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Proximity relations and the fate of VC-backed startups: evidence from a worldwide 33-year-long dataset

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Abstract

The characteristics of financial arrangements established to finance startups affect their fate. Among these features, we particularly focus on the proximities and differences between venture capital (VC) investors in syndicated investments. We consider the proximities between investors in a startup and between them and the startup. On the background of the theoretical literature dealing with proximity relations, we distinguish five types of proximities between VC investors and between VC investors and the startups they finance: geographic, institutional, organizational, social and cognitive proximities. We then test six hypotheses regarding the impacts of these proximities on the likelihood of three events that can happen to VC-backed startups: obtaining a later stage round of funding; going public; being merged or acquired. We implement these tests on a 34-year-long-68-countries-large sample, using survival models adapted to account for tied failures and competing events. We find that the five forms of proximity relations are influential, but with distinct roles. We also find that their impacts are nonlinear, in the sense that too much proximity/distance always ends-up reverting the effects of proximity/distance. Finally, we observe that, like theoretical literature predicts, cognitive proximity is positively correlated to the probability of a M&A, but negatively correlated to the likelihood of an IPO.

Keywords: Venture capital; syndication; startups; proximity relations; cognitive proximity

JEL Codes: G24; G34; L21; L26; M13

1. Introduction

The venture capital (VC) market has proven successful in supporting the creation of innovative businesses worldwide. This is not only because it provides efficient ways of managing agency problems (Gompers, 1995, Gompers and Lerner, 2006, Tykvová, 2007), but also because it helps handling knowledge spillovers (Antonelli and Teubal, 2010) and contributes to developing useful innovation networks (Ferrary and Granovetter, 2009). The literature that considers VC deals as optimal financial contracts solving asymmetric information and market failure problems has provided valuable insights (Lockett and Wright, 1999, Casamatta and Haritchabalet, 2007, Bayar et al., 2020). However, a large strand of alternative literature also underlines that syndicated VC deals¹ generate teams of investors and investees engaged in interactive learning and coordination processes wherein mutual understanding, trust, and smooth communication are crucial capabilities (Brander et al. (2002), Audretsch and Keilbach (2007), Sorenson and Stuart (2008), Antonelli and Teubal (2010), Bottazzi et al. (2016)). These desirable human interactions for effective business relationships certainly result from the terms and restrictions of financial contracts, but just as much from the social structures in which economic interactions take place.

In this sense, proponents of the evolutionary approach to innovation, entrepreneurship, and economic development (Nelson and Winter, 1973, 1982, Nelson, 1985), have long emphasized that competitive advantage is derived from different capabilities (technical, managerial, strategic, organizational, etc.), which are based on knowledge accumulated or transmitted through interactive learning processes. More recently, scholars from the so-called “proximity school” described in the *Handbook of Proximity Relations* (Torre and Gallaud, 2022), have emphasized that this knowledge-based process of economic development requires that agents would find socioeconomic arrangements

¹ Syndication is frequent. In our sample of 33,833 startups and 58,243 VC deals, the mean number of investors per VC deal is 2.8, 42.5% of roundtables are made of three or more investors, and almost 10% of deals are with six or more investors.

that reduce the coordination costs and facilitate the diffusion of knowledge and information. The proximity approach calls these arrangements proximity relations, or simply "proximities", because they reduce geographic, social, and intellectual distances and their costs. If geographic distance has long been acknowledged as a crucial determinant of economic development (Krugman, 1992), advocates of the "proximity approach" have underlined that the success of any economic endeavor requiring knowledge exchange and good coordination between agents depends also on social, cognitive, organizational, and institutional proximities between these agents (Bellet et al., (1992), Gilly and Torre, eds, (2000), Boschma, 2005a). In the *Handbook of Proximity Relations*, proximity is defined as a multidimensional space whose dimensions are made up of the factors that facilitate coordination and exchange: the dimension of physical distance of course, but also the key elements of social organization that shape economic coordination like networks, learning and knowledge sharing, institutions, and organizational practices. Proximity measures are then the different distance metrics of this multidimensional space.

Just like collaborative research, strategic alliances or joint ventures, VC syndication creates teams of entrepreneurs and investors that need to coordinate themselves and circulate information and knowledge between them. Being an organizational arrangement, VC syndicates can be seen as a form of proximity usually called "organizational proximity". The members of those teams are more or less distant from a cognitive, cultural, geographical or social point of view. Consequently, the fate of VC-backed startups could be strongly influenced by the proximity relations characterizing these teams. Some empirical studies on VC operations deal with geographic proximity (e.g., Lerner, 1995, Lutz et al., 2013), institutional proximity (e.g., Dai and Nahata, 2016; Tykvová and Schertler, 2014; Moore et al., 2015) or relational proximity (e.g., Hochberg et al., 2007, 2010; Sorenson and Stuart, 2001, 2008), but they do not consider all the dimensions of proximity in an integrated framework taking into account both geographic, relational, institutional, organizational, and cognitive proximities. Yet, this is what the proximity approach strongly advocates for, emphasizing that the ability of each dimension of proximity to solve coordination problems interacts with the other forms of proximity (Boschma, 2005b). This gap

needs to be filled because the different forms of proximity are correlated, which can lead to over- or underestimation of the different proximity dimensions.

Moreover, we argue that cognitive proximity/similarity, defined as the degree of overlap of agents' knowledge bases (Nooteboom, 2000, Balland et al., 2015), is an important concept to understand VC deals because venturing startups is a risky and innovative activity requiring at the same time strong mutual comprehension and new ideas. VC actors accumulate new knowledge through their involvement in multiple ventures over time, which implies that their cognitive proximities keep on changing and modify continuously their knowledge bases. In that perspective, the concept of cognitive proximity is inherently evolutionary and should not be confounded with the static cognitive biases resulting from shared exogenous characteristics such as the familial, cultural, educational, or professional background.

We also know of no studies on VC-backed startups that have considered the possibly nonlinear influence of proximities. Yet, recent literature has emphasized that proximity is not always desirable. It can sometimes generate negative effects due to redundancies, congestions, technological lock-in, hold-up problems, or even conflicts. Its influence can evolve over time and depends on different types of contingencies such as the industry, the state of the business cycle, or the type of knowledge produced or exploited (see e.g. Torre and Rallet, 2005, Balland et al., 2015). Finally, to the best of our knowledge, there are no studies dealing with the two types of links created by venture capital operations, those between investors (especially in syndications), and those between investors (venture capital funds) and beneficiaries (venture capital-backed startups).

The goal of this article is to account for this dynamic, nonlinear, contingent and systemic nature of the proximities characterizing VC syndicates, in an empirical study of the fate of VC-backed startups. For that purpose, *we test two main sets of hypotheses* on a global dataset, using dynamic measures of the five forms of proximities: 1) the first series of hypotheses asserts that the five dimensions of proximity should be significant, that they will play different roles, and that their effects will be nonlinear; 2) the second predicts that cognitive proximity of VC deals will be positively correlated to the probability that the startup will be merged or acquired and negatively correlated to the likelihood

that it will undergo an IPO (Initial Public Offering). Our empirical results support these two hypotheses. The *added value of our empirical strategy* is firstly that we test the effects of proximities at two different levels: proximities between investors in the syndicate, and proximities between investors and investees. Secondly, we do that on a 34-year-long-68-countries-large sample including 18934 startups. Thirdly, we estimate survival (or “duration”) models to test the impact of time-varying proximity measures on the probabilities of different events for these startups (IPO, M&A (Mergers or Acquisitions), later stage of funding). These estimates are corrected for non-proportional hazards, tied failures and competing events.

The rest of the paper is organized as follows: section 2 presents the literature on VC, startups, their proximity relations and the proximity approach, and elaborates the hypotheses; section 3 presents the database, econometric method, and variables; section 4 and 5 present the results; section 6 concludes.

2. Theory, empirical literature review, and hypotheses

In this section, we present the “proximity school of thought”, intellectually located at the crossings of economic geography, regional studies and evolutionary economics, that provides a valuable integrated framework for an analysis of the role of proximity relations in VC-backed business venturing. We then show that some empirical studies of VC have used various operational measures of proximities or distances, but we notice that they have not tested them in such an integrated framework. We argue that the proximity approach could help fill this gap, and we derive the hypotheses that this approach suggests about the way proximity relations might affect the fate of VC-backed startups.

2.1. The conceptual framework: three strong claims of the proximity approach useful to analyze the impacts of VC syndication on the fate of startups

Top-level venture capitalists add value to the new ventures they invest in by providing intangible assets such as expertise, experience, coaching, networking, business contacts, and opportunities (Brander et al., 2002, Lerner, 1994, Lockett and Wright, 2001, Manigart et al., 2006, Sørheim, 2012). To create competitive advantage, all these capabilities must be coherently combined and mixed with

good knowledge of relevant markets, legal environment, and incumbent competitors. A large literature using Schumpeterian, evolutionary and innovation systems theories has shown that this requires efficient knowledge exchange mechanisms, and interactive learning processes (Penrose, 1959, Kogut and Zander, 1993, Nelson and Winter, 1973, 1982, Winter, 1985, Malerba and McKelvey, 2019). Venture capital deals create the kind of business ties that make knowledge transfer possible (Caselli, 2010), but they are also confronted with coordination frictions, especially in syndicated VC (Nanda and Rhodes-Kropf, 2018). Proponents of the proximity approach claim that proximity relations affect coordination frictions and influence knowledge transfer mechanisms (Torre and Gallaud, 2022). They differentiate five dimensions to measure proximity relations: the dimension of physical distance that allows or prevents face-to-face interactions, but also the elements of social organization that contribute to economic coordination and knowledge diffusion: education and learning processes that shape knowledge bases; institutions that influence values, norms, and beliefs; organizational arrangements and work practices that facilitate coordination and reduce transaction costs; social networks and social capital that create trust and confer influence power. For this reason, the typology of relevant proximities is divided into two main categories, geographic proximities and organized proximities, the latter being further subdivided into cognitive, institutional, organizational and relational/social proximities.

This proximity approach claims an interactionist and evolutionary background based, for example, on Granovetter (1973) and Nelson and Winter (1985). It also refers to transaction costs and institutional economics, acknowledging that interactions at a distance are costly because of information gaps, risks of hold-ups, conflicts, and costly monitoring (North, 1991). Many economic organizations are then seen as relational devices designed to create proximities through long-term personal relationships, networks, face-to-face contacts, institutions, contractual and organizational arrangements, or diffusion of shared norms and knowledge (North, 1991, Williamson, 2000).

Assessing the significance of this “proximity school” is well beyond the scope of this empirical study². Our goal here is simply to use its integrated and structured view of proximity relations to

² See, for example, Zimmermann et al. (2022), Balland et al. (2022), Filippi et al. (2022), and Stimson (2022).

conceive an empirical modeling of how VC relationship structures and their proximities can affect the fate of VC-backed startups. The core ideas of this proximity approach are simple. Firstly, *Geographic proximity* is defined as the distance separating two economic entities, adjusted for transportation costs and time. Reducing this distance permanently or temporarily facilitates face-to-face interaction, knowledge transfer and coordination (Torre, 2008, Torre and Gallaud, 2022). The central assertion of the proximity approach is to consider that, since geographic proximity does not guarantee communication nor comprehension, other forms of non-geographic proximities (also called “organized proximities”) also matter and can act as substitutes or complements to geographic proximity (Boschma (2005a and b). Proponents of this approach consider that four types of organized proximities can facilitate knowledge exchange and economic coordination (Boschma and Frenken, 2010, Boschma and Martin, 2010): 1) *relational or social proximities* created by various networks connecting people and organizations; 2) *organizational proximities* generated by workplace arrangements and organizational practices bringing the agents closer within and between organizations; 3) *cognitive proximities* created by learning processes that form common knowledge bases, allowing people to understand themselves; and 4) *institutional proximities* producing shared values and norms that also facilitate comprehension and exchange.

The **first strong claim** of the proximity approach is that the five dimensions of proximity play clearly differentiated roles. This means that the five dimensions of proximity are not redundant. They all contribute differently to economic development and business success (Boschma, 2005, a and b). They are complementary and cannot totally substitute each other. For example, cognitive proximity strongly influences the type and the amount of knowledge transferred between interacting agents, and it can be supported in this task by geographic proximity, which enables face-to-face interactions, and institutional proximity, which facilitates mutual understanding. In the circumstances wherein cognitive proximity is low, geographic and institutional proximities will only partially compensate the lack of common knowledge. In strategic situations where coordination is more important than knowledge transfer, relational and organizational proximities that facilitate trust building may become more

important than cognitive proximity. These differentiated but interacting effects of the five proximity dimensions have an important empirical implication: one could overstate or understate the impact of one proximity dimension because the others have been ignored. For example, measuring the effect of social proximity by the density of a collaborative network does not separate the pure effect of social interaction from the influence of the values, norms, beliefs, and knowledge bases of socially interconnected agents. If the proximity approach is correct, these effects should not be redundant and need to be measured in separated variables that tend to remain significant when integrated together in econometric estimations. VC deals are economic arrangements that create relational structures between syndicated investors and between these investors and the managers of startups. Since efficient knowledge transfers and good coordination are key to value creation in a startup, one can expect that the five dimensions of proximity relations will play a role in determining the fate of VC-backed startups.

More recently, proximity scholars have formulated a **second strong assertion**: proximity relations are constantly changing over time, and this generates proximity effects that are nonlinear and reverse themselves beyond certain thresholds. The intrinsic evolutionary nature of proximity relations is due to the fact that relational structures and agents' proximities influence each other and co-evolve: agglomeration of economic activities alters geographic proximities, social decoupling modifies social proximities, learning changes cognitive proximities, integration transforms organizational proximities, and institutionalization alters institutional proximities (Balland et al., 2015). Therefore, beneficial proximities may become undesirable if they become too accentuated, and beneficial distances/differences may become harmful if they become too important. The main arguments mentioned in the proximity literature to explain reverting effects are congestions, conflicts, competitive pressure, hold-up problems, knowledge spillovers, and technological lock-in. For example, too much geographic proximity may generate negative agglomeration externalities as infrastructures become congested, local markets are filled up with competitors and risks of knowledge leakage become too high. Another example often found in the literature is that of arrangements that build organizational and relational proximities through collaborative networks but may end up with strategic conflicts,

technological rivalry, and costly renegotiations between partners. In collaborative research, cognitive proximity fosters mutual understanding and knowledge sharing, but it can also lead to technological lock-in because partners too cognitively similar do not generate enough new ideas for radical innovation (see, e.g., Nootboom 2000, Boschma, 2005b). Lock-in risk is not limited to the cognitive dimension: there can be geographic lock-in (Amin and Wilkinson 1999), organizational lock-in (Saxenian 1994), institutional lock-in (Freeman and Perez 1988), or relational lock-in (Uzzi 1997). In summary, there is always an optimal level of proximity/distance between partners. Too dissimilar, they cannot work together. Too similar, they will not learn from each other and may become closed to new ideas. Since this nonlinearity of proximity effects has been documented in many domains, we expect that it also exists with respect to the proximities that characterize VC deals.

There is another interesting element to the cognitive proximity-cognitive lock-in dilemma just mentioned. As Nootboom (2000) first pointed out, the optimal level of cognitive proximity is not the same for every type of activity. A good empirical illustration of this is in the study of Broeckel and Boschma (2012), who found that too much cognitive proximity in the Dutch aviation knowledge network reduced firms' innovative performance. Other scholars have underlined that this trade-off does not work the same way in all situations, noting that cognitive proximity is particularly good when knowledge exploitation for incremental innovation is the strategy, while on the contrary, cognitive distance is more desirable when knowledge exploration for radical innovation is the goal (Gilsing and Nootboom, 2006, Nootboom et al. 2007, Brossard and Vicente, 2010). This is the **third strong claim of the proximity approach** that may prove useful for understanding the choices of VC-backed startups. If startups are generally created with the aim of introducing new products or services to the markets, not all of them are radically new. Consequently, one could wonder whether the degree of cognitive proximity between a startup's stakeholders influences its fate, since the latter is largely determined by the degree of novelty of its product or service (Bayar and Chenamur, 2012, 2020). We expect that cognitive proximity will be good only for those startups whose strategy is based on knowledge exploitation rather than knowledge exploration.

Before deriving from these three strong claims the hypotheses that can be tested about how proximity relationships between VC investors and investees may influence the fate of VC-backed startups, we know assess whether they are sufficiently accounted for in empirical studies of VC-backed startups.

2.2 VC-backed startups and proximities in the empirical literature

Geographic proximity in VC markets: the so-called « one-hour rule » of equity investments

An early empirical study of US biotech companies by Lerner (1995) found that the physical proximity of venture capitalists to portfolio companies was an important determinant of a venture capitalist's board membership. Cumming and Dai (2010) also studied US VC markets and observed that new ventures backed by neighboring VC investors are more successful. Lutz et al. (2013) found that the probability of a financing relationship between VC investors and investees in Germany decreases with the distance between them. Pe'er and Keil (2013) noticed that the survival of startups is influenced by their location in clusters. Interestingly, Chemmanur et al. (2016) obtained empirical results supporting the claim of proximity theorists that too much geographic proximity is not always desirable. Using a worldwide sample of cross-border VC investments, they found evidence that firms backed by syndicates with international and local VCs are more likely to exit successfully³ and have better post-IPO operating performance than those backed by syndicates composed entirely of local or international VCs. More recently, Colombo et al. (2019) found that ventures are more likely to seek external equity when some VC investors are nearby, and Tian et al. (2020) revealed a nonlinear effect of a VC's geographic distance on the technological performance of VC-backed companies in China.

Institutional proximity and VC markets

³ For a VC fund or an entrepreneur, a successful exit means the sale of its share with capital gain, thanks to an IPO or M&A. Successful exits are what make the risky business of VC profitable. A good indicator of a startup's performance or potential is the arrival of new investors. This is why startups' performance is very often proxied by successful exits in the empirical literature.

A few studies have examined the impact of cultural or institutional distance on the functioning of VC financing. Focusing on cross-border VC deals around the world, Li et al. (2014) found that cultural and institutional distances had negative impacts on the fate of VC-backed ventures. Dai and Nahata (2016) obtained similar results. Tykvová and Schertler (2014) provided evidence that the negative impact of institutional distance cannot be mitigated by investment syndication with local VC investors, whereas the negative impact of geographic distance can. However, Chemmanur et al. (2016) displayed the opposite results in emerging nations. Bottazzi et al. (2016) obtained results in favor of the institutional proximity factor: the higher the measure of trust among European nation, the higher the probability of receiving VC funds. Furthermore, Moore et al. (2015) find that institutional distance between VC investors and investee firms, measured by three dimensions (regulatory, normative and cultural), reduces cross-border VC investments.

Relational/social proximity and VC deals

Inspired by Sorenson and Stuart (2001), who showed that US venture capitalists with strong positions in the syndication network invest more frequently in spatially distant companies, quite a number of studies are devoted to analyzing the effects of relational/social proximity in VC markets. De Clercq and Sapienza (2006) underlined that social proximity affected positively the way US-based VC firms perceive the performance of their portfolio companies. Hochberg et al. (2007) found that VC funds with higher network centrality had significantly better fund performance. Checkley et al. (2010) showed that network centrality Granger-causes IPO exit shares of portfolio companies in the UK, and Trapido (2012) showed that social proximity in VC syndication networks has positive performance implications. Dealing with the issue differently, Alexy et al. (2012) found that VCs characterized by high levels of relational centrality (in terms of degree or brokerage) provide larger investment amounts. Jääskeläinen and Maula (2014) examined cross-border venture capital exits in EU-15 countries and found that the more a venture has non-domestic syndication ties, the more likely it is to exit a non-domestic market. Hain et al. (2016) noticed that institutional trust seems more important for investments in emerging economies, while relational trust is more important for investments in developed

economies. Meuleman et al. (2017) observed that structural embeddedness (captured by indirect ties) and institutional proximity facilitate cross-border partnering. Shao and Sun (2021) found that structural and cognitive capital appear to facilitate venture capital financing in China.

Organizational proximity

We could not find any empirical studies that explicitly assessed the impact of any form of organizational proximity on VC financing. One can hypothesize that this is due to the difficulty of finding distinct measures of relational/social proximity on the one hand and organizational proximity on the other. Syndicated VC investments generate relational proximity among syndicate investors and, at the same time, organizational proximity between the VC firms to which they belong. As a result, one can assume that studies on the impact of VC syndication on the success of portfolio companies essentially investigate the impact of some form of organizational proximity between VC firms. They are numerous and almost unanimous in showing that the organizational proximity created by investment syndication provides many benefits (see, e.g., Bayar et al., 2020; Casamatta and Haritchabalet, 2007; Lerner, 1994; Lockett and Wright, 2001; Manigart et al., 2006; Wright and Lockett, 2003).

Cognitive proximity in VC deals: the neglected factor

Cognitive proximity between two actors is alternatively defined as the degree of similarity in the way they perceive, interpret, understand, and evaluate the world (Nooteboom, 2000) or as the degree to which they share the same knowledge base and expertise (Boschma, 2005a). We found no study of VC deals based on the latter definition, but a few that can be related to the former. In the first, Franke et al. (2006) analyzed the evaluations made by a small sample of Austrian and German VC firms regarding prospective target startups. They found that VC investors with an engineering or business background tended to give higher ratings to startup teams with similar backgrounds. Murnieks et al. (2011) studied US VC deals and found that venture capitalists rate entrepreneurs with the same decision-making processes as themselves more favorably. Gompers et al. (2016) evidenced that venture capitalists who share the same ethnic, educational, or professional background are more likely to syndicate with each

other, and this homophily reduces the probability of investment success. Du (2016) found that VC investors prefer to form VC syndicates with partners with similar experience levels. It could indicate that cognitive proximity can reduce some transaction costs. In Moore et al. (2015), “cultural-cognitive distance” is defined as “*the knowledge sets and shared understandings possessed by the people within a country (Busenitz and Barney 1997)*”. They find that normative and cultural-cognitive distance reduce cross-border VC investments.

These five studies provide clear evidence that educational, professional, and cultural similarities create interaction biases that affect the selection of projects and partners in VC. They provide evidence of cognitive biases in VC deals resulting from exogenous characteristics of investors. However, the cognitive similarities they consider do not account for the fact that knowledge bases evolve through agents’ experience and learning over time. The proximity approach states that cognitive proximity is a matter of overlapping knowledge bases that evolve over time. This requires dynamic measures of knowledge overlap between agents or organizations. To the best of our knowledge, there are no empirical studies using this definition of cognitive proximity in VC operations⁴.

To summarize the empirical literature on the impact of the five forms of proximity relations in VC deals and startups’ funding, we can identify three main gaps: 1) no empirical work has integrated the five proximity dimensions all together, and the organizational dimension has been neglected, while the cognitive dimension has been apprehended in an overly static manner; 2) None of these studies tests the potential nonlinearity of the effects of proximity relations; 3) the cognitive dimension is integrated in the form of static characteristics that capture cognitive biases. We argue that VC stakeholders are learning agents; this requires dynamic measures of cognitive proximities. We also underlined in section 2.1 that cognitive proximity can be useful in some circumstances but can also lead to technological lock-in and thus be a disincentive to radical innovation. This should be tested on VC-backed startups, differentiating them according to their strategic goals. This brings us to the derivation of our hypotheses.

⁴ The study of Awounou N’dri and Boufaden (2020) could be considered an exception since they mobilize a measure of “skills’ complementarity” between startups and their VC investors which is based on sectoral specialization similarities. However, they do not call it “cognitive distance” and their measure is a static dummy variable.

2.3 Hypotheses

In this section, we propose two sets of hypotheses. The first one is related to the influence of the five proximity dimensions on the fate of VC-backed startups and to the different roles of these dimensions. The second one is related to the differentiated roles of cognitive proximity in relation to the different strategic positions of startups.

As first noted above in section 2.1, proponents of the proximity approach have argued that five dimensions of proximity relations play differentiated but interacting roles. In sections 2.1 and 2.2, we have explained why this implies that the existing empirical literature, which separately tests the impacts of some dimensions of proximity relations in VC deals, may overstate or understate them. We have also argued that the general case should be that several of the five forms of proximity play a role in improving coordination and knowledge transfers in VC operations, and thus affect the fate of VC-backed startups. This leads to the following first set of hypotheses.

Hypothesis 1.a.: In an integrated empirical approach where all the five proximity dimensions are considered, we expect that they will all significantly influence the fate of VC-backed startups.

As developed in section 2.1, this multidimensional vision of proximity relations allows us to differentiate the roles of the different proximity dimensions: some are more important for knowledge transfers (cognitive, geographic, and institutional proximities), while others are essential for trust building and better coordination (geographic, organizational, and social proximities). In the life of a startup, there are fundraising phases where trust between investors and investees is essential (Shepherd and Zacharakis, 2001). As shown by Kollmann et al. (2014) and Botazzi et al. (2016), the probability that VC investors will fund a startup increases with trust. Attracting new investment requires proximity relations that help build trust. Proximity relations that stimulate knowledge transfers are more likely to influence the quality and the quantity of innovation, which is an important determinant of VC-backed startups' exit choices (Schwienbacher, 2008, Bayar and Chemmanur, 2011). Therefore:

Hypothesis 1.b: trust-related proximity dimensions, namely geographic, organizational, and social proximity will influence the likelihood of a startup's success in later-stage fundraising, while cognitive proximity will also influence the probability of IPO and M&A exits.

Several studies have demonstrated that investment syndication in VC deals is a symptom of low trust, showing that the probability of VC syndication increases with distrust (e.g. Wright and Lockett, 2003, Kollmann et al., 2014 and Bottazzi et al., 2016). Syndication is a form of organizational proximity that is used as a substitute for trust when the latter is lacking, but building trust in a team becomes difficult when the team gets too large: the more numerous are VC funds in the syndicate, the less the organizational control of the syndicate is easy, and the lower is the effective organizational proximity. In contrast, having only one fund in the syndication is equivalent to the highest organizational proximity possible. Thus, we make the following assumption:

Hypothesis 1.c: the larger is the syndication, the lower will be the probability for a startup to receive a new round of funding

We also underlined in section 2.1 that proximity scholars generally predict nonlinear effects of proximities because congestion problems, conflicts with competitors, hold-up issues, knowledge spillovers, and technological lock-in tend to develop as proximity increases, to the point where they can reverse the positive effects of proximities. This reversal tendency also applies to the effects of distance: if there are some positive effects of distance, for example in the cognitive dimension because it brings new ideas, or in the organizational dimension, because trust-based mechanisms are preferred to tight control devices, too much cognitive or organizational distance could become negative beyond a certain threshold. We therefore make the following hypothesis:

Hypothesis 1.d: the effects of the proximity variables on the likelihood of late-stage funding, IPO, or M&A operations will be reversed beyond certain thresholds.

We recalled in section 2.1 that several scholars, starting with Nootboom (2000), have emphasized that cognitive proximity is not always a good thing because there is a trade-off between cognitive distance, which stimulates the emergence of new ideas, and cognitive proximity, which facilitates knowledge absorption (Boschma 2005b, Broeckel and Boschma, 2012). Other scholars have underlined that cognitive proximity is particularly good when knowledge exploitation for incremental innovation is the strategy, while on the contrary, cognitive distance is more desirable when knowledge exploration for radical innovation is the goal (Gilsing and Nootboom, 2006, Nootboom et al. 2007, Brossard and Vicente, 2010). We now want to underline that VC-backed startups are not all equally innovative, as some are more oriented towards disruptive innovation projects, while others are more of the incremental innovation type (Boyer and Blazy, 2014, Colombelli et al., 2016). It has long been recognized that these different innovation strategies of startups are correlated with exit choices. More innovative firms are more likely to go public than firms with imitative or derivative projects because, when the new product/service is sufficiently differentiated, the potential business-stealing effect for incumbent firms is smaller than if the startup's new product is a close substitute for theirs. Thus, for incumbent firms, the gains from acquiring startups to limit entry are reduced when the startup's product is sufficiently differentiated. Then the acquisition premium is lower, and the IPO premium becomes more attractive in comparison (Schwienbacher, 2008). Moreover, for startups with disruptive innovations, remaining independent is critical if the strategy is to challenge incumbents with the new product or service. Indeed, dominant firms in technology industries tend to acquire startups in order to shut them down and short-circuit the development of competing technologies (Lemley and McCreary, 2021). If the new product or project proposed by the startup is less differentiated, market entry may prove difficult. In this case, "an acquirer may be able to provide considerable support to the firm in the product market, thus increasing its chances of succeeding against competitors and establishing itself in the product market" (Bayar and Chemmanur, 2011).

Since cognitive proximity has been shown to support incremental innovations, and since the latter have been shown to raise the likelihood of M&A exits for startups, we can formulate the following proposition:

Hypothesis 2.a.: cognitive proximity between VC investors and between investors and investees positively influences the likelihood that a startup will be merged or acquired.

On the contrary, since cognitive distance has been shown to produce more disruptive innovations that increase the likelihood that a startup will eventually go public, we can formulate the following proposition:

Hypothesis 2.b.: cognitive distance between VC investors and between investors and investees positively influences the likelihood of a startup going public.

Note that the definition of cognitive proximity that we use here is the evolutionary one proposed by proximity theorists (see, e.g., Boschma, 2005a & b, or Balland et al., 2015). It takes into account the fact that proximities and relations co-evolve: proximities create new relationships; these relationships change agents and thus modify their proximities over time. VC actors accumulate new knowledge through their involvement in multiple ventures and projects over time; this requires that cognitive proximity be measured dynamically. We propose such an approach in the empirical section below. It differs from the static similarity-based cognitive biases that have been measured in many VC studies (see *infra*). We now come to the description of our empirical strategy and results.

3. Data, econometric method, and variables construction

3.1. Dataset construction and endogeneity issues

First, it is not our goal to explain how venture capitalists select startups, nor to compare the performance of VC-backed startups with that of other startups. Hypotheses 1.a, 1b, 1c, 1d, 2A and 2b can be tested with an empirical model of the determinants of the likelihood that a VC-backed startup

will attract investors, either for an additional round of financing, or for a merger and acquisition, or for an IPO. For that purpose, we will use a duration model that predicts the likelihood of the event of interest conditional on the time elapsed before the event.

We extracted data on startups and their VC investors over 34 years between 1980 and 2014⁵. The data were extracted from Dow Jones' VentureSource database. They cover VC deals in 66 countries worldwide. We selected only startups that had received at least one round of VC funding in their lifetime. Our sample covers 24 industrial sectors. Unsurprisingly, the three most represented sectors are "IT, internet and software services" (28%), "Pharmaceuticals biotechnology life sciences and tools" (12%), and "Technology hardware communications equipment electronic components" (11%). Appendix 1 shows the complete distribution of the observed startups across sectors.

For each startup in the dataset, we extracted information on its investors and investment types, on industry segments, and on localizations. We also have information on their VC funding round types ("seed, 1st, 2nd, ..., 9th, later, restart"), and on the other sources of new funding, such as private equity investments and debt financing. Some of these funding rounds are called "exit" events in the VC literature, meaning that some investors liquidate their investment in a way or another: acquisitions, mergers, IPOs or SPOs, judicial liquidations, etc. When VC investors liquidate their investments and some new non-VC investors take over, the company is no longer VC-backed and therefore no longer tracked in the database.

Consequently, the dataset has a duration/survival structure: startups in the cross-sectional dimension but funding or exit event dates instead of calendar dates in the longitudinal dimension. The initial sample included many startups (51,969), but missing data (for example, investors' identification, deals' dates, etc.) led us to drop some observations. However, the number of observations remains large (18934 startups; 78082 deals). More importantly, as illustrated in Figure 1, the losses of observations appeared to be evenly distributed across countries, except for Japanese and Irish companies. We also

⁵ For cost reasons, we could not extract data from Venturesource beyond this date. However, these 34 years of worldwide data already provide a great amount of variability in terms of geography, industries, and business cycles.

confirmed that these information gaps were evenly distributed across startup sizes and industry segments.

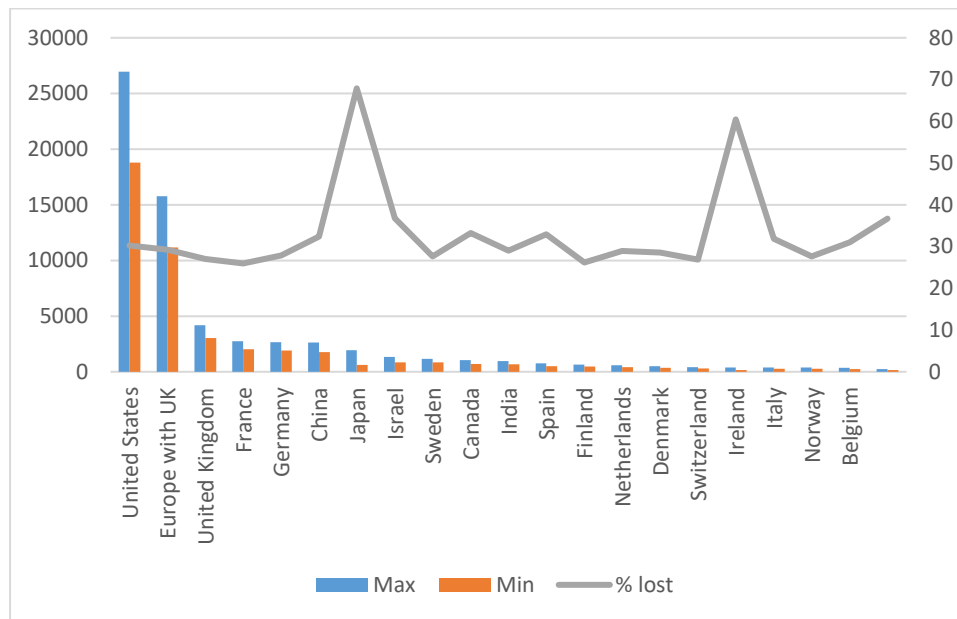


Figure 1. Maximum and minimum number of startups in the study sample

There is a selection issue regarding our sample: we only observe VC-backed startups. This would be an unsolvable problem if we wanted to assess the impact of VC funding on the performance of startups, because we would have to separate the “treatment” effect of the VC investment from the “selection” effect attributable to the ability of VC investors to select the most promising startups. This is not our goal however, but we must acknowledge that our results only explain the determinants of the fate of VC-backed startups, and not those of non-VC-backed startups.

A frequent source of endogeneity in startups studies is survivorship bias, when the dependent variable can only be observed for startups that have survived or passed a certain selection process. It requires the use of methods such as the Heckman procedure to disentangle the determinants of survival from the determinants of the dependent variable. The VentureSource data, like any other VC dataset that we know of, are certainly not free of such selection issues. We actually observed that quantitative performance indicators were very often missing, even for surviving startups. We therefore decided to construct dependent variables based on investment events, as is usually done in the VC empirical

literature. Indeed, events such as a later stage funding, a M&A, an IPO, etc.⁶, can be interpreted as success events because the startup attracts new investors and former VC investors can sell their shares. All these events are always reported in the dataset, even if the startup eventually goes bankrupt. Once a startup is tracked, its investment events are carefully reported by VentureSource. They are observed even if the startup performs poorly or eventually goes bankrupt. Thus, our dependent variables are not observed on the condition that the startup survives, but on the condition that it received VC funding and that the VentureSource data managers obtained sufficient information about the startup to include it in the database. The only selection criteria used by VentureSource data managers to decide which startups to track are the availability of information and the size of data management staff. These elements may bias the representativeness of the dataset, but they are not correlated with startups' future investment events, which are unknown at the time of selection. Overall, we can hope that there is no survivorship bias when the dependent variables are based on investment events. Moreover, given the reputation of the data provider, we can hope that it is representative of the universe of VC-backed startups. However, we must acknowledge that we could not implement a true representativeness test on the dataset due to the lack of comparison information. There is no information on the characteristics of the entire universe of startups. All we can argue here is that our dataset exhibits a great diversity in terms of size, sector, and location of startups and VC.

We deal with unobserved heterogeneity by introducing a large list of control variables that are potentially correlated with our proximity-independent variables. For example, according to the National Bureau of Economic Research (NBER), there have been five business cycle peaks and five troughs in the US across these 34 years. This requires the business cycle to be controlled for because we know that the investment events we study are more likely during business booms than during downturns (Block and Sandner, 2009, 2011; Koellinger and Roy Thurik, 2012). We also introduce controls for size, sector, location, and VC funds' experience and supportiveness (see below).

⁶ Other investment events reported in the database are, for example: 1st, second, third,..., round investment, acquisition financing, corporate investment, angel investment, debt-type investments, management buy-outs, etc.

We must emphasize that our survival modelling methodology did not allow us to use instrumental variables regressions to address endogeneity biases possibly caused by measurement error, simultaneity, or remaining unobserved heterogeneity. Unfortunately, the conditions under which the instrumental variable (IV) technique can be applied within a survival Cox proportional hazard model are rather restrictive (Uddin et al. , 2023), and it has been beyond our reach to develop a reliable statistical method for doing so. However, given the size and variety of the sample, we can expect that our variables are not affected by significant measurement errors, and that our control variables correctly address unobserved heterogeneity. Moreover, we can hope that it is unlikely that past proximities are caused by future funding or exit events, and it seems difficult to imagine that VC syndicates would arrange their team's proximities in relation to anticipated funding or exit events that will occur years later. All in all, we can argue that the duration before our events of interest cannot reversely cause the different forms of proximity relations constructed during startups' past funding events.

3.2. Dependent variables and econometric method: dealing with censoring, nonlinear hazard rates, competing events and tied failures

We have explained in section 3.1 why we use event-based dependent variables. This generates some specific properties of the data that need to be addressed. More precisely, we want to analyze the determinants of the duration (in days) until a startup undergoes three types of events: 1) receiving a "later" stage of VC funding, 2) an IPO, and 3) an M&A. We therefore define three dependent variables: *later*, which is a dummy variable equal to 1 when the startup benefits from a new VC funding round; *IPO* which is a dummy variable equal to 1 when the startup goes public; and *mergeracqui* which is a dummy variable equal to 1 when the startup is merged or acquired.

Considering each of these three events as a state change, our econometric models estimate the likelihood of transition from one state to another, conditional on the number of days elapsed before this transition occurs. The startups we observe enter the dataset at their creation and exit only if they experience an IPO, an M&A, or other exit events such as a judicial liquidation. Thus, surviving is not a

condition to be included in the dataset and to have the dependent variable observed. Startups that collapse before any of these three events remain included in the econometric analysis. However, these variables are duration dependent, and affected by censoring, which requires proper modelling tools.

Indeed, there is no left censoring in this dataset since the events of interest cannot occur before entry, but there is left truncation in the form of delayed entry, however. There is also right censoring because many startups in the sample experience the events of interest after the observation period. These problems can be addressed by various techniques but, since the durations-before-investment-events we model are non-normally distributed, we use a Cox proportional hazard model (Cox, 1972). This is a semiparametric approach to modeling hazard rates, in which the baseline hazard rate is not specified. Only the effects of the covariates are given in the functional form, according to the following formula:

$$h(t|x_j) = h_0(t)\exp(x_j\beta_x) \quad (1)$$

where x_j is the vector of covariates for subject j , and β_x is the vector of regression coefficients.

The key advantage of the Cox approach is that it eliminates the risk of biasing the estimates of β_x due to incorrect parameterization of the baseline hazard rate $h_0(t)$. However, there is another possible source of bias if the proportional hazard assumption does not hold. In fact, we admit this by writing (1):

$$\frac{h(t|x_j)}{h(t|x_m)} = \frac{\exp(x_j\beta_x)}{\exp(x_m\beta_x)}$$

This implies that the relative hazards of subjects j and m depend only on their respective covariate values and do not vary over time. If this assumption is incorrect, the coefficient β_x will be biased. To address this issue, we implement the following approach. First, we implement simple Cox estimations and assess the validity of the proportional hazard hypothesis using Schoenfeld residual tests to identify the covariates that do not satisfy the proportional hazards hypothesis. We then implement stratified Cox regressions that exclude the categorical variables that have failed the Schoenfeld test. These are instead used as stratification variables with specific baseline hazards. The quantitative variables that failed the Schoenfeld test are replaced by time-varying coefficient variables. This makes the relative hazards time-dependent, eliminating the potential bias resulting from non-proportional hazards.

Even when stratified, the simple Cox model has another limitation: it does not consider tied failures, i.e., subjects experiencing the same events at the same time. In our sample, where time is measured in days, several companies may experience an IPO, a M&A, or any other financial event on the same day. Since the parameter estimation of Cox model is based on the maximization of the likelihood function, the latter has to account for these tied failures, by making a hypothesis about the way they occur. We chose to present the results of stratified Cox models using the Efron correction method for tied failures, but we carefully checked that they were not significantly changed by using other available methods.

Finally, we check robustness using maximum likelihood competing-risks regressions following the method of Fine and Gray (1999). Indeed, IPOs, M&A, and bankruptcies are competing events for startups: if one of these three events happens, the others will never occur or will occur only after a significant period of time⁷.

3.3. Proximity variables

In order to test our hypotheses, we construct four time-varying proximity measures. We also include squared values of these proximity measures to test hypothesis 1d.

Cognitive proximity

Empirical studies of cognitive proximity are often based on observation of patent technologic classes and measures of their overlap (e.g., Jaffe, 1989; Nooteboom et al., 2007; Krafft et al., 2014). However, this approach is only relevant for organizations that produce or use patents. This is not the case for VC funds, and only a small proportion of startups have already filed patents when they receive VC funding⁸. Moreover, patents characterize formal knowledge but leave out all other kinds of tacit, uncodified knowledge (Caragliu, 2022).

⁷ Note that the event “obtaining a later-stage funding” is not competing with IPO and M&A. Note also that a startup that goes public might become the target of an M&A later, but we can still consider that the probability of being merged or acquired is significantly reduced for a significant period after the IPO.

⁸ For example, a 2011 TechCrunch study over a sample of 12,404 US technology startups reported that only 19% of them had filed at least one patent application prior to receiving any funding.

Because knowledge bases consist of the techniques, skills and know-how that characterize professions and industries, we can assume that fine-grained sectoral proximities satisfactorily reflect cognitive proximities. Thus, we will use the industry classification to compare the knowledge bases of VC investors and startups. Our dataset contains three-digit industry codes (GICS) that distinguish twenty-four industries. We suppose that startups belonging to the same 3-digit industry will have very similar knowledge bases. We will also assume that venture capitalists' knowledge bases result from the accumulated sectoral knowledge they have acquired from the firms they have financed in the past. Consequently, we measure cognitive proximity between investors who co-finance a startup using an index of co-specialization, according to the following the formula:

$$cogprox_inv_{T-1} = 1 - \left(AV_{j=1...24} \left(SE_{i=1...N}^j \left(\frac{\sum_{t=1}^{T-1} n_{ijt}}{\sum_{t=1}^{T-1} N_{it}} \right) \right) \right)$$

We measure the cognitive proximity between a startup belonging to sector k and its investors of a given deal by an index of co-specialization between the startup and its investors, according to the formula:

$$cogprox_stup_inv_{T-1} = AV_{i=1...N} \left(\frac{\sum_{t=1}^{T-1} n_{ikt}}{\sum_{t=1}^{T-1} N_{it}} \right)$$

where $i = 1 \dots N$ are the investors in the financing round (deal), $j = 1, \dots, 24$ is the industry sector (3-digits GICS classification), t is the index of the day ($t = 1$ is the first day the investor is observed), $T - 1$ is the day before the considered deal, k is the sector of the startup, $\sum_{t=1}^{T-1} n_{ijt}$ is the number of investments made by investor i in sector j until day $T - 1$, $\sum_{t=1}^{T-1} N_{it}$ is the total number of investments made by investor i day $T - 1$, $\sum_{t=1}^{T-1} n_{ikt}$ is the number of investments made by investor i in sector k of the considered startup until day $T - 1$, $SE_{i=1...N}^j$ is the standard error across investors of investment rates in sector j ; $AV_{j=1...24}$ is the averaging operator across sectors, $AV_{i=1...N}$ is the averaging operator across investors.

Geographic-institutional proximity

We use a combined measure of geographic and institutional proximity. We measure the extent to which the investors in a VC deal are from the same state (for the US) or country, and the extent to which they are from the same state or country as the startup they are funding in that deal. For each deal, we compute the index of geographic-institutional proximity between investors as follows:

$$geoprox_{inv} = 1 - \frac{\text{Number of different states(countries) of investors of the deal}}{\text{Number of investors of the deal}}$$

The index of geographic-institutional proximity between investors and startups is calculated for each deal as follows:

$$geoprox_{stup_{inv}} = \frac{\text{Number of investors in the deal from the same state(country) as the startup}}{\text{Number of investors of the deal}}$$

The variable *geoprox_{inv}* must be used and interpreted with care. Indeed, it is difficult to decide what value it should have in the case of a single investor: 0 because there is no connection with another investor in that deal, or 1 because there is no better geographic proximity than with oneself? That is why we decided to define this variable only when there is more than one investor in the deal. This means that the estimates that include the variable *geoprox_{inv}* only considered cases of syndicated investment in the last deal before the event in question. Therefore, we introduce this variable only as a robustness check, which consists in reducing the sample to the cases of syndicated VC deals.

Organizational proximity

As recalled earlier, organizational proximity can be defined as the existence of organizational practices and arrangements that facilitate coordination within and between organizations and can substitute trust when it is lacking. In the context of VC deals, we believe that the syndication of investments is the dominant practice that creates organizational proximity to deal with trust and control problems. However, the larger the syndicate is, the higher is the risk of loss of control and reduction of

trust, i.e. the lower is the organizational proximity of the syndication. Accordingly, we create an inverted organizational proximity measure for VC deals defined as⁹:

$$orgaprox = \text{number of investors in the syndicate}$$

Relational/social proximity

Finally, we measure relational/social proximity using the accumulated social capital of VC investors. Investors accumulate social capital by working in teams with other investors and jointly managing successful projects. We thus define:

$$socialprox = AV_{i=1...N} \left(\frac{ipo_{iT-1}}{\sum_{t=1}^{T-1} N_{it}} \right)$$

where the ipo_{iT-1} is the number of startups introduced in the public stock market in which investor i invested before day $T-1$. Of course, since this is a measure of past successful relationships, it is more a measure of social capital than a direct quantification of ongoing social connections. However, a high correlation between the two has been documented.

The labels of the variables indicate their format. For example, in “*cogprox_invr1_pct_sqr*”, *r1* means that the variable is measured at the last funding round before the event, *_pct* means it is in percentages, and *_sqr* means it is squared.

3.4. Control variables

To test the impact of these proximity measures on the duration before our three events of interest, we introduce a set of control variables that account for the characteristics of startups and VC investors, as well as the impact of the business cycle. In the literature, the usual controls for startups’ success are size, sector, location. They are introduced in the form of categorical dummies. The location of a startup is identified by the dummies *Northam*, for the US and Canada, *Eur*, for European countries (including

⁹ Since the size of the syndicate is naturally correlated to the financial amount invested in the deal, we introduce this amount as a control variable in all regressions, in order to make sure that *orgaprox* captures a pure effect of the size of the syndicate not confounded with the size of the investment.

UK), and *Asia*, for Asian locations. Other areas are in the reference category¹⁰. We also create the dummy *high tech*, which indicates whether a startup belongs to one of the following sectors: GICS 201, 351, 352, 451, 452, 453 and 501 (see Appendix 1); and all the other sectors are in the reference category¹¹. We introduce a three-modal categorical variable based on the number of employees (*employrank*) to account for the size of the startup. We also introduce the amount of capital raised in the VC deal prior the event (*amountrank*). For the latter two variables, the choice of a categorical rather than a quantitative specification is driven by the desire to obtain comparable hazard ratios; this does not affect the main results.

Although the proximity variables control for VC investors' characteristics (syndication, reputation, and specialization), we introduce two other VC-related control variables. A measure of VC investors' experience (*nbcieinvmo*), which is equal to the average (across investors) number of companies in which the members of the VC syndicate have invested prior the deal in question. Then, we consider the "fidelity" or "supportiveness" of VC investors: do they participate in many deals with different startups, or do they tend to focus their investments on a few startups in which they invest multiple times? To account for these potentially different investment strategies, we create the variable *supportiveness*, which is equal to the ratio of the average number of deals in which investors have previously participated to the average number of companies in which they have invested.

To control for the impact of the business cycle, we introduce the variable *expansionUS*, which equals one if, at the time of the event, the US economy is in a period of economic expansion according to the NBER business cycle dating committee.

The descriptive statistics of the variables are presented in Table 1.

¹⁰ To save space in the tables, we do not introduce 68 dummies for the 68 countries of the sample, but this has no significant consequence on our results of interest.

¹¹ To save space, we do not introduce 24 dummies for the 24 sectors, but we can provide the corresponding estimates on demand. The results of interest do not change.

Table 1. Variables definitions and descriptive statistics

Variables	Definitions	Observations	Mean	St. dev.	Min	Max
<i>Events:</i>						
<i>later</i>	Dummy variable equal to 1 when the startup benefits from a new VC funding round	78082	0.33	0.47	0	1
<i>IPO</i>	Dummy variable equal to 1 when the startup goes public	78082	0.02	0.15	0	1
<i>mergeracqu</i>	Dummy variable equal to 1 when the startup is merged or acquired	78082	0.09	0.28	0	1
<i>Proximity measures:</i>						
<i>cogprox_inv</i>	Time-varying index of co-specialization between the investors of the startup	63810	0.80	0.10	0.6	1
<i>cogprox_stup_inv</i>	Time-varying index of co-specialization between the startup and its investors	63810	0.27	0.23	0	1
<i>geoprox_inv</i>	Time-varying index of geographic-institutional proximity between investors of the startup	41079	0.28	0.25	0	0.92
<i>geoprox_stup_inv</i>	Time-varying index of geographic-institutional proximity of the startup with its investors	71593	0.46	0.42	0	1
<i>orgaprox</i>	Time-varying size of the VC syndicate	78080	2.41	2.00	1	15
<i>relationalprox</i>	Average Share of investors' company portfolio that went public (also time-varying)	63810	0.13	0.16	0	1
<i>Business cycle indicator</i>						
<i>expansionUS</i>	Dummy equal to 1 whenever the USA are in an expansion period according to the NBER business cycle dating committee	78082	0.88	0.33	0	1
<i>Control variables</i>						
<i>employrank</i>	Ranking of startups according to their number of employees (time-invariant)	69473	2.03	0.81	1	3
<i>amountrank</i>	Ranking of startups according to the financial amount of the VC deal (time-varying)	62422	1.99	0.83	1	3
<i>northam</i>	Dummy equal to 1 if the startup is based in Canada or in the US	78082	0.64	0.48	0	1
<i>Eur</i>	Dummy equal to 1 if the startup is based in Europe, including UK	78082	0.27	0.44	0	1
<i>Asia</i>	Dummy equal to 1 if the startup is based in Asia	78082	0.06	0.23	0	1
<i>high tech</i>	Dummy (variable <i>high tech</i>) indicating whether a startup belongs to one of the "high tech" sectors (time-invariant)	78082	0.69	0.46	0	1
<i>nbcienvmoy</i>	Average number of startups the investors of the syndicate have invested in before the considered deal	71741	0.28	0.84	0	13.61
<i>supportiveness</i>	Ratio of the average number of deals the investors of the syndicate have been involved into to <i>nbcienvmoy</i>	63585	112.31	36.84	0	357.68

4. Results

We first present the results of stratified Cox models corrected for tied failures by the Efron method. In these estimates, the variables that do not pass the proportional hazard test are either stratified or specified with a time-varying coefficient (Table 2)¹². The tables do not present coefficients but hazard ratios (and their significance), that is to say the percentage change in the likelihoods that the dependent variables become equal to 1 when the independent variables increase by one unit.

Regarding our proximity variables of interest, we first find that all the forms of proximity relations described by the variables *cogprox*, *geoprox*, *orgaprox* and *socialprox* have a significant impact on at least one of the three dependent variables. Thus, none of the proximity dimensions appears to be irrelevant, **in line with hypothesis 1a**. In an integrated proximity approach using all the five proximity dimensions¹³, we still find that three of the five proximities (geographic, organizational, social) have a significant impact on the likelihood of a later stage financing, that two of them have a significant impact on the probability of an IPO (cognitive and social proximity), and that three of them have a significant impact on the odds of a merger or acquisition (geographic, organizational and social proximity). However, the effects of the proximity variables turn out to be rather small: the strongest hazard ratio in this first series of estimates is 0.868147, meaning that a one-unit increase in the corresponding proximity measure

¹² Including all the variables and controls defined above, we first implement unstratified Cox models to identify the variables that do not pass the Schoenfeld residuals test for the proportional hazard hypothesis. Results of these preliminary estimates are available upon request. When the proportional hazard hypothesis is not relevant for a covariate, we implement two types of solutions: if the covariate is qualitative, it becomes a stratification variable in the subsequent stratified Cox estimations, using a different baseline hazard for each stratum. If the covariate is quantitative, we use a time-varying specification of its coefficient to relax the proportional hazards hypothesis. The other goal of these preliminary estimates is to test the significance of the covariates *geoprox_inv_pct* and *geoprox_inv_pct_sqr*, which measure geographic proximity between investors (not to be confused with geographic proximity between investors and startups). Since they are never significant, we no longer use them, thus gaining more than ten thousand observations (the non-syndicated cases where this variable cannot be defined).

¹³ We recall that the geographic and institutional dimensions are unfortunately mixed in the same variable.

reduces the IPO probability by 13.2%¹⁴. Since the standard error of *cogprox_inv* is 0.10, this is not a large magnitude effect.

The results also **corroborate hypothesis 1b**: the likelihood of a later stage funding, an event requiring trust from investors, is significantly influenced only by those proximities that mainly play a trust-building role (geographic, organizational and social proximity). Cognitive proximity has a significant impact only on IPO events. The finding that cognitive proximity has no significant impact on M&A likelihood is not fully in line with hypothesis 1b however, but we obtain a significant impact of the expected sign in the second series of estimates presented below. Relatedly, **hypothesis 1c**, which states that the size of the VC syndicate, interpreted as a form of organizational distance, should have a negative correlation with the likelihood of a later stage funding is also supported by the significant and inferior to one hazard ratio of the variable *orgaprox* in the first column estimation. Finally, we see in Table 2 that, when a proximity variable and its squared value are both significant, it is always with an inverse effect for the square, **validating empirically hypothesis 1d**. This complements the results of Tian et al. (2020), who found a nonlinear effect of VCs' geographic proximity. Note however that the second-order effects we find here are always much weaker than the first-order effects: the reverting tendency of proximity effects exists but its impact on the fate of VC-backed startups is of very weak magnitude.

At this stage, cognitive proximity only has a significant effect on the likelihood of an IPO, which is negative as expected: as already mentioned, one additional unit of cognitive distance between VC investors increases the probability of an IPO by 13.2% (hazard ratio of 0.868147), and one supplementary unit of cognitive distance between VC investors and the startup increases the IPO probability by 1.9% (hazard ratio of 0.980649). Thus, **hypothesis 2b is validated empirically, but hypothesis 2a is not**.

¹⁴ This can also be interpreted in the reversed way: one supplementary unit of cognitive distance between VC investors raises the probability of an IPO by 13,2%.

Compared to other studies, our positive and significant first-order impact of geographic proximity on the odds of obtaining a later-stage financing is consistent with the findings of Lutz et al., 2013, but contradicts those of Colombo et al. (2019). The effect we obtain here is smaller (a 0.27% increase in probability for one unit change). Our results are consistent with the findings of Cumming and Dai (2010) and Chemmanur et al. (2016) that geographic-institutional proximity between VC investors and startups slightly increases the probability that a startup will be the target of an M&A (by about 0.37%). Our results also complement those of Checkley et al. (2001), who found a positive impact of VC investors' social capital (network centrality) on IPO exit shares. Here we find that social capital has a positive impact on all three kind of events, later stage fundings, IPO exits and M&A exits. Note, however, that the amplitude is small. The increase in the probability of the three events is less than 1.7%, but this is the only proximity variable that always positively affects the occurrence of the three events. Finally, the finding that our organizational proximity variable, defined as the size of VC syndicate, has a negative impact on the probability of obtaining later-stage funding and on the probability of being merged or acquired may be consistent with the problem of coordination frictions in large syndicates highlighted by Nanda and Rhodes-Kropf (2018), as well as with the evidence that large syndicates require more negotiation time before an M&A (Nguyen and Vu, 2021).

Overall, we can conclude that our results do not contradict most previous studies and complement them in interesting ways. The fact that our proximity variables tend to have smaller effects is not surprising and can be explained by the fact that, unlike most previous research on VC operations, we include all the five proximity dimensions all together in our estimates.

Finally, and unsurprisingly, the **control variables** have effects depending on the type of the event considered. Regarding the conditional probability that a startup will access a new financing round, size in terms of amount invested, *amountrank*, has a positive impact. Size in terms of number of employees, *employrank*, also strongly increases the probability (by about

115%) that the startup will go public. Localization in Asia significantly increases the probability of going public and significantly decrease the probability of being merged or acquired. The control variable for investor support is never significant but the control for their experience, *nbcieinvmoyr1*, is significant with a small effect, positive on the odds of later-stage financing, and negative on the odds of going public or being merged or acquired. We could not estimate the business cycle dummy because it is a stratification variable in the IPO regression. It is not significant in the M&A estimation, but significant with a negative impact in the later-stage funding estimation.

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Table 2. Time before the event, stratified regressions corrected for tied failures

Covariates	Events		
	Later stage of funding	IPO	M&A
cogprox_invr1_pct	0.995516 (0.016)	0.868147* (0.056)	1.060459 (0.037)
cogprox_invr1_pct_sqr	1.000040 (0.000)	1.000945* (0.000)	0.999657 (0.000)
cogprox_stupkinvr1_pct	1.001115 (0.001)	0.980649** (0.004)	1.000680 (0.003)
cogprox_stupkinvr1_pct_sqr	0.999982 (0.000)	1.000151* (0.000)	0.999996 (0.000)
geoprox_stup_invr1_pct	1.002729** (0.001)	0.995571 (0.003)	1.003663* (0.002)
geoprox_stup_invr1_pct_sqr	0.999980** (0.000)	1.000039 (0.000)	0.999973 (0.000)
orgaproxr1	0.993399** (0.002)	1.006944 (0.004)	0.909361** (0.019)
orgaproxr1_sqr	0.999930 (0.000)	1.000275 (0.000)	1.004421* (0.002)
socialproxr1_pct	1.000370* (0.000)	1.006673** (0.001)	1.016991** (0.003)
socialproxr1_pct_sqr	0.999996 (0.000)	0.999656** (0.000)	0.999764** (0.000)
expansionUS	0.909712** (0.018)		0.985842 (0.045)
employrank		2.152693** (0.117)	
amountrankr1	1.120158** (0.011)	0.996890 (0.040)	1.033690 (0.021)
northam		0.889839 (0.172)	
eur	0.947211 (0.040)	1.139237 (0.233)	0.968491 (0.096)
asia	0.957949 (0.060)	1.934172** (0.410)	0.400193** (0.084)
supportivenessr1	0.999912 (0.000)	0.999909 (0.001)	1.000221 (0.000)
nbcieinvmojr1	1.000032** (0.000)	0.999976** (0.000)	0.999875** (0.000)
Strata variables	ht northam employrank orgaproxr1	ht expansionUS orgaproxr1	Employrank northam ht
Time varying covariates	orgaproxr1_sqr socialproxr1_pct socialproxr1_pct_sqr	orgaproxr1_sqr socialproxr1_pct nbcieinvmojr1	none
Function for time-varying covariates	ln(_t)	ln(_t)	none
Number of observations	32378	32378	32378
Number of subjects	14503.00	13409.00	14503.00
Wald χ^2	377.32	944.79	159.61
SE method	Robust cluster	Robust cluster	Robust cluster
Estimation method	Efron	Efron	Efron

** p<.01, * p<.05

5. A robustness check: dealing with competing events

In the previous estimates, we did not take into account the fact that some of our events of interest are competing risks. Unlike censoring, which prevents the event from being observed, a competing event prevents another event from occurring. If a later-stage funding does not prohibit a subsequent M&A or IPO, an M&A prevents a subsequent IPO, and conversely. Unfortunately, in the stratified Cox model, competing events are treated as censored: when they occur, the likelihood is computed as if the competitor events could still occur after the observation period. This is wrong since competitor events of a competing event can no longer happen once the latter has occurred. Competing risks survival models modify the computed likelihoods accordingly.

We therefore run additional competing risks regressions based on the method of Fine and Gray (1999). The results are shown in Table 3. They are consistent with the conclusions from the stratified Cox model presented in section 4, with only two differences regarding the proximity variables of interest. Firstly, geographic proximity now has a significant negative impact on the likelihood of going public and, secondly, cognitive proximity now has the expected significant positive impact on the likelihood of undergoing an M&A, providing the empirical validation of hypothesis 2a that was not obtained in the previous estimates.

Regarding the control variables, the most important change is that the business cycle dummy is now significant, with a strong positive effect on the probability of going public, and with a negative effect on the probability of being merged or acquired. Around the world, startups tend to go public during booms, and are more likely to be sold (or refinanced) during recessions. The only other change in controls is that the dummy for startups' location in North America has now a significant and positive impact on the likelihood of being merged or acquired.

Table 3. Time before the event, competing-risk model

Covariates	Events	
	IPO	M&A
cogprox_invr1_pct	0.848797* (0.056)	1.087291* (0.039)
cogprox_invr1_pct_sqr	1.001070* (0.000)	0.999498* (0.000)
cogprox_stupkinvr1_pct	0.981276** (0.005)	1.002892 (0.003)
cogprox_stupkinvr1_pct_sqr	1.000140* (0.000)	0.999982 (0.000)
geoprox_stup_invr1_pct	0.993664* (0.003)	1.004121* (0.002)
geoprox_stup_invr1_pct_sqr	1.000053 (0.000)	0.999965* (0.000)
orgaproxr1	1.007874 (0.005)	0.909577** (0.020)
orgaproxr1_sqr	1.000230 (0.000)	1.002762 (0.002)
socialproxr1_pct	1.006056** (0.001)	1.011290** (0.003)
socialproxr1_pct_sqr	0.999714** (0.000)	0.999763** (0.000)
expansionUS	4.711696** (0.816)	0.887216* (0.042)
Employrank	2.490702** (0.139)	0.810197** (0.018)
amountrank1	0.970276 (0.040)	1.009531 (0.021)
Northam	0.819775 (0.162)	1.308121** (0.123)
Eur	1.182489 (0.246)	0.948787 (0.093)
Asia	2.114189** (0.459)	0.287741** (0.059)
Ht	1.116553 (0.076)	0.957805 (0.036)
supportivenessr1	0.999715 (0.001)	1.000257 (0.000)
nbcieinvmojr1	0.999978* (0.000)	0.999887** (0.000)
Time varying covariates	orgaproxr1 orgaproxr1_sqr socialproxr1_pct nbcieinvmojr1	none
Function used for time-varying covariates	ln(_t)	none
Number of observations	32378	32372
Number of subjects	13409.00	13407.00
Wald χ^2	1149.21	362.79
SE method	Robust cluster	Robust cluster
Competing event(s)	exittype== 2 3	exittype== 1 3

** p<.01, * p<.05

6. Conclusions

To study the effects of venture capital relationship structures on the fate of VC-backed startups, we adopted an integrative and dynamic approach of proximity relations, inspired both by evolutionary theories of entrepreneurship and innovation (Nelson and Winter, 1973, 1982, Nelson, 1985), and by the so-called “proximity School” (Bellet et al., 1992, Gilly and Torre, 2000, Boschma, 2005a, Torre and Gallaud, 2022). These theories suggest considering VC syndicates as collective learning teams whose relational structures can decisively influence the fate of the new ventures they finance, manage and monitor. The survival and development of startups depends heavily on the ability of these teams to benefit from knowledge transfers and solve coordination problems. We believe that these theoretical backgrounds provide a relevant complement to agency theories that analyze VC deals as optimal contracts designed by rational agents to solve incentive problems (Lockett and Wright, 1999, Gompers and Lerner, 2006, Casamatta and Haritchabalet, 2007, Bayar et al., 2020).

In our empirical approach to the influence of venture capital proximity relations on the fate of startups, we considered not only the proximities between investors co-investing in a startup but also the proximities between them and the startup they finance. We introduced time-varying measures of the five forms of proximity proposed in the proximity literature (Boschma, 2005a), and we proposed and tested six hypotheses, on a sample of 18934 startups observed over 34 years in 68 countries. Let us recall the hypotheses formulated: 1.a) In an integrated empirical approach where all the five proximity dimensions are considered, they should all significantly influence the fate of VC-backed startups; 1.b) trust-related proximity dimensions, namely geographic, organizational, and social proximity, should influence the likelihood of a startup’s success in later-stage fundraising, while cognitive proximity should also influence the probability of IPO and M&A exits; 1.c) the larger is the size of a VC syndicate funding a startup, the lower should be the probability that this startup will receive later-stage funding; 1.d) the

effects of the proximity variables on the likelihood of startups' late-stage funding, IPO, or M&A should reverse themselves beyond certain thresholds; 2.a.) cognitive proximity between VC investors and between investors and investees should positively influence the likelihood that a startup will be merged or acquired; 2.b) cognitive distance between VC investors and between investors and investees should positively influence the likelihood that a startup will go public. We used Cox proportional hazard models, stratified and adjusted for tied failures, to test these hypotheses, and we checked robustness with maximum likelihood competing risks estimates. The empirical results obtained provide evidence in favor of all six hypotheses.

As emphasized in our literature review, we are not the first to study the impact of proximities in VC deals. There are several empirical studies that show the influence of geographic, social or institutional proximities on VC-backed startups' innovation, performance, successful exit events, ability to attract VC funds or cross-border VC investments. There are also studies that show the influence of some cognitive biases, but we found only one study using a measure of cognitive proximity defined as knowledge bases overlap akin to the one we have used here (Awounou N'dri and Boufaden, 2020). Our main contribution to this empirical literature is that we integrate the five proximity dimensions all together and do so with time-varying proximity measures. We are also the first to test the potential nonlinearity of the effects of proximity relations in a study of VC-backed startups, and to address the cognitive dimension in a way that accounts for the intrinsically evolutionary nature of knowledge bases. This allows us to show that cognitive proximity is correlated with startups' strategic choice between IPO and M&A, which is also a new result.

These empirical findings have several practical implications. Firstly, they support the claim of proximity scholars that too much proximity does not always have positive effects. The fact that proximity effects are not linear, and can be positive or negative depending on the event experienced by the startups, stems from the trade-offs between mutual understanding and lock-

in, and between the benefits of cooperation and the costs of rivalry. Thus, VC syndicates have to find a balance between too similar and too dissimilar investors. Secondly, in contexts where inputting new ideas is crucial for startups, cognitive differences may be more desirable than cognitive proximities, as it has also been found by Awounou N'dri and Boufaden (2020). Our study adds that this makes the cognitive proximity effect strategy dependent for VC-backed startups. Startups that end up being merged or acquired, presumably because their product or service was not radically new, experience a positive cognitive proximity effect, while those that end up going public experience a negative cognitive proximity effect, meaning that their odds of going public increase when their VC investors are more dissimilar. This finding has practical implications for both VC funds and founder-managers of venture-backed startups. For those planning an IPO, it will be important to limit cognitive similarity in the final round of financing. For those who prefer an M&A exit, it will be important to strengthen it.

There remain some limitations to this study that would require further research. Firstly, the measure of geographic-institutional proximity that we used could be split to separate the institutional and the geographic dimensions, and to compute the latter much more precisely than at the state/country level. However, this would require the extraction of fine-grained localization information on the sampled startups and their VC investors. We are also aware of the limitations of our measure of organizational proximity based on the number of members in VC syndicates. Syndication is an organizational practice that creates opportunities for interaction among VC funds' managers, and between them and startups' managers, but it is certainly more a matter of quality of interaction than quantity. For this reason, we had to interpret our variable as an indicator of organizational distance rather than organizational proximity, emphasizing that when the syndicate is large, coordination and control are more complex, which means that the organizational proximity of the syndication is lower. This could

be addressed by a more qualitative organizational proximity indicator derived from detailed information on the organizational structures of the VC funds composing VC syndicates.

Appendix 1. Startups distribution across industrial sectors (GICS classification)



Industry	Percentage	Observations
101: Energy equipment oil gas and consumable fuels	0,68	509
151: Construction materials chemicals containers metals and mining and forest products	1,53	1149
201: Aerospace and defense construction and engineering industrial conglomerates machinery and electrical equipment	1,69	1269
202: commercial and professional services	6,90	5171
203: Transportation infrastructures air freight airlines marine road and rail	0,31	233
251: Automobiles and components	0,25	185
252: Household durables leisure products leisure goods textiles apparel and luxury goods	2,30	1725
253: Hotels restaurants leisure and education services	4,09	3068
254: Media broadcasting movies and entertainment cable and satellite advertising and publishing	6,65	4984
255: Retailing and distributors	5,32	3988
301: Food and staples retailing	0,22	162
302: Beverages and agricultural products	0,91	679
303: Household products and personal products	0,42	313
351: Health care equipment and services	8,43	6318
352: Pharmaceuticals biotechnology life sciences and tools	12,27	9194
401: Banks and thrifts and mortgages	0,50	378
402: Diversified finance services	0,64	477
403: Insurance	0,24	181
404: Real estate investment trusts management and development	0,53	395
451: IT internet and software services	28,32	21216
452: Technology hardware communications equipment electronic components	11,27	8442
453: Semiconductors	0,43	324
501: Telecommunication services	4,87	3645
551: Gas water electric and renewable energy utilities	1,22	916
TOTAL	100,00	74921

Compliance with Ethical Standards

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extracted data is a company selling its data, we can only provide restricted access to our dataset, and only for reproducibility tests. Usage of this dataset for another purpose is strictly forbidden. We thank Amélie Adatte for her help in preparing the dataset.

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