shown in Figure 2, for shareholding or outward-holding firms, we identify the references of advisors, managers, holdings and shareholders; for individuals, such as managers, advisors and individual investors, we detect all previous and contemporaneous professional positions and further investments. We then proceed to the third step, and construct a matrix that report all the undirected links among each VC-backed ISC and each VC firm in our sample.

[7]In our data, the sectoral classification is provided at 4 digits 2007 NAICS code. In the NAICS, the fourth digit refers to a specific industry group, like 3342 - Communications Equipment Manufacturing, the third indicates the relative sub-sector, like 334 - Computer and Electronic Product Manufacturing, and the first two digits refer to the sector, like 31-33 - Manufacturing.

Using this matrix-network, we measure the relational proximity between each dyad and its intensity, with two indicators: the inverse of the minimum number of steps needed to find a link between its partners; the total number of links among the VC and the ISC of each dyad, respectively.

Figure 2. Simplified illustration of the relational network and its adjacency matrix, built considering, for each ISC and VC in our dyadic sample, the managers and advisors, inward (shareholders) and outward (holdings) investments, and all the links of the same kind to other firms and individuals of each node up to the third step.



Confirming their expected role, both these relational proximity variables exhibit higher means in successful investment-pairs than in potential ones, as shown in Table A.5 (Appendix).

3.4 Control variables

In estimating the role of the previous proximity variables, we should retain that firms' location choices could correlate both with these variables and with relevant unobservables - such as the quality of the managerial team - in turn arguably correlated with the probability that an ISC receives an investment. While this is not sufficient to make causal inference on our results, to attenuate the potential bias entailed by these issues, we test for numerous ISCs-, VCs-, and location-specific controls. As for $ISC\!-\!specific$ controls, we include: the age of the firm, the number and characteristics of their managers, and the actual fulfilling of each of the innovative requirements to be considered as ISC (see Section 3.1. We also consider the one-year lagged measure of a number of productivity related variables (production costs, costs of research and advertising, per capita value added, value of production, patents rights, labor cost and labor productivity) and of profitability related ones (revenues, debt/equity ratio, return on investments, return on equity; earnings before interest, taxes, depreciation and amortization).[8]

As for the *VC−specific* controls, these include: size proxies, such as the number of shareholders, managers, employees and companies in the corporate group, along with age, location, and the statistics of previous investments.

In addition to the previous factors, we also control with two dummies for the following circumstances: the fact that ISC had prior VC investments, and that the focal investment was realised in syndication with other VCs[9].

Finally, we also consider a set of *location−specific* controls. First, we retrieve from the Eurostat database at NUTS3 level: population, density, firms demography (entry/exit) by 2-digit NACE code, and the 2000-2018 GDP growth. Second, to proxy for the presence of specific industrial clusters in the area of the focal firms, we consider the number of active high-growth firms by 2-digit NACE code per year. Third, still by 2-digit NACE code and location (at NUTS3 level, this time), we resort to data on patent applications to the European Patent Office, to account for the innovative capacity of the environment firms operate in.

In addition to the previous set of controls, we plug in the estimates area (NUTS1 region) fixed effects meant to control for the notable Italian North-South development divide. Table A.3 and A.4 in the Appendix report the descriptive statistics for the controls. Out of them, we retain only those controls that displayed significant coefficients when regressed individually, namely if the investment occurred in syndication, ISCs age, and the lagged GDP at ISC local (NUTS3) level.

4 Results

4.1 Baseline model: unpacking spatial proximity

Table 1 reports the results of different specifications of a baseline model, in which only geographical (Models 1 and 2) and functional proximities (Models 4 - 8) are alternatively considered. Before moving to the illustration of the relative results, let us notice that the retained controls show the expected sign. The fact that the focal ISC has had a prior VC investment increases the probability of its matching with a new one. Consistently with previous studies (Sorenson and Stuart, 2001), syndication provides VC firms with an additional set of information, which increases the chance of a successful matching with a financed ISC. The startup age (with an average at finance of 2.8 years, Table A.3)) is negatively correlated with the probability of observing a match. Finally, the (1-year lagged) GDP at NUTS3 level exhibits the expected positive and significant sign. Coming to our focal regressors, as expected, both geographical and functional proximities, in nearly all

[8]Given the presence of missing values for all the above balance-sheet variables, these will only serve to verify the robustness of the identification strategy, and will be omitted in the final models to avoid observations losses.

[9]We use this dummy to account for the diminished salience of distance in syndicated deals, guaranteed by risk, information and costs sharing between VC investors (Sorenson and Stuart, 2001). However, as this was already investigated in the literature (Tykvová and Schertler, 2014; Catalini and Hui, 2018), and our focus is on that between VC-investors and target firms, we do not measure the relational proximity between different VCs participating in the investments. Still, syndicated investments represent only 14% of the observed operations and, when they are excluded from the sample as a robustness check (see Section A.4), general results in terms of significance of the coefficients hold.

the dimensions we have captured them, significantly increase (with) the probability of observing a successful VC-ISC pair.[10]

Table 1. Baseline model

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Geographical proximity								
Geographical proximity	0.000***	0.000*						
	(0.000)	(0.069)						
Geographical proximity^2		-0.000						
		(0.836)						
Functional proximity								
Functional proximity			0.195***	0.477***				
(by any means of transport)			(0.000)	(0.001)				
Functional proximity, squared				-0.018**				
(by any means of transport)				(0.046)				
Dummy: Travel time <2hours					1.010***			
(by any means of transport)					(0.000)			
Dummy: Travel time <1/2hours						1.574***		
(by any means of transport)						(0.000)		
Dummy: Minimum travel time is by car							0.881***	
							(0.000)	
Co-location								
Co-location: same city								1.979***
								(0.000)
Co-location: same province (NUTS3)								1.405
								(0.101)
Co-location: same region (NUTS2)								1.451***
								(0.000)
Controls								
Dummy: ISC had prior VC investment	1.035***	1.036***	1.043***	1.038***	1.007***	1.031***	0.976***	1.054***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)
Dummy: syndicated investment	2.465***	2.463***	2.478***	2.484***	2.511***	2.514***	2.496***	2.479***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
ISC's age at finance	-0.122**	-0.125**	-0.111*	-0.096	-0.146**	-0.132**	-0.111*	-0.128**
	(0.043)	(0.020)	(0.066)	(0.117)	(0.016)	(0.027)	(0.062)	(0.033)
L1. GDP, at ISCs NUTS3 (MEUR)	-0.000	-0.000	-0.000	-0.000	-0.000***	-0.000***	0.000	-0.000***
	(0.463)	(0.414)	(0.375)	(0.263)	(0.006)	(0.001)	(0.749)	(0.009)
Area FE	yes	yes	yes	yes	yes	yes	yes	yes
Constant	-3.772***	-3.768***	-3.812***	-3.839***	-4.141***	-3.876***	-4.479***	-4.297***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	8480	8480	8480	8480	8480	8480	8480	8480
VIF	1.251	1.251	1.252	1.252	1.415	1.306	1.334	1.345
Estimated probability. Robust pval in parenthesis (*** p<0.01, ** p<0.05, * p<0.1)								
Marginal effects (covariates at median values)								
Geographical proximity at 200km	4.21e-05	4.78e-05						
Geographical proximity at 100km	4.21e-05	4.78e-05						
Geographical proximity at 50km	4.21e-05	4.78e-05						
Functional proximity: at 2hours			0.00254	0.00598				
Functional proximity: at 1hour			0.00255	0.00600				
Functional proximity: at 1/2hour			0.00256	0.00605				
Dummy: Travel time <2hours =1					0.0146			
Dummy: Travel time <1/2hours =1						0.0466		
Dummy: Minimum travel time is by car =1							0.0192	
Same city								0.0518
Same province								0.0367
Same region								0.0379

While both geographical and functional proximities appear relevant, the lower panel of Table 1 shows that, being located at a geodetic distance of 200km increases the baseline probability of observing a successful VC-ISC pair by no more than 0.004%. On the other hand, being located at a comparable 2-hours travel distance has an effect three times higher

[10]The only exception is the co-location within the same province, which is not significant in Model 8. This result could depend on the low number of ISCs and VCs located in the same province but not in the same city, given that most funds and firms locate in metropolitan areas that are in province capitals and that we exploit a mutually exclusive dummy.

(up to a positive 0.6% in Model 4), and comparable to the 1.4% average marginal effect of being located within a two-hours route (Model 5). Finally, the effect is appreciable also with respect to the dummy for the minimum travel route by car (+ 1.9%) and substantially more for being located within half an hour of travelling (+4.7)%.[11]

In conclusion, consistently with recent evidence about the managers' perception of their comparative relevance, we find that the geodetic distance between partners is not the most accurate proxy for predicting successful VC deals. Indeed, the relational needs involved in this type of investments are the most favored by the accessibility easiness of the partners, reflected by a functional rather than geographical kind of proximity. However, like the geographical one, also the functional proximity between partners only helps up to a certain extent, passing which its limiting the set of viable deal opportunities prevails.

4.2 Augmented model: tangible and intangible proximities

Table 2 reports the results for the model in which the role of tangible proximity is augmented with that of the intangible ones and with their respective interactions. These interactions reveal to us the extent to which the latter can, as expected, attenuate the binding role of the former on the probability of a successful VC-ISC pair.

Given the natural correlation between geographical and functional proximities, and the higher explicative role of the latter emerged in the previous section, in all the specifications of this augmented model we only retain a functional kind of tangible proximity. More precisely, among the different proxies of this functional proximity, we notice that the within 2-hours travel dummy between partners does not appear significantly correlated with any measure of intangible proximity (see Table A.9 in the Appendix). Furthermore, this latter variable shows a high predictive power with respect to the outcome variable and consistent marginal effects among different specifications. On this basis, we will stick to this variable of functional proximity – the dummy: travel time < 2 hours – in all of the specifications of Table 2.

Starting with the role of *industrial proximity*, Models (1) - (3) show that it significantly increases (with) the chance of a successful VC-ISC pair, but with some important specifications.

First of all, the variable at stake reveals significantly positive only for low to intermediate degrees of sectoral disaggregation of the considered ones: that is, at the more aggregated 2 (Model 1) and 3 (Model 2) digits of the NAICS classification. This interestingly suggests that, when the industry-group environment that the partners share is very specific – 4 digits (in Model 3), like an ISC in Basic Chemical Manufacturing targeted by a VC with previous experience of it – the entailed learning return for the VC is possibly too narrow to make the VC itself retain the deal sufficiently enriching to be concluded. Conversely, at the sector (2digits) and subsector (3 digit) level, the enabling mechanisms of the VC-ISC matching we have envisaged in Section 2.2.1 seem to work.

As a second nuance , Model (7) in Table 2 shows that, as we argued in Section 2.2.1, the role of industrial proximity in facilitating the match between ISC and VC appears to inter-operate with that of tangible proximity. More precisely, the interaction between industrial proximity (at 3 digits) and the dummy for travel times below 2 hours turns

[11]Being co-located in the same city or region has the strongest effects, +5.2% and +3.8% respectively. However, these measures appear highly correlated with relational proximity, suggesting that they could confound with it and cannot be considered as solely *tangible*.

out significantly negative. As we have hypothesised, the experience entailed by industrial proximity could increase the VC knowledge sources to the point of compensating for the disadvantages of targeting more geographically distant ISCs. In brief, it would seem that the industrial proximity between VC and target companies is capable to extend the geographical coverage of their relationship.

Table 2. Augmented model

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Functional proximity							
Dummy: travel time<2hours	1.005***	1.007***	1.008***	1.060***	0.844***	1.036***	1.429***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)
Industrial proximity							
Industrial proximity 2 digits	1.005***						
	(0.000)						
Industrial proximity 3 digits		1.019***				0.498*	2.023***
		(0.000)				(0.052)	(0.000)
Industrial proximity 4 digits			0.484				
			(0.183)				
Relational proximity							
Relational proximity				3.788***		3.535***	4.297***
				(0.000)		(0.000)	(0.000)
N. of ties (intensity)					1.556***		
					(0.000)		
Interactions							
Industrial proximity 3digits * Dummy travel time<2hours							-1.423***
							(0.008)
Relational proximity*Industrial proximity							-1.367*
							(0.069)
Relational proximity * Dummy travel time<2hours							0.152
							(0.848)
Controls							
Dummy: ISC had prior VC investment	1.095***	1.084***	1.027***	1.087***	1.096***	1.116***	1.118***
	(0.000)	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)
Dummy: syndicated investment	2.531***	2.525***	2.505***	2.591***	2.527***	2.595***	2.594***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
ISC's age at finance	-0.153**	-0.150**	-0.148**	-0.150**	-0.131**	-0.156**	-0.145**
	(0.012)	(0.013)	(0.014)	(0.015)	(0.035)	(0.012)	(0.020)
L1. GDP, at ISCs NUTS3 (MEUR)	-0.000**	-0.000**	-0.000***	-0.000***	-0.000**	-0.000***	-0.000***
	(0.012)	(0.011)	(0.007)	(0.001)	(0.013)	(0.001)	(0.001)
Area FE	yes	yes	yes	yes	yes	yes	yes
Constant	-4.394***	-4.385***	-4.183***	-4.802***	-4.237***	-4.837***	-5.376***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	8,473	8,473	8,473	8,473	8,473	8,473	8,473
VIF	1.377	1.376	1.375	1.375	1.375	1.348	2.771
Estimated probability. Robust pval in parenthesis (*** p<0.01, ** p<0.05, * p<0.1)							
Marginal effects (covariates at median values)							
Dummy: Travel time <2hours =1	0.0116	0.0117	0.0140	0.0131	0.0102	0.0116	0.0166
Industrial proximity at 33%	0.0161	0.0166	0.00788			0.00656	0.0457
Industrial proximity at 50%	0.0191	0.0197	0.00855			0.00714	0.0645
Industrial proximity at 75%	0.0234	0.0242	0.00942			0.00789	0.0967
Relational proximity at 3 steps-distance				0.0867		0.0704	0.100
Relational proximity at 2steps-distance				0.165		0.128	0.209
Relational proximity at 1step-distance				1.097		0.751	1.789
N. of ties, at 1 tie (Relational)					0.0314		
N. of ties, at 2 ties (Relational)					0.0409		
N. of ties, at 3 ties (Relational)					0.0559		

Coming to the role of *relational proximity*, the first indicator with which we have tried to capture it, in terms of the (inverse of the) length of the relational distance between VC and ISC (Model 4), is significantly and positively correlated with their successful match. This suggests that, as expected, the interlink between VC and ISC created by their investment and/or professional relationships facilitates their matching. The relevance of relational proximity gets confirmed when its intensity, in terms of number of social ties that link the partners between them, is considered (Model 5). This is also significantly positive and confirms that, by extending previous studies about the role of relational networks in VC deal selection (Catalini and Hui, 2018), the relational proximity between VC and ISC is also a crucial aspect to retain.

Looking at the marginal effects that relational proximity has for different degrees (steps) of relational distance between pairs, an important specification emerges (lower panel of Table 2). While relevant for concluding a VC deal, the network position of the involved actors has an effect that decays rapidly with the number of their separating steps: being at one step distance doubles (+109.7%) the probability of observing a successful pair, while the marginal effect lowers at a +16.5% when the distance between the focal partners in the network is of two steps. This is consistent with the rapid increase of the marginal effects of having progressively more linking ties between partners: from one tie (3.1%) to three ties (5.6%). In brief, not only is relational proximity relevant, but the matching we are observing is very sensitive to its change.

In concluding the analysis of relational proximity, interesting results emerge by looking at the relative interaction terms in Models (7) and (8) of Table 2 . To start with, let us notice that the interaction between industrial proximity (at 3 digits) and relational proximity (Model 7) is significantly negative, suggesting an interesting relationship of substitution between the two: a deeper (social) industrial experience of the partner, enables the focal VC to successfully target an ISC at a longer relational (industrial) distance.

However, Model (8) reveals that, inconsistently with our expectations, relational proximity does not behave like the industrial one in negatively moderating the role of tangible proximity. Indeed, the interaction between the former and the dummy for the functional distance to be lower than 2 hours, is not significant. Unlike what Sorenson and Stuart, 2001 found with respect to the relational proximity between syndicated VC firms, that between VC and ISC is not capable to compensate for the disadvantages that a longer geographical distance between the two could entail. In other words, while getting closer and trusted relationships with other VC firms might render, according to Sorenson and Stuart, 2001, the focal VC more spanning its investments across space, having the same kind of relationships with potential ISC does not render less close investments more palatable to VC firms. While both kinds of relational proximity facilitates the match – as revealed by the relative dummy among the controls of Table 2 – their power of widening the geographical scope of the relationship is instead different and limited to the relational proximity among VCs.

At this point, it should be considered that, as Table A.9 (in the Appendix) reveals, industrial and relational proximities are significantly correlated, diminishing the reliability of their estimated coefficients.[12] Nevertheless, it is possible to compare the magnitude and significance of their coefficients when simultaneously included (Model 6 and 7 in Table 2), which indicate that relational proximity is the one that matters the most in determining the VC-ISC match. The same indicative result emerges by considering the full Model (7), in which all the proximities at stake (functional, industrial and relational) and all their addressed interactions are considered.

[12]Because of word constraints, we only report each model's mean VIF at the bottom of Tables 1 and 2. However, we controlled the Variance Inflation Factor for each regressor and model, finding a value above 5 only for the interaction term between travel proximity dummy and relational proximity (VIF of 7.01) in Model 7, accounting for a model Mean VIF of 2.9.

4.3 Additional estimates and robustness checks

The results that we have obtained about the role of proximities in driving the probability of a successful VC-ISC pair appear substantially robust with respect to two important checks, which we also report in Appendix A.4.

The first robustness check concerns the possible presence of spatial autocorrelation in the phenomenon we are investigating. Indeed, this could be suggested by the spatial inequalities in the distribution of startup firms and VC offices we have highlighted in Section 3.1. Quite interestingly, excluding ISCs and VCs located in agglomerated areas, has the sole effect of increasing the magnitude of the coefficients of the individual and interacted intangible proximity terms. This result provides further evidence about the result that intangible proximities effectively counteract the barrier of physical distance with respect to Venture Capital funds.

The second robustness check that we perform concerns the presence of idiosyncratic VC investments and funds, as results might be affected by second and syndicated VC investments, which the literature has shown to differ from first and solo ones (Berchicci *et al.*, 2011, Catalini and Hui, 2018, Cumming and Dai, 2010). The main results of our analysis do not change when carrying out this second kind of checks (see Appendix A.4).

5 Conclusions

The idiosyncratic geography of VC investments in innovative start-ups represents one of the most relevant sources of widely ascertained regional gaps in innovation. Local biases in VC investments are in fact as diffused as innovative clusters in metropolitan areas. However, recent evidence seems to suggest that the geographical proximity between the partners of the VC deal does not consistently account for their combined evidence.

An important advancement in understanding the geographical distribution of VC investments, and to possibly account for this and possibly other clashes, can be obtained by making the literature on (innovation) financing talk more with that of economic geography: in particular, by drawing from the latter a manifold notion of proximity, which considers its tangible and non-tangible variants, and the possible interactions of their effects.

By implementing such a disciplinary combination, in this article we have proposed an original investigation of the role that different dimensions of proximity can have in predicting a successful matching between VC funds and innovative startups seeking for finance. This new theoretical framework has been applied to an original investigation of the universe of Italian ISC with respect to the VC market: an immature kind of market, whose knowledge is still scanty and in need of more scrutiny when compared to other countries. In contributing to fill this gap, we have exploited a recent legal (i.e. exogenous) identification of innovative start-up companies in Italy, which has allowed us to consider their entire population. By combining different sources, we have obtained a rich dataset, with which to build up already known and novel proxies of their proximity to VC funds and to address the role of these proximities in their successful matching.

Our results have first of all provided updated evidence of the existence and magnitude of regional gaps in the Italian VC market, showing that VC offices are clustered and polarised in some portions of the territory. In investigating the determinants of these gaps, we have first of all found that a tangible proximity matters, but more in functional than in geographical terms: that is, in facilitating the accessibility (by car more by plane) of partners rather than in reducing their distance. Furthermore, the effect is concave and points to the case of an excessive proximity for the deal to occur. These results convey a systematic generalisation of what has emerged from specific studies reporting managers' statements about their indifference and preference for a short physical and travel distance, respectively (Fritsch and Schilder, 2006 and Martin *et al.*, 2005). The implications of such a result are also particularly important. This is so both for future research on local biases in innovation financing, which are encouraged to incorporate a more nuanced idea of spatial proximity; and for policy makers, who should consider the development of local transport infrastructures a crucial leverage to promote effective VC deals.

We have also shown that the relationship between VC and ISC in search of finance is helped by a varied set of intangible proximities. Among these proximities, relational proximity, as reflected in the professional and investment networks of the partners, emerges as the strongest predictor of the VC-ISC matching. Furthermore, unlike the other proximities, which show a non-monothonic relationship with it, the relational one uniquely exhibits a positive exponential trend with respect to the probability of observing a successful VC-ISC pair. Also this result generalises and integrates previous findings in the financial literature (Catalini and Hui, 2018, Hermann *et al.*, 2016, Sorenson and Stuart, 2001) and has important implications. On the one hand, future research should more closely look at the role of networks in facilitating start-ups in search of financing: in particular, by addressing how strategic holdings in firms directly connected to VC funds could improve their access to risk capital. On the other hand, policy makers should consider that networking incentives could complement or inform public policies aimed at addressing funding gaps and at supporting the development of the VC market.

A last set of interesting results concerns the specific contingencies under which tangible and intangible proximities help the matching between VC and ISCs, as well as the substituting relationship we have detected between them. Previous evidence about the role of network (i.e., relational) proximity among VCs in spanning the geographical boundaries of their deals (Sorenson and Stuart, 2001) does not appear extendable to the network proximity between VC and ISC, requiring more research on this extension. Still, another form of intangible proximity, represented by the industrial experience that link the parties (i.e., industrial proximity), can play the same role. Accordingly, managers and policy makers should retain that the extra costs of scanning and monitoring more distant, and possibly more promising deals, can be attenuated, though at the cost of lower VC diversification.

As usual, our empirical analysis is not free from limitations. Although, as we noticed, the unobserved heterogeneity in the quality of startup projects could be ruled out through the application of a dyadic model, other endogeneity issues could remain. In order to address them, future research should concentrate on the identification of valid instruments for making our focal regressors - both relational and functional proximity - exogenous. A second limitation is represented by the focus of our analysis on a country with low financial-development, like Italy. While suited for the analysis of the role of proximity in mitigating regional equity gaps, such a choice obviously hinders the external validity of the results. A follow-up application in a cross-country framework would thus be required for the sake of generalization of the results that we have obtained.

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Appendix A

A.1 Location Quotient

Following Martin *et al.* (2005), in order to detect regional concentrations of VC investments that are below or above the average, we calculate a modified version of the location quotient usually applied in the literature on industrial clusters[13] defined as the ratio between: at the numerator, the share of VC-backed startups located in the region over the total of VC-backed Italian innovative startups; at the denominator, the share of all firms created in the region over the total of new firms in the country in the same period of time (2012-2018).[14]

The location quotient (LQ) denotes, at both NUTS3 and NUTS2 level, an over-concentration of investments in six of the twenty NUTS2 Italian regions, with the region of Milan (Lombardy) exhibiting an LQ 2.5 times above one (and reaching 5.3 at NUTS2 level in its capital province). The majority of the other regions instead exhibit an under-concentration of VC-capital investments, especially those located in the South and in the Northeast of the country, where a large number of firms are located but both VC funds and VC-investments are lacking. Overall, the indicator actually points to the existence of large regional equity gaps in the Italian market of VC investments in ISCs.[15]

A.2 Rare Events correction

Rare events, referred to also as imbalanced dataset or class imbalance in the statistical and data science literature, have been receiving increasing attention in the last two decades, especially since the resurgence of big-data.

When the proportion of ones (or successes) in a population is rare, when using a logistic regression to investigate its determinants its probability may be severely underestimated, and the coefficients biased towards zero. According to King and Zeng, 2001, this is the case especially that this could in fact happen when the proportion of ones over zeros is below 5%. The 'success' observations are the most informative, and yet in logistic regressions they have a smaller contribution to variance. The latter is in fact an inverse function of the odds-ratio $\pi_i(1-\pi)$, which in rare events tend to be larger, since the estimated probability in case of success π_i approaches 0.5. To address the rarity of the event under analysis, we compare different strategies among penalized estimation (Firth, 1993[16]), MLE estimation, and mixed-methods (King and Zeng, 2001; 2002)[17], contributing to the still

[13]The location quotient indicates over-concentration when its value is above 1, and under-concentration for values below 1.

[14]Data for firms demography are issued by Infocamere,Labour Market Areas would have possibly been a more suitable geographical level of analysis for this indicator, but NUTS3 regions where the most fine-grained data on firms demography available for the same years of the ISCs' sample.

[15]As we will see, to account for such a disparity, which is likely to derive not only by VC location and local bias, but also by the persistence of the Italian North-South development and productivity divide, area fixed effects will be included in the model.

[16]In its seminal 1993 paper, Firth proposed a type of penalized likelihood regression which, by imposing a 'Jeffreys prior' on model coefficients (such that $A(\beta) = \frac{1}{2} logdet(I(\beta)))$ to correct for small-sample and rare-event bias in Maximum Likelihood estimates.

[17]The methodology proposed by (King and Zeng, 2001) starts from a random selection of one 'potential' pair for each 'observed' one, and progressively increase the proportion of zeros up to when no further efficiency gains in terms of standard errors size is obtained. The process of random selection of zeros and full sampling of ones is an endogenous stratified sampling method that

relatively scarce existence of cross-discipline methodological comparisons including all the above. Through model comparison we select Firth methodology on the original sample, and maintain the methodology for the rest of the article, for two reasons. Firstly, as shown in Table A.8, the Firth-penalized logistic method applied on the full sample outperformed King and Zeng's mixed method in terms of minimisation of standard errors for almost all models disregarding the inclusion of controls and main covariates. This result is in line with a number of recent dedicated publications (Leitgob, 2020; Rainey, 2016Bacaksiz and Koç, 2021; Puhr *et al.*, 2017) who found penalized logistic with Jeffrey's prior to be suitable for bias and SE minimization. However, it must be noted that, while Firth (1993)'s penalization is preferred for providing unbiased parameter estimates, it has been found to be biased towards zero in prediction (Puhr *et al.*, 2017; Elgmati *et al.*, 2015). As such, our marginal effects are likely to underestimated. Secondarily, given the results' high-comparability between traditional MLE on the full sample, the Firth-Penalized ML on the full sample and King and Zeng corrected logistic on the reduced samples, we opt to work with for the original dataset, avoiding data manipulation, increasing the reliability and replicability of our results.

A.3 Network distance

The network distance between each VC and each ISC is defined as the *number of steps needed to find an undirected link between them*. Undirected links, which identify "relations that do not distinguish between senders and receivers, like alliance partners" (Yang *et al.*, 2017, p. 11), were calculated in terms of inward (shareholders) and outward-holdings of firms, funds and of their managers and advisors. Previous-to-the-investment professional positions of managers and advisors of all firms involved in the network were also added to the same symmetric matrix, and treated equally and jointly to obtain our minimum-number-of-steps variable for all dyads.

A.4 Additional estimates and robustness checks

The results we have obtained about the role of proximities in driving the probability of a successful VC-ISC pair appear substantially robust to two important checks. The first concerns the possible presence of spatial autocorrelation in the phenomenon we are investigating, as suggested by the spatial inequalities in the distribution of startup firms and VC offices we have highlighted in Section 3.1. To check for its actual presence and effects, we have first referred to the Local Market Areas (LMAs hereinafter) of the Italian territory, identified by the national statistical office (Istat) as "sub-regional geographical areas where the bulk of the labour force lives and works, and where establishments can find the largest amount of the labour force necessary to occupy the offered jobs" (Istat, 2014, p.1). With respect to these LMAs, Figure A.3 shows that a significant Moran (1948)'s global index of spatial autocorrelation is revealed only by the number of ISCs. Accordingly, the ISCs located in those LMAs where the local Moran's index (for the number of ISCs) was found significant at 5% level have been excluded from the original sample before re-estimating

introduces a bias in the logistic model. The bias can be easily solved by weighting the exogenous variables by the true successes proportion in the population (King and Zeng, 2001). The weighting factor take this form $w_i = diag[\hat{\pi}_i(1 - \hat{\pi}_i)\omega_i]$, where ω_i is the true success proportion in the population.

the full model. The spatial auto-correlation analysis has been repeated with respect to Italian NUTS3 regions (i.e. Italian provinces). At this level of analysis, as shown in Figure A.4, no variable appears significantly correlated at the global level, with the exception of the province of Milan, exhibiting significant local autocorrelation throughout the whole set of variables, and of those of Milan and Rome, revealing the same autocorrelation for the number of ISCs. On this basis, the full model has been re-estimated by excluding these two provinces, which are also the ones hosting the largest number of VC funds offices and whose exclusion thus allows us to control for outlier areas.

The model proves robust to the exclusion of ISCs located in both LMAs and NUTS3 regions where the number of ISCs reveals significantly spatially autocorrelated. In particular, when ISCs (Columns 1-2 of Table A.10) or VCs (Column 3) located in such areas are excluded the marginal effects of both the measures of intangible proximity, *i.e.* industrial (at sub-sector level) and relational, more than double with respect to the same model estimated on the full sample (Model 7 of Table 2), suggesting that outside the most advantaged areas, intangible proximity dimensions play a stronger role.

The second robustness check that we perform concerns the presence of idiosyncratic VC investments and funds, as results might be affected by second and syndicated VC investments[18], which the literature has shown to differ from first and solo ones in terms of signalling effects, information asymmetries, and of strategies to reduce the risks of investing in technologically or physically distant firms (Berchicci *et al.*, 2011, Catalini and Hui, 2018, Cumming and Dai, 2010). In our period of analysis (2014-2019), only 20 investments were done in syndication with another VC partner (all among Italian VCs), while three foreign VCs participated in 1 joint operation. As Table A.10 (in Columns 4-6) shows, the removal of the 23 syndicated investment-pairs from the sample does not change the results substantially. Our results are also robust to the exclusion of foreign VC, as shown in Column 7 of Table A.10.

[18]As is well-know, syndication is a common practice in VC investments, denoting the joint presence of multiple investors in providing the funding needed by one company.

Additional Tables and Figures

Table A.3. ISC and location-specific control variables, descriptive statistics

Variable	Obs	Mean	Std.Dev.	Min	Max
ISC characteristics					
Age at finance	8480	2.79	1.41	0.00	5.44
N. of managers	8480	4.08	3.18	0.00	15.00
Female managers, share	8278	0.15	0.25	0.00	1.00
N. of employees	6110	3.76	4.67	0.00	28.00
Investment type					
Dummy: ISC had prior VC investment	8480	0.03	0.18	0.00	1.00
Dummy: syndicated investment	8480	0.02	0.15	0.00	1.00
Innovativity requirements (Law 221/2012)					
R&D>15% of prod.costs	8480	0.67	0.47	0.00	1.00
Patents ownership	8480	0.20	0.40	0.00	1.00
2/3 MA degree or 1/3 PhD holders	8480	0.22	0.41	0.00	1.00
Profitability					
Net worth (TEUR)	6113	517.02	1511.90	-5.52	11261.49
Revenues (TEUR)	6183	246.94	540.86	0.00	3299.24
Net profit (TEUR)	6183	-210.62	500.45	-3666.00	205.10
EBITDA (TEUR)	6113	-147.59	340.88	-2692.20	342.55
Location specific					
Population at legal office seat, th., 2012	8480	2316.87	1394.61	182.48	4321.24
Population density at legal office seat, sqkm, 2012	8480	1011.53	821.61	49.50	2622.00
GDP, province, (Million EUR), 2012	8480	91.28	64.36	4.27	156.00
EPO patent appl., per million inhabs, 2012	8480	72.16	43.81	2.72	201.06
N. of active high growth firms, per 4digit NACE, 201	8480	638.10	1080.30	4.00	12791.00
N. of active firms, per 4digit NACE, 2012	8480	21443.80	33501.10	151.00	333068.00
N. of events organized in coworking spaces, 2012	8480	149.33	163.55	0.00	399.00

Table A.4. VC-specific control variables, descriptive statistics

Data source	Variable	Obs	Mean	Std.Dev.	Min	Max
		VC characteristics				
Orbis, BvD	N. of shareholders	8480	16.92	46.34	0.00	245.00
	N. of companies in corporate group	8480	3.52	5.62	0.00	38.00
	N. of employees	7660	4.20	6.54	0.00	29.00
	N. of managers	8480	8.71	8.36	0.00	39.00
	Managers, age	7226	48.94	7.02	30.33	58.00
	VC fund, age	8480	10.31	7.73	2.95	40.29
	Legal office in a metro area, dummy	8480	0.88	0.32	0.00	1.00
Registro delle imprese	VC fund is an Incubator, dummy	8480	0.11	0.32	0.00	1.00
	VC fund is a Start-up, dummy	8480	0.07	0.25	0.00	1.00
		Investments				
Own elaboration on Orbis and AIDA (BvD) data	N. of investments, per NACE 4digits	8480	1.14	2.24	0.00	16.00
	N. of investments, per NACE 3digits	8480	1.50	2.94	0.00	25.00
	N. of investments, per NACE 2digits	8480	1.47	2.91	0.00	25.00
	N. of investments, per sector	8480	2.12	4.29	0.00	43.00
	Sh. of investments, per NACE 4digits	8480	0.05	0.12	0.00	1.00
	Sh. of investments, per NACE 3digits	8480	0.07	0.15	0.00	1.00
	Sh. of investments, per NACE 2digits	8480	0.07	0.15	0.00	1.00
	Sh. of investments, per sector	8480	0.14	0.22	0.00	1.00
	N. of investments, per city	8480	0.60	1.41	0.00	8.00
	N. of investments, per province	8480	0.63	1.28	0.00	8.00
	N. of investments, per region	8480	8.22	13.41	0.00	68.00
	Sh. of investments, per city	8480	0.06	0.14	0.00	0.89
	Sh. of investments, per province	8480	0.08	0.19	0.00	1.00
	Sh. of investments, per region	8480	0.76	0.41	0.00	1.00
		Productivity				
Own elaboration on Orbis and AIDA (BvD) data	Value of production (TEUR)	528	399.67	710.73	0.00	3470.34
	Labor costs (TEUR)	369	25703.09	16681.07	0.00	82360.00
	Labour productivity (TEUR)	376	6.08	12.47	0.00	79.30
	R&P costs (TEUR)	144	153.41	212.22	0.00	1015.06
	Value added (TEUR)	528	-67.20	381.29	-2673.74	1082.04
	Value added per capita (TEUR)	314	6989.33	34318.17	-38420.00	111780.00
	Patents right (TEUR)	144	28.19	76.43	0.00	342.20
	Licenses (TEUR)	144	1.61	3.17	0.00	10.64
	Operative turnover, (TEUR)	528	2027.00	4375.78	0.00	21592.00

Table A.5. Proximity/distances descriptive statistics by value of the dependent variable.

Type	Variable	Y	Obs	Mean	Std.	Min	Max
Geographical	Geographical proximity	0	8320	336.72	5791.76	0.00	100000.00
		1	160	6875.77	25382.09	0.00	100000.00
Functional	Functional proximity	0	8320	0.11	1.06	0.00	16.67
		1	160	1.41	4.38	0.00	16.67
	Dummy: travel time<2hours	0	8320	0.68	0.47	0.00	1.00
		1	160	0.81	0.40	0.00	1.00
	Dummy: travel time<1/2hour	0	8320	0.19	0.39	0.00	1.00
		1	160	0.43	0.50	0.00	1.00
	Dummy: min. travel by car	0	8320	0.41	0.49	0.00	1.00
		1	160	0.61	0.49	0.00	1.00
Co-location	Dummy same city	0	8320	0.19	0.39	0.00	1.00
		1	160	0.45	0.50	0.00	1.00
	Dummy same province	0	8320	0.00	0.06	0.00	1.00
		1	160	0.01	0.08	0.00	1.00
	Dummy same region	0	8320	0.04	0.19	0.00	1.00
		1	160	0.09	0.28	0.00	1.00
	Dummy same area	0	8320	0.12	0.33	0.00	1.00
		1	160	0.08	0.27	0.00	1.00
Relational	Relational proximity	0	8320	0.17	0.09	0.00	1.00
		1	160	0.27	0.28	0.00	1.00
	N. of ties	0	8320	0.02	0.18	0.00	3.00
		1	160	0.35	0.77	0.00	6.00
Industrial	Industrial proximity (2digits)	0	8320	0.18	0.29	0.00	1.00
		1	160	0.26	0.39	0.00	1.00
	Industrial proximity (3digits)	0	8320	0.16	0.28	0.00	1.00
		1	160	0.25	0.39	0.00	1.00
	Industrial proximity (4digits)	0	8320	0.08	0.20	0.00	1.00
		1	160	0.09	0.24	0.00	1.00

Table A.6. Proximity variables: definition, calculation and data sources

Definition	Variable	Calculation	Specifics and data sources
Geographical Proximity: inverse of the length of the shortest path between two points, calculated along the ellipsoidal surface of the Earth.	*Geographical proximity*	Inverse of the minimum geodetic distance among all ISC and VC offices (Vincenty's 1975 equation)	Based on VC and ISC offices coordinates, at exact-address precision. **Source:** own calculation on *AIDA BvD* data.
Functional proximity: inverse measure of "the distance separating any two nodes such that it reflects the net effect of nodal properties upon their propensity to interact" (Brown and Horton, 1970, p.76)	*Functional proximity*	Inverse of the minimum travel-time in minutes among all ISC and VC offices	Inverse of travel times (by car, flight, train or ferry or a mix of them) at exact address precision. **Source:** own calculation on data from *hereAPI*, *rome2rio.com* and *openflights.org*
	Dummy: travel time<2hours	Dummy: minimum travel-time is within two hours	Travel time (by car, flight, train or ferry or a mix of them) is within two hours, at exact address precision. **Source:** own calculation on data from *hereAPI*, *rome2rio.com* and *openflights.org*
	Dummy: travel time<1/2hour	Dummy: minimum travel-time is within half an hour	Travel time (by car, flight, train or ferry or a mix of them) is within half an hour, at exact address precision. **Source:** own calculation on data from *hereAPI*, *rome2rio.com* and *openflights.org*
	Dummy: minimum travel time is by car	Dummy: minimum travel-time is by car	Minimum travel time is by car. **Source:** own calculation on webscraped data from *hereAPI*, *rome2rio.com* and *openflights.org*
Co-location: joint presence in the same territory of the ISC and VC offices	*Dummy: same city*	Mutually exclusive dummy variables, indicating if a VC branch is located in the same city, province or region of the ISC offices.	VC and ISC have at least one office in the same municipality. **Source:** AIDA BvD.
	Dummy same province		VC and ISC have at least one office, if not in the same municipality, in the same province. **Source:** AIDA BvD.
	Dummy same region		VC and ISC have at least one office, if not in the same municipality or province, in the same region. **Source:** AIDA BvD.
Relational proximity: a measure encompassing more than one non-tangible dimensions of proximity, such as social, cognitive and organizational ones (Moodysson and Jonsson, 2007)	*Relational proximity*	Inverse of the network distance (Number of steps to find a link among each VC and ISC)	Network distance: calculated considering undirected links among all holdings, investors and managers of ISCs and VCs. **Source:** own calculation on AIDA and ORBIS data.
	N. of ties	Number of ties existing among each VC and ISC	Number of ties: number of common names among managers, holdings, investors in any role in the two firms. **Source:** own calculation on AIDA and ORBIS data.
Industrial proximity: "Shared knowledge base, needed in order to communicate, understand, absorb and process new information successfully" (Boschma, 2005, p. 64)	*Industrial proximity (2 digits)*	Share of VC previous investment in the same ISC division (2digit NAICS code)	Per each VC investment: ratio among the number of investments in any type of firm within a specific NAICS code, on the total number of firms funded from 01/01/2012 up to the date of the investment under analysis. **Source:** own calculation on AIDA and ORBIS BvD data.
	Industrial proximity (3 digits)	Share of VC previous investment in the same ISC group (3digit NAICS code)	
	Industrial proximity (4 digits)	Share of VC previous investment in the same ISC industry (4digit NAICS code)	

Table A.7. ISCs, VC, and investments geographical distribution and location quotient.
Note: the location quotients here reported are calculated without including second investments.

Area	NUTS3 Data Province: NUTS3 (capital regions only)	LQ NUTS3	NUTS2 Data Region: NUTS2	LQ NUTS2	N. of ISCs N.	Share	N. of VC offices N.	Share	N. of VC-backed ISCs N.	Share	N. of VC-ISC investments N.	Share
	Milano	**5.29**	Lombardia	**2.64**	2587	**25.3%**	17	**58.6%**	57	**41.9%**	69	**43.1%**
	Torino	**1.87**	Piemonte	**1.12**	541	5.3%	2	6.9%	11	8.1%	12	7.5%
	Genova	0.56	Liguria	0.57	191	1.9%	1	3.4%	2	1.5%	3	1.9%
	Aosta	0.00	Valle D'Aosta	0.00	21	0.2%	0	0.0%	0	0.0%	0	0.0%
NorthWest		***1.93***		*1.09*	*3340*	***32.7%***	*20*	***69.0%***	***70***	***51.5%***	***84***	***52.5%***
	Trento	0.96	Trentino	0.45	265	2.6%	0	0.0%	1	0.7%	1	0.6%
	Bologna	0.47	Emilia	0.50	905	8.9%	1	3.4%	5	3.7%	7	4.4%
	Venezia	0.00	Veneto	0.49	866	8.5%	1	3.4%	5	3.7%	1	0.6%
	Trieste	0.00	Friuli	0.48	220	2.2%	0	0.0%	1	0.7%	7	4.4%
NorthEast		*0.36*		*0.48*	*2256*	***22.1%***	*2*	*6.9%*	*12*	*8.8%*	*16*	*10.0%*
	Firenze	**2.40**	Toscana	1.04	438	4.3%	2	6.9%	10	7.4%	13	8.1%
	Roma	**1.90**	Lazio	**1.44**	1139	11.2%	3	10.3%	22	16.2%	25	15.6%
	Ancona	0.00	Marche	0.28	370	3.6%	0	0.0%	1	0.7%	1	0.6%
	Perugia	0.00	Umbria	0.00	193	1.9%	0	0.0%	0	0.0%	0	0.0%
Center		*1.07*		*0.69*	*2140*	*21.0%*	*5*	*17.2%*	***33***	***24.3%***	***39***	***24.4%***
	Cagliari	**2.74**	Sardegna	**1.42**	149	1.5%	1	3.4%	5	3.7%	5	3.1%
	Palermo	0.00	Sicilia	0.59	497	4.9%	1	3.4%	6	4.4%	6	3.8%
Islands		***1.37***		*1.00*	*646*	*6.3%*	*2*	*6.9%*	*11*	*8.1%*	*11*	*6.9%*
	Potenza	**1.32**	Basilicata	0.83	110	1.1%	0	0.0%	1	0.7%	1	0.6%
	Napoli	0.43	Campania	0.43	804	7.9%	0	0.0%	6	4.4%	6	3.8%
	Bari	0.30	Puglia	0.22	401	3.9%	0	0.0%	2	1.5%	2	1.3%
	L'Aquila	0.00	Abruzzo	0.00	218	2.1%	0	0.0%	0	0.0%	0	0.0%
	Catanzaro	0.00	Calabria	0.25	224	2.2%	0	0.0%	1	0.7%	1	0.6%
	Campobasso	0.00	Molise	0.00	74	0.7%	0	0.0%	0	0.0%	0	0.0%
South		*0.34*		*0.29*	*1831*	*17.9%*	***0***	*0.0%*	*10*	*7.4%*	*10*	*6.3%*
Italy, totals		*0.50*		*0.64*	*10213*		*29*		*136*		*160*	

Table A.8. Comparison of sampling and estimation methods for rare events bias correction. Models have been ordered from smaller (left) to larger (right) root mean squared error (RMSE).

Model with functional proximity, without controls.

	Sample	Full Sample	Full Sample	Sample 1:7	Sample 1:6	Sample 1:5	Sample 1:4	Sample 1:3	Sample 1:2	Sample 1:1
	Method	Firth ML	logit	KingZeng	KingZeng	KingZeng	KingZeng	KingZeng	KingZeng	KingZeng
Functional proximity										
Dummy: Travel	Coeff.	0.653***	0.665***	0.605***	0.607***	0.632***	0.663***	0.627***	0.613***	0.602**
time <2hours	St.Err.	0.200	0.201	0.21	0.212	0.214	0.217	0.222	0.233	0.262
Constant	Coeff.	-4.432***	-4.448***	-4.398***	-4.400***	-4.417***	-4.439***	-4.415***	-4.406***	-4.401***
	St.Err.	0.179	0.181	0.187	0.189	0.19	0.192	0.197	0.205	0.228
N		8,480	8,480	1,280	1,120	960	800	640	480	320
Marginal effects covariates at median values										
Dummy: Travel time<2hours =1		0.0149	0.0151	0.0136	0.0137	0.0143	0.0152	0.0142	0.0138	0.0135

Model with functional proximity and controls.

	Sample	Full Sample	Full Sample	Sample 1:7	Sample 1:6	Sample 1:5	Sample 1:4	Sample 1:3	Sample 1:2	Sample 1:1
	Method	Firth ML	logit	KingZeng	KingZeng	KingZeng	KingZeng	KingZeng	KingZeng	KingZeng
Functional proximity										
Dummy: Travel	Coeff.	1.010***	1.020***	0.924***	0.886***	0.901***	0.952***	0.816***	0.823***	0.603*
time <2hours	St.Err.	0.24	0.242	0.26	0.261	0.264	0.267	0.276	0.297	0.336
Controls										
Dummy: ISC had prior	Coeff.	1.007***	0.977***	0.897**	0.843**	0.742**	0.835**	0.811**	0.679	0.434
VC investment	St.Err.	0.31	0.316	0.365	0.368	0.372	0.387	0.412	0.443	0.45
Dummy: syndicated	Coeff.	2.511***	2.510***	2.555***	2.427***	2.453***	2.510***	2.641***	2.571***	2.476***
investment	St.Err.	0.232	0.234	0.306	0.309	0.324	0.346	0.398	0.459	0.625
ISC's age at finance	Coeff.	-0.146**	-0.147**	-0.160**	-0.163**	-0.157**	-0.166**	-0.179***	-0.177**	-0.149*
	St.Err.	0.0605	0.0607	0.0661	0.0646	0.0644	0.0657	0.0678	0.0705	0.0805
L1. GDP, at ISCs	Coeff.	-4.68e-06***	-4.62e-06***	-5.20e-06***	-5.39e-06***	-5.95e-06***	-6.45e-06***	-5.40e-06***	-6.51e-06***	-6.58e-06**
	St.Err.	1.72E-06	1.73E-06	1.96E-06	1.97E-06	1.98E-06	2.04E-06	2.1E-06	2.25E-06	2.67E-06
Constant	Coeff.	-4.141***	-4.173***	-3.895***	-3.799***	-3.744***	-3.725***	-3.697***	-3.532***	-3.376***
	St.Err.	0.298	0.3	0.318	0.324	0.331	0.333	0.349	0.38	0.451
Area FE		yes	yes	yes	yes	yes	yes	yes	yes	yes
N		8,473	8,473	1,278	1,118	958	798	638	478	318
Marginal effects (covariates at median values)										
Dummy: Travel time<2hours =1		0.0146	0.0145	0.0139	0.0208	0.0174	0.0237	0.0189	0.0123	0.0119

Model with functional, industrial, relational proximities and controls.

	Sample	Full Sample	Full Sample	Sample 1:7	Sample 1:6	Sample 1:5	Sample 1:4	Sample 1:3	Sample 1:2	Sample 1:1
	Method	Firth ML	logit	KingZeng	KingZeng	KingZeng	KingZeng	KingZeng	KingZeng	KingZeng
Functional proximity										
Dummy: Travel	Coeff.	1.036***	1.051***	0.994***	0.922***	0.947***	0.988***	0.825***	0.827***	0.676*
time <2hours	St.Err.	0.248	0.25	0.276	0.277	0.277	0.284	0.292	0.317	0.36
Industrial proximity										
Industrial proximity	Coeff.	0.498*	0.490*	0.691**	0.772**	0.831***	0.852***	0.878***	0.898**	1.026**
(3digits)	St.Err.	0.256	0.257	0.315	0.313	0.32	0.324	0.335	0.362	0.406
Relational proximity										
Relational proximity	Coeff.	3.535***	3.548***	3.817***	3.953***	3.763***	3.750***	3.405***	3.481***	3.828***
	St.Err.	0.364	0.368	0.596	0.654	0.666	0.708	0.702	0.821	1.128
Controls										
Dummy: ISC had prior	Coeff.	1.116***	1.090***	0.970**	0.924**	0.829**	0.946**	0.937**	0.773	0.657
VC investment	St.Err.	0.315	0.321	0.391	0.401	0.408	0.434	0.468	0.517	0.559
Dummy: syndicated	Coeff.	2.595***	2.599***	2.748***	2.610***	2.642***	2.683***	2.810***	2.721***	2.636***
investment	St.Err.	0.238	0.24	0.313	0.316	0.331	0.357	0.411	0.476	0.658
ISC's age at finance	Coeff.	-0.156**	-0.157**	-0.192***	-0.190***	-0.182***	-0.187***	-0.202***	-0.200***	-0.160*
	St.Err.	0.0621	0.0624	0.0704	0.0693	0.069	0.0701	0.0721	0.074	0.0818
L1. GDP, at ISCs	Coeff.	-5.67e-06***	-5.64e-06***	-6.18e-06***	-6.31e-06***	-6.87e-06***	-7.14e-06***	-5.93e-06***	-6.84e-06***	-6.94e-06**
NUTS3 (MEUR)	St.Err.	1.75E-06	1.76E-06	2.03E-06	2.04E-06	2.06E-06	2.13E-06	2.19E-06	2.35E-06	2.86E-06
Constant	Coeff.	-4.837***	-4.876***	-4.680***	-4.607***	-4.542***	-4.539***	-4.447***	-4.308***	-4.314***
	St.Err.	3.13E-01	3.16E-01	3.55E-01	3.65E-01	3.75E-01	3.79E-01	3.90E-01	4.36E-01	4.84E-01
Area FE		yes	yes	yes	yes	yes	yes	yes	yes	yes
N		8,473	8,473	1,278	1,118	958	798	638	478	318
Marginal effects (covariates at median values)										
Dummy: Travel time<2hours =1		0.0116	0.0115	0.0109	0.0169	0.0136	0.0189	0.0145	0.00912	0.00989
Industrial proximity at 50%		0.00714	0.00687	0.0107	0.0208	0.0181	0.0250	0.0239	0.0155	0.0251
Relational proximity at 2steps-distance		0.128	0.127	0.150	0.270	0.190	0.251	0.186	0.123	0.201

Table A.9. Pairwise correlation, dependent and proximity variables

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)
Dependent variable																		
(1) Y=VC-ISC deal, dummy	**1.000**																	
Spatial proximity																		
(2) Geographical proximity	**0.131**	**1.000**																
geodetic	0.000																	
Functional proximity																		
(3) Travel proximity	**0.145**	**0.920**	**1.000**															
	0.000	0.000																
(4) Dummy	**0.036**	**0.046**	**0.074**	**1.000**														
Min. travel by car	0.001	0.000	0.000															
(5) Dummy	**0.049**	**0.053**	**0.079**	**-0.266**	**1.000**													
Min. travel<2hours	0.000	0.000	0.000	0.000														
Co-location																		
(6) Co-location	**0.089**	**0.138**	**0.209**	**0.329**	**0.285**	**1.000**												
same city	0.000	0.000	0.000	0.000	0.000													
(7) Co-location	**0.006**	**-0.004**	**-0.005**	**0.041**	**0.047**	**-0.030**	**1.000**											
same province	0.583	0.705	0.647	0.000	0.000	0.006												
(8) Co-location	**0.035**	**-0.014**	**-0.019**	**0.100**	**0.156**	**-0.099**	**-0.012**	**1.000**										
same region	0.001	0.211	0.074	0.000	0.000	0.000	0.265											
(9) Co-location	**-0.017**	**-0.025**	**-0.037**	**0.092**	**-0.027**	**-0.183**	**-0.022**	**-0.074**	**1.000**									
same area	0.118	0.020	0.001	0.000	0.015	0.000	0.038	0.000										
Industrial proximity																		
(10) Industrial proximity	**0.041**	**0.042**	**0.026**	**0.007**	**-0.004**	**0.003**	**0.047**	**-0.023**	**0.101**	**1.000**								
2 digits	0.000	0.000	0.016	0.495	0.707	0.748	0.000	0.032	0.000									
(11) Industrial proximity	**0.043**	**0.047**	**0.032**	**0.019**	**0.004**	**0.024**	**0.007**	**-0.018**	**0.095**	**0.946**	**1.000**							
3 digits	0.000	0.000	0.003	0.076	0.694	0.025	0.535	0.105	0.000	0.000								
(12) Industrial proximity	**0.012**	**-0.009**	**-0.012**	**0.023**	**0.002**	**0.022**	**0.036**	**-0.012**	**0.063**	**0.571**	**0.605**	**1.000**						
4 digits	0.267	0.424	0.265	0.038	0.856	0.043	0.001	0.253	0.000	0.000	0.000							
Relational proximity																		
(13) Relational proximity	**0.150**	**0.245**	**0.246**	**0.011**	**0.025**	**0.083**	**-0.001**	**-0.003**	**-0.017**	**0.137**	**0.143**	**-0.033**	**1.000**					
	0.000	0.000	0.000	0.310	0.023	0.000	0.902	0.758	0.110	0.000	0.000	0.002						
(14) N. of ties	**0.209**	**0.261**	**0.344**	**0.035**	**0.039**	**0.068**	**-0.008**	**0.051**	**-0.034**	**0.130**	**0.141**	**-0.002**	**0.603**	**1.000**				
	0.000	0.000	0.000	0.001	0.000	0.000	0.458	0.000	0.002	0.000	0.000	0.835	0.000					
Controls																		
(15) ISC prior VC investment	**0.037**	**-0.003**	**0.002**	**0.012**	**-0.003**	**0.008**	**-0.011**	**-0.034**	**0.001**	**-0.056**	**-0.050**	**-0.041**	**-0.010**	**-0.012**	**1.000**			
Dummy	0.001	0.788	0.853	0.273	0.796	0.487	0.300	0.002	0.898	0.000	0.000	0.000	0.365	0.252				
(16) Syndicated investment	**0.142**	**0.023**	**0.020**	**0.014**	**0.008**	**0.021**	**-0.010**	**0.001**	**0.015**	**-0.009**	**-0.007**	**0.006**	**0.009**	**0.015**	**0.001**	**1.000**		
Dummy	0.000	0.031	0.071	0.197	0.458	0.049	0.381	0.954	0.173	0.408	0.526	0.565	0.427	0.163	0.940			
(17) ISC's age at finance	**-0.015**	**-0.012**	**-0.037**	**0.019**	**-0.051**	**-0.049**	**-0.027**	**-0.020**	**-0.023**	**0.025**	**0.011**	**0.027**	**-0.001**	**-0.014**	**-0.010**	**0.069**	**1.000**	
	0.170	0.274	0.001	0.083	0.000	0.000	0.013	0.065	0.035	0.021	0.297	0.013	0.892	0.199	0.363	0.000		
(18) L1. GDP, at ISCs NUTS3	**0.001**	**0.002**	**0.042**	**0.640**	**-0.337**	**0.448**	**0.000**	**-0.203**	**-0.015**	**-0.022**	**-0.002**	**0.008**	**0.001**	**-0.007**	**0.019**	**0.028**	**-0.015**	**1.000**
	0.891	0.888	0.000	0.000	0.000	0.000	0.970	0.000	0.160	0.047	0.823	0.446	0.898	0.537	0.076	0.009	0.179	

Figure A.3. Spatial Autocorrelation Analysis, at LMA level.

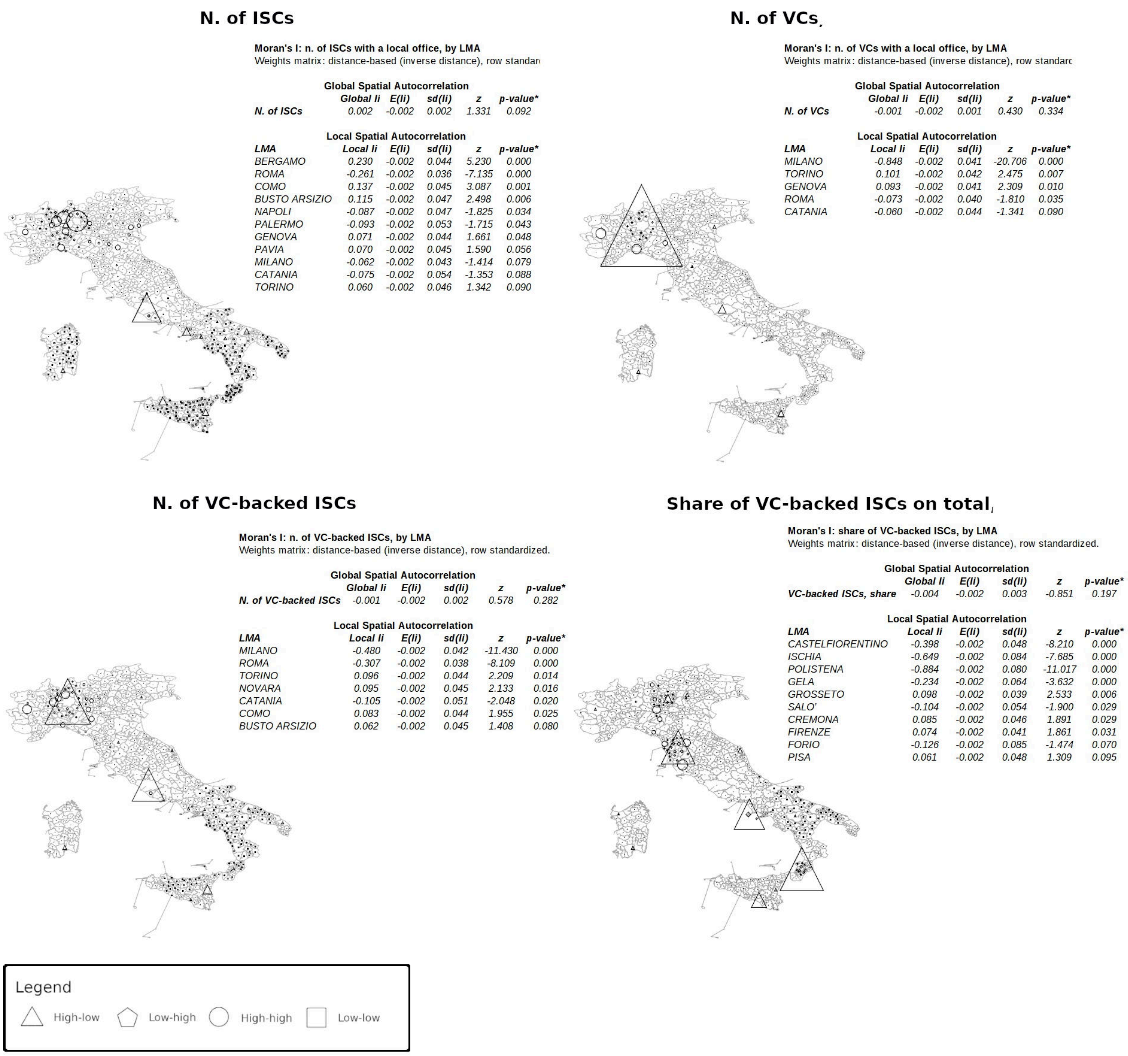

Figure A.4. Spatial Autocorrelation Analysis, at NUTS3 level.

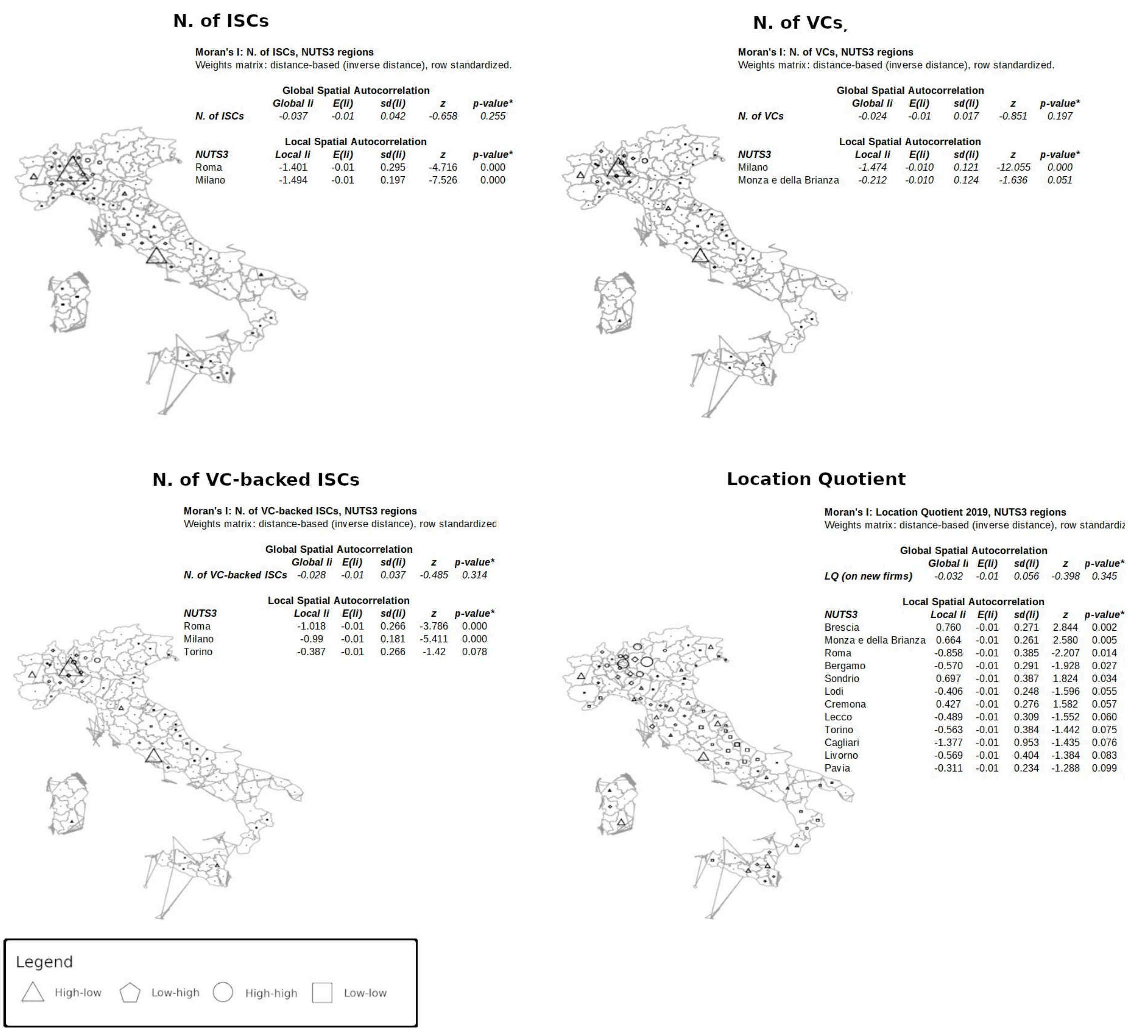

Table A.10. Robustness Checks: exclusion of spatially autocorrelated Local Labour Markets by number of ISCs or per number of VCs (as listed in figures Figure A.3 and Figure A.4), of firms located in Milan, of syndicated and second investments and of foreign funds.

	No ISCs located in Milan (NUTS3)	No Spatially Autocorr. SLL, n.ISCs	No Spatially Autocorr. SLL, n.VCs	No Syndication	No Second Investments	No Second-No Syndication	No Foreign VCs
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Functional proximity							
Dummy: travel time<2hours	1.375***	1.496***	1.350***	1.334***	1.329***	1.209***	1.494***
	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.003)	(0.000)
Industrial proximity							
Industrial proximity 3 digits	2.312***	2.337***	2.322***	2.188***	2.149***	2.298***	2.346***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Relational proximity							
Relational proximity	4.509***	4.517***	4.496***	4.530***	4.247***	4.382***	4.288***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Interactions							
Industrial proximity 3digits * Dummy travel time<2hours	-1.201**	-1.229	-1.199**	-1.326**	-1.275**	-1.124**	-1.617***
	(0.040)	(0.107)	(0.041)	(0.017)	(0.021)	(0.046)	(0.003)
Industrial proximity 3digits * Relational Proximity	-2.307**	-2.138*	-2.307**	-1.616**	-1.797**	-2.080***	-1.533**
	(0.027)	(0.071)	(0.027)	(0.034)	(0.020)	(0.008)	(0.047)
Relational proximity * Dummy travel time<2hours	0.556	0.325	0.571	-0.066	0.514	0.447	0.168
	(0.590)	(0.802)	(0.580)	(0.936)	(0.552)	(0.615)	(0.835)
Controls							
Dummy: ISC had prior VC investment	0.962**	1.313**	0.961**	1.079***	-	-	1.064***
	(0.025)	(0.039)	(0.026)	(0.002)			(0.002)
Dummy: syndicated investment	2.582***	2.806***	2.583***	-	2.560***	-	2.554***
	(0.000)	(0.000)	(0.000)		(0.000)		(0.000)
ISC's age at finance	-0.137*	-0.092	-0.142*	-0.175***	-0.150**	-0.182***	-0.153**
	(0.062)	(0.360)	(0.060)	(0.008)	(0.019)	(0.007)	(0.017)
L1. GDP, at ISCs NUTS3 (MEUR)	-0.000***	-0.000	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***
	(0.004)	(0.143)	(0.005)	(0.007)	(0.000)	(0.002)	(0.001)
Area FE	yes	yes	yes	yes	yes	yes	yes
Constant	-5.506***	-5.263***	-5.471***	-5.313***	-5.283***	-5.202***	-5.399***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	5,612	2,926	5,491	8,269	7,673	7,509	7,700
Proportion of ones	1.84%	1.91%	1.31%	1.58%	1.88%	1.60%	1.95%
Estimated probability. Robust pval in parenthesis (*** p<0.01, ** p<0.05, * p<0.1)							
Marginal effects (covariates at median values)							
Dummy: Travel time <2hours =1	0.0266	0.0489	0.0260	0.0227	0.0239	0.0196	0.0275
Industrial proximity at 33%	0.0958	0.0370	0.0964	0.0768	0.0786	0.0794	0.0937
Industrial proximity at 50%	0.142	0.0550	0.143	0.111	0.113	0.117	0.140
Industrial proximity at 75%	0.225	0.0878	0.228	0.173	0.174	0.186	0.223
Relational proximity at 3 steps-distance	0.182	0.0692	0.181	0.162	0.153	0.145	0.159
Relational proximity at 2steps-distance	0.392	0.149	0.388	0.350	0.315	0.306	0.330
Relational proximity at 1step-distance	3.733	1.427	3.675	3.369	2.631	2.736	2.812