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REGULAR ARTICLE

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

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Abstract

The characteristics of the financial arrangements established to finance startups affect the fate of startups. 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 investors and the startup. Against 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. We then test six hypotheses regarding the impacts of these proximities on the likelihood of three events occurring in VC-backed startups: obtaining a later-stage round of funding, going public, and being merged or acquired. We implement these tests on a 33-year-long, 68-country 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 have distinct roles. We also find that the impacts of these proximities are nonlinear in the sense that too much proximity/distance always ends up reverting the effects of proximity/distance. Finally, we observe that as the theoretical literature predicts, cognitive proximity is positively correlated with the probability of a merger and acquisition (M&A) but negatively correlated with the likelihood of an initial public offering (IPO).

Keywords Venture capital · Syndication · Startups · Proximity relations · Cognitive proximity

JEL Classification G24 · G34 · L21 · L26 · M13

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1 Introduction

The venture capital (VC) market has proven successful in supporting the creation of innovative businesses worldwide because it not only provides efficient ways in which to manage agency problems (Gompers 1995; Gompers and Lerner 2006; Tykvovà 2007) but also helps handle 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 for solving asymmetric information and market failure problems provides 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 deals[1] 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 result not only from the terms and restrictions of financial contracts but also 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 agents to find socioeconomic arrangements that reduce coordination costs and facilitate the diffusion of knowledge and information. The proximity approach refers to these arrangements as proximity relations, or simply "proximities", because they reduce geographic, social, and intellectual distances and costs. Although 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 also depends on the social, cognitive, organizational, and institutional proximities among these agents (Bellet et al. 1992; Gilly and Torre 2000; Boschma 2005a). In the *Handbook of Proximity Relations*, proximity is defined as a multidimensional space whose dimensions are composed 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, such as networks, shared learning and knowledge, institutions, and organizational practices. Proximity measures are then the different distance metrics of this multidimensional space.

[1] Syndication is frequent. In our sample of 27,810 startups and 78,082 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 involve six or more investors.

Like collaborative research, strategic alliances, or joint ventures, VC syndication creates teams of entrepreneurs and investors that need to coordinate among themselves and circulate information and knowledge among them. As an organizational arrangement, VC syndicates can be seen as a form of proximity, usually called "organizational proximity". The members of these teams are more or less distant from a cognitive, cultural, geographical, or social point of view. Consequently, the fate of VC-backed startups can be strongly influenced by the proximity relations characterizing these teams. Some empirical studies on VC operations address geographic proximity (e.g., Lerner 1995; Lutz et al. 2013), institutional proximity (e.g., Dai and Nahata 2016; Tykvovà and Schertler 2014; Moore et al. 2015) and relational proximity (e.g., Sorenson and Stuart 2001, 2008; Hochberg et al. 2007, 2010) , but none considers all the dimensions of proximity in an integrated framework that takes into account geographic, relational, institutional, organizational, and cognitive proximities. However, this integration is strongly advocated by the proximity approach, 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 the 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 for understanding VC deals because VC startups are risky and innovative activities requiring 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 continue to change and continuously modify their knowledge bases. From this perspective, the concept of cognitive proximity is inherently evolutionary and should not be confounded by the static cognitive biases resulting from shared exogenous characteristics such as familial, cultural, educational, or professional background.

To our knowledge, no studies on VC-backed startups that consider the possibly nonlinear influence of proximities exist. However, recent literature has emphasized that proximity is not always desirable, as it can sometimes generate negative effects due to redundancies, congestion, technological lock-ins, hold-up problems, or even conflicts. The influence of proximity 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 our knowledge, there are no studies dealing with the two types of links created by VC operations: those between investors (especially in syndications) and those between investors (VC funds) and beneficiaries (VC-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 this purpose, *we test two main sets of hypotheses* on a global dataset using dynamic measures of the following five forms of proximities: (1) the first series of hypotheses asserts that the five dimensions of proximity should be significant, that they play different roles, and that their effects are nonlinear; (2) the second series predicts that the cognitive proximity of VC deals is positively correlated with the probability of the startup being merged or acquired and negatively correlated with the likelihood of it undergoing an initial public offering (IPO). Our empirical results support these two hypotheses. The *value added of our empirical strategy* is first that we test the effects of proximities at two different levels: proximities between investors in the syndicate and proximities between investors and investees. Second, we use a 33-year-long, 68-country sample including up to 27,810 startups. Third, we estimate survival (or “duration”) models to test the impact of time-varying proximity measures on the probabilities of different events for these startups (IPOs, mergers and acquisitions (M&As), and later-stage funding). These estimates are corrected for nonproportional 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; Sections 4 and 5 present the results; and Section 6 concludes the paper.

2 Theory, empirical literature review, and hypotheses

In this section, we present the “proximity school of thought”, intellectually located at the cross section of economic geography, regional studies, and evolutionary economics, which provides a valuable integrated framework for an analysis of the role of proximity relations in VC-backed business ventures. We then show that although some empirical studies on VC use various operational measures of proximity or distance, they do not test them in such an integrated framework. We argue that the proximity approach can help fill this gap, and we derive the hypotheses suggested by this approach regarding how proximity relations may affect the fate of VC-backed startups.

2.1 Conceptual framework: Three strong claims of the proximity approach useful for analyzing the impacts of VC syndication on the fate of startups

Top-level venture capitalists add value to the new ventures in which they invest by providing intangible assets such as expertise, experience, coaching, networking, business contacts, and opportunities (Lerner 1994; Lockett and Wright 2001; Brander et al. 2002; Manigart et al. 2006; Sørheim 2012). To create a competitive advantage, all of these capabilities must be coherently combined and mixed with good knowledge of relevant markets, the legal environment, and incumbent competitors. A large body of literature using Schumpeterian, evolutionary, and innovation systems theories has shown that this approach requires efficient knowledge exchange mechanisms and interactive learning processes (Penrose 1959; Nelson and Winter 1973, 1982; Nelson 1985; Kogut and Zander 1993; Malerba and McKelvey 2019). Although VC deals create the kind of business ties that make knowledge transfer possible (Caselli 2010), 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 reduce coordination frictions and influence knowledge transfer mechanisms (Torre and Gallaud 2022). These proponents differentiate the following five dimensions to measure proximity relations: the dimension of physical distance that allows or prevents face-to-face interactions; 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; and 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 and organized proximities – with 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 (1985). This approach also refers to transaction costs and institutional economics, acknowledging that interactions at a distance are costly because of information gaps, the 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 the 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 study[2]. Our goal here is simply to use the integrated and structured view of proximity relations to conceive an empirical model 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. First, *geographic proximity* is defined as the distance between 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 that since geographic proximity does not guarantee communication or comprehension, other forms of nongeographic proximity (also called "organized proximities") are also important and can act as more or less efficient substitutes for geographic proximity (Boschma 2005a, 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 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.

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

The first strong claim of the proximity approach is that the five dimensions of proximity play clearly differentiated roles, which means that they are not redundant. All five dimensions contribute differently to economic development and business success (Boschma 2005a, b) and are imperfect substitutes for one another. For example, cognitive proximity strongly influences the type and amount of knowledge transferred between interacting agents and can be supported in this task by geographic proximity, which enables face-to-face interactions, and institutional proximity, which facilitates mutual understanding. In circumstances where the degree of cognitive proximity is low, geographic and institutional proximities only partially compensate for 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 can over- or understate the impact of one proximity dimension because the other dimensions are 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, then these effects should not be redundant and need to be measured as separate variables that tend to remain significant when integrated into econometric estimations. VC deals are economic arrangements that create relational structures between syndicated investors and between these investors and startup managers. Since efficient knowledge transfer and good coordination are key to value creation in startups, the five dimensions of proximity relations are expected to 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, which 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 coevolve; the 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 these reverting effects are congestion, conflicts, competitive pressures, hold-up problems, knowledge spillovers, and technological lock-ins. For example, too much geographic proximity may generate negative agglomeration externalities as infrastructures become congested, local markets become filled with competitors, and the risk of knowledge leakage becomes too high. Another example often found in the literature is that of arrangements that build organizational and relational proximities through collaborative networks but that may result in strategic conflicts, technological rivalry, and costly renegotiations between partners. In collaborative research, although cognitive proximity fosters mutual understanding and knowledge sharing, it can also lead to technological lock-ins because partners who are too cognitively similar do not generate enough new ideas for radical innovation (see, e.g., Nooteboom 2001; Boschma 2005b). In fact, lock-in risk is not limited to the cognitive dimension; 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) can also exist. In summary, there is always an optimal level of proximity/distance between partners. When the partners are too dissimilar, they cannot work together; while when they are too similar, they do not learn from one another 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 of the abovementioned cognitive proximity-cognitive lock-in dilemma. As Nooteboom (2000) first noted, the optimal level of cognitive proximity is not the same for every type of activity. A good empirical illustration of this situation is the study of Broekel and Boschma (2012), who find that too much cognitive proximity in the Dutch aviation knowledge network reduces firms' innovative performance. Other scholars underline that this tradeoff does not work the same way in all situations, noting that cognitive proximity is particularly good when knowledge exploitation for incremental innovation is the chosen strategy, while in contrast, cognitive distance is more desirable when knowledge exploration for radical innovation is the goal (Gilsing and Nooteboom 2006; Nooteboom et al. 2007; Brossard and Vicente 2010). This claim is the third strong claim of the proximity approach, which may prove useful for understanding the choices of VC-backed startups. Although startups are generally created with the aim of introducing new products or services to markets, not all of them are radically new. Consequently, one can 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 Chemmanur 2012, 2020). We expect cognitive proximity to be good only for those startups whose strategy is based on knowledge exploitation rather than on 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 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

2.2.1 Geographic proximities in VC markets

An early empirical study of US biotech companies by Lerner (1995) reveals that the physical proximity of venture capitalists to portfolio companies is an important determinant of a venture capitalist's board membership. Cumming and Dai (2010) also study US VC markets and observe that new ventures backed by neighboring VC investors are more successful than are those not backed by such investors. Lutz et al. (2013) find that the probability of a financing relationship forming between VC investors and investees in Germany decreases with the distance between them. Pe'er and Keil (2013) note that the survival of startups is influenced by their location in clusters. Interestingly, Chemmanur et al. (2016) obtain 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 find evidence that firms backed by syndicates with international and local VC are more likely to exit successfully[3] and have better post-IPO operating performance than do those backed by syndicates composed entirely of local or international VC. More recently, Colombo et al. (2019) find that ventures are more likely to seek external equity when some VC investors are nearby, and Tian et al. (2020) reveal a nonlinear effect of a VC firm's geographic distance on the technological performance of VC-backed companies in China.

2.2.2 Institutional proximity and VC markets

A few studies examine the impact of cultural or institutional distance on the functioning of VC financing. Focusing on cross-border VC deals worldwide, Li et al. (2014) find that cultural and institutional distances have negative impacts on the fate of VC-backed ventures. Dai and Nahata (2016) obtain similar results. Moreover, Tykvovà and Schertler (2014) provide evidence that the negative impact of institutional distance cannot be mitigated by investment syndication with local VC investors as can the negative impact of geographic distance. However, Chemmanur et al. (2016) report the opposite results in emerging nations. Additionally, Bottazzi et al. (2016) obtain results in favor of the institutional proximity factor: the greater the measure of trust within the European nation is, the greater 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 dimensions), reduces the number of cross-border VC investments.

2.2.3 Relational/social proximity and VC deals

Inspired by Sorenson and Stuart (2001), who show that US venture capitalists with strong positions in the syndication network invest more frequently in spatially distant companies, many studies are devoted to analyzing the effects of relational/social proximity in VC markets. De Clercq and Sapienza (2006) underline that social proximity positively affects the way in which US-based VC firms perceive the performance of their portfolio companies. Hochberg et al. (2007) find that VC funds with greater network centrality have significantly better fund performance. Checkley et al. (2010) show that network centrality Granger-causes IPO exit shares of portfolio companies in the UK, and Trapido (2012) shows that social proximity

[3] For a VC fund or an entrepreneur, a successful exit means the sale of its share with capital gain, owing 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, which is why startups' performance is very often proxied by successful exits in the empirical literature.

in VC syndication networks has positive performance implications. By addressing this issue differently, Alexy et al. (2012) find that VCs characterized by high levels of relational centrality (in terms of degree or brokerage) provide larger investments. Jääskeläinen and Maula (2014) examine cross-border VC exits in EU-15 countries and find that the more a venture has nondomestic syndication ties, the more likely it is to exit a nondomestic market. Hain et al. (2016) note that institutional trust seems more important for investments in emerging economies, while relational trust is more important for investments in developed economies. Furthermore, Meuleman et al. (2017) observe that structural embeddedness (captured by indirect ties) and institutional proximity facilitate cross-border partnering, while Shao and Sun (2021) find that structural and cognitive capital appear to facilitate VC financing in China.

2.2.4 Organizational proximity

We cannot find any empirical studies that explicitly assess the impact of any form of organizational proximity on VC financing. One can hypothesize that this is due to the difficulty in 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. Such studies are numerous and almost unanimous in showing that the organizational proximity created by investment syndication provides many benefits (see, e.g., Lerner 1994; Lockett and Wright 2001; Wright and Lockett 2003; Manigart et al. 2006; Casamatta and Haritchabalet 2007; Bayar et al. 2020).

2.2.5 Cognitive proximity in VC deals: A neglected factor

Cognitive proximity between two actors is alternatively defined as the degree of similarity in the way in which they perceive, interpret, understand, and evaluate the world (Nooteboom 2001) or as the degree to which they share the same knowledge base and expertise (Boschma 2005a). We find no study of VC deals based on the latter, but a few studies can be related to the former. First, Franke et al. (2006) analyze the evaluations made by a small sample of Austrian and German VC firms regarding prospective target startups and find that VC investors with engineering or business backgrounds tend to give higher ratings to startup teams with similar backgrounds. Murnieks et al. (2011) study US VC deals and find that venture capitalists rate entrepreneurs who have the same decision-making processes as their own more favorably. Gompers et al. (2016) show that venture capitalists who share the same ethnic, educational, or professional backgrounds are more likely to syndicate with one another, and this homophily reduces the probability of investment success. Du (2016) finds that VC investors prefer to form VC syndicates with partners with similar experience levels, which can indicate that cognitive proximity can reduce some transaction costs. According to 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). The above authors find that normative and cultural-cognitive distance reduce the number of cross-border VC investments.

The above five studies provide clear evidence that educational, professional, and cultural similarities create interaction biases that affect the selection of projects and partners in VC, and that there also exists cognitive biases in VC deals resulting from the exogenous characteristics of investors. However, the cognitive similarities they consider do not result from the evolution of knowledge bases through agents' experience and learning over time. The proximity approach states that cognitive proximity is precisely a matter of overlapping knowledge bases that evolve over time. This assertion suggests dynamic measures of knowledge overlap between agents or organizations. To our knowledge, there are no empirical studies using this definition of cognitive proximity in VC operations[4].

To summarize the empirical literature on the impact of the five forms of proximity relations in VC deals and startup funding, we identify the following three main gaps: (1) no empirical work integrates the five proximity dimensions together, and the organizational dimension is neglected, while the cognitive dimension is apprehended in an overly static manner; (2) none of these studies test for the potential nonlinearity of the effects of proximity relations; and (3) the cognitive dimension is integrated in the form of static characteristics that capture cognitive biases. We argue that VC stakeholders are learning agents, which requires dynamic measures of cognitive proximity. We also underline, in Section 2.1, that although cognitive proximity can be useful in some circumstances, it can also lead to technological lock-ins and thus be a disincentive to radical innovation. This relationship should be tested on VC-backed startups, differentiating them according to their strategic goals, which brings us to the derivation of our hypotheses.

2.3 Hypotheses

In this section, we propose two sets of hypotheses. The first set 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 set 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 argue that the five dimensions of proximity relations play differentiated but interacting roles. In Sections 2.1 and 2.2, we explain 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 these relations. We also argue 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, thus leading to the following hypothesis:

[4] The study of Awounou N'dri and Boufaden (2020) can be considered an exception since these authors 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.

Hypothesis 1a: In an integrated empirical approach where all five proximity dimensions are considered, we expect them all to 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 transfer (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 of VC investors funding a startup increases with increasing levels of trust. Attracting new investment requires proximity relations that help build trust. Proximity relations that stimulate knowledge transfer are more likely to influence the quality and quantity of innovation, which is an important determinant of the exit choices of VC-backed startups (Schwienbacher 2008; Bayar and Chemmanur 2011). Therefore, the following hypothesis is proposed:

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

Several studies demonstrate that investment syndication in VC deals is a symptom of low levels of trust, showing that the probability of VC syndication increases with increasing levels of distrust (e.g., Wright and Lockett 2003; Kollmann et al. 2014; 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 becomes too large: the more numerous VC funds are in the syndicate, the less easy the organizational control of the syndicate and the weaker the effective organizational proximity. In contrast, having only one fund in the syndicate is equivalent to the strongest possible organizational proximity. Thus, we make the following assumption:

Hypothesis 1c: The greater the level of syndication is, the more organizational distance there is, and the lower the probability of the startup receiving a new round of funding.

We also underline, 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-ins tend to develop as proximity strengthens 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 about new ideas or in the organizational dimension because trust-based mechanisms are preferred over tight control devices, then too much cognitive or organizational distance can become negative beyond a certain threshold. We therefore propose the following hypothesis:

Hypothesis 1d: The effects of proximity variables on the likelihood of late-stage funding, IPOs, or M&A operations reverse beyond certain thresholds.

We recall in Section 2.1 that several scholars, starting with Nooteboom (2001), emphasize that cognitive proximity is not always good because it involves a trade-off between cognitive distance, which stimulates the emergence of new ideas, and cognitive proximity, which facilitates knowledge absorption (Boschma 2005b; Broekel and Boschma 2012). Other scholars underline that cognitive proximity is particularly good when knowledge exploitation for incremental innovation is the strategy, while cognitive distance is more desirable when knowledge exploration for radical innovation is the goal (Gilsing and Nooteboom 2006; Nooteboom et al. 2007; Brossard and Vicente 2010). We now want to emphasize that VC-backed startups are not all equally innovative, as some are more oriented towards disruptive innovation projects, while others are more oriented towards incremental innovation (Boyer and Blazy 2014; Colombelli et al. 2016). It has long been recognized that these different innovation strategies of startups are correlated with their exit choices. More innovative firms are more likely to go public than are 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 decreases, and the IPO premium becomes more attractive (Schwienbacher 2008). Moreover, for startups with disruptive innovations, remaining independent is critical if the strategy is to challenge incumbents with a new product or service. Indeed, dominant firms in technology industries tend to acquire startups 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, then 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 is shown to support incremental innovations and since the latter is shown to increase the likelihood of M&A exits for startups, we can formulate the following hypothesis:

Hypothesis 2a: Cognitive proximity between VC investors and between investors and investees positively influences the likelihood of a startup being merged or acquired.

In contrast, since cognitive distance is shown to produce more disruptive innovations that increase the likelihood of a startup eventually going public, we can formulate the following hypothesis:

Hypothesis 2b: 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 definition proposed by proximity theorists (see, e.g., Boschma 2005a, b; Balland et al. 2015). They argue that proximities and relations coevolve: proximities create new relationships, and 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, which requires that cognitive proximity be measured dynamically. We propose such an approach in the below empirical section. This approach differs from the static similarity-based cognitive biases measured in many VC studies (see *supra*). We now provide a description of our empirical strategy and results.

3 Data, econometric method, and variable construction

3.1 Dataset construction and endogeneity issues

First, it is not our goal to explain how venture capitalists select startups or to compare the performance of VC-backed startups with that of other startups. Hypotheses 1a, 1b, 1c, 1d, 2a and 2b can be tested with an empirical model of the determinants of the likelihood of a VC-backed startup attracting investors for an additional round of financing, for an M&A, or for an IPO. For this purpose, we use a duration model that predicts the likelihood of the event of interest conditional on the time elapsed before the event.

We extract data on startups and their VC investors over 33 years between 1982 and 2014[5]. The data are extracted from Dow Jones' VentureSource database and cover VC deals in 68 countries worldwide. We select only those startups that receive 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 Table 4 shows the complete distribution of the observed startups across sectors.

For each startup in the dataset, we extract information on its investors and investment types, industry segments, and localizations. We also have information on their VC funding round types ("seed, 1st, 2nd, …, 9th, later, restart") and on their 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 one way or another, whether

[5] For cost reasons, we could not extract data from VentureSource beyond this date. However, these 33 years of worldwide data already provide a great amount of variability in terms of geography, industry, and business cycle.

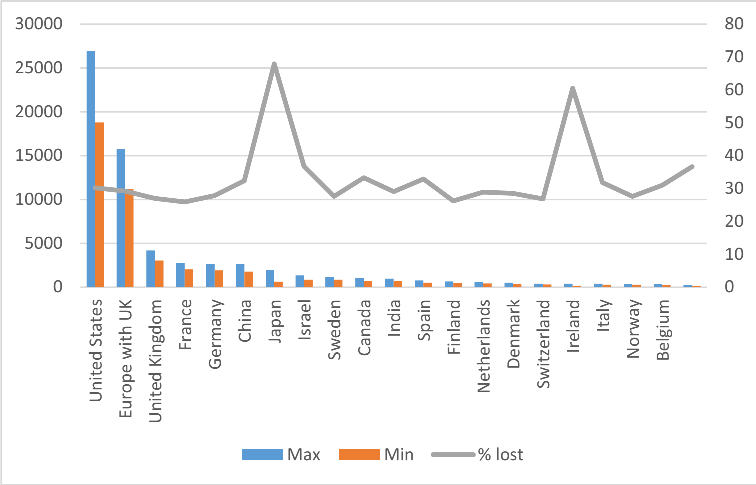

Fig. 1 Maximum and minimum number of startups in the study sample

through M&As, IPOs or secondary public offerings (SPOs), or 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 exhibits 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 includes many startups (51,969), but missing data (for example, those on investors' identification and deal dates) lead us to drop some observations. However, the number of exploitable observations remains large (27,810 startups and 78,082 deals). More importantly, as illustrated in Fig. 1, the losses of observations appear to be evenly distributed across countries, except for Japanese and Irish companies. We also confirm that these information gaps are evenly distributed across startup size and industry segment.

The following selection issue regarding our sample exists: we observe only 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 VC investment from the "selection" effect attributable to the ability of VC investors to select the most promising startups. However, this is not our goal, and we must acknowledge that our results explain only the determinants of the fate of VC-backed startups and not those of non-VC-backed startups.

A frequent source of endogeneity in startup studies is survivorship bias, when the dependent variable can be observed only for startups that have survived or passed a certain selection process. Methods such as the Heckman procedure are required 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 observe that quantitative performance indicators are often missing, even for surviving startups. We therefore decide to construct dependent variables based on investment events, as is usually done in the VC empirical literature. Indeed, events such as later-stage funding, an M&A, and an IPO[6] can be interpreted as successful events because the startup attracts new investors and since former VC investors can sell their shares. All of 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. These events 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 receives VC funding and that the VentureSource data managers obtain 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 the data management staff. Although these elements may bias the representativeness of the dataset, they are not correlated with startups' future investment events, which are unknown at the time of selection. Overall, we 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 hope that it is representative of the universe of VC-backed startups. However, we must acknowledge that we cannot 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 that we can argue here is that our dataset exhibits great diversity in terms of the size, sector, and location of VC-backed startups.

We address 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 33 years. This situation requires the business cycle to be controlled because we know that the investment events we study are more likely to occur during business booms than during business 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).

We must emphasize that our survival modeling methodology does not allow us to use instrumental variable (IV) regressions to address endogeneity biases possibly caused by measurement error, simultaneity, or remaining unobserved heterogeneity. Unfortunately, the conditions under which the IV technique can be applied within a Cox survival proportional hazards model are rather restrictive (Uddin et al. 2023), and it is beyond our reach to develop a reliable statistical method for such an approach. However, given the size and variety of the sample, we can expect our variables not to be affected by significant measurement errors and our control variables to correctly address unobserved heterogeneity. Moreover, we hope that it is unlikely that past proximities are caused by future funding or exit events, and it

[6] Other investment events reported in the database are, for example, first, second, third,…, round investment, acquisition financing, corporate investment, angel investment, debt-type investments, and management buy-outs.

seems difficult to imagine that VC syndicates would arrange their team's proximities in relation to anticipated funding or exit events that would occur years later. Overall, we 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 censorship, nonlinear hazard rates, competing events, and tied failures

In Section 3.1 we explain why we use event-based dependent variables. This approach 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 the following three types of events: (1) receiving a "later" stage of VC funding, (2) an IPO, and (3) an M&A. We therefore define the following 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 *Mergeracqu,* 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 another exit event such as a judicial liquidation. Thus, surviving is not a condition for these startups to be included in the dataset and to have the dependent variable observed. Startups that collapse before any of these three events occur remain included in the econometric analysis. However, these variables are duration-dependent, and affected by censoring, which requires proper modeling tools.

Indeed, there is no left censoring in this dataset since the events of interest cannot occur before entry; however, there is left truncation in the form of delayed entry. 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 nonnormally distributed, we use a Cox proportional hazards model (Cox 1972), which 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 functional form according to the following formula:

$$h\left(t|x_j\right) = h_0(t)\exp(x_j\beta_x) \tag{1}$$

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

The key advantage of the Cox approach is that it eliminates the risk of biasing the estimates of β_x due to the 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) as follows:

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

This situation 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, then the coefficient βx is biased. To address this issue, we implement the following approach. First, we implement simple Cox estimations and assess the validity of the proportional hazards 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 for which the Schoenfeld test fails. These variables are instead used as stratification variables with specific baseline hazards. The quantitative variables that fail the Schoenfeld test are replaced by time-varying coefficient variables, which 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, an M&A, or any other financial event on the same day. Since the parameter estimation of the Cox model is based on the maximization of the likelihood function, the latter must account for these tied failures by hypothesizing how they occur. We chose to present the results of stratified Cox models using the Efron correction method for tied failures, but we carefully check that they are not significantly changed when using other available methods.

Finally, we perform robustness checks using maximum likelihood competing risk regressions following the method of Fine and Gray (1999). Indeed, IPOs, M&As, and bankruptcies are competing events for startups: if one of these three events occurs, then the other events never occur or occur only after a significant period[7].

3.3 Proximity variables

To test our hypotheses, we construct four time-varying proximity measures. We also include the squared values of these proximity measures to test Hypothesis 1d.

3.3.1 Cognitive proximity

Empirical studies of cognitive proximity are often based on observations of patent technological classes and measures of their overlap (e.g., Jaffe 1989; Nooteboom et al. 2007; Krafft et al. 2014). However, this approach is relevant only for organizations that produce or use patents. This situation is not the case for VC funds, and only a small proportion of startups have already filed patents when they receive VC

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

funding[8]. Moreover, patents characterize formal knowledge but exclude other kinds of tacit, uncodified knowledge (Caragliu 2022).

Because knowledge bases consist of the techniques, skills, and knowledge that characterize professions and industries, we can assume that fine-grained sectoral proximities satisfactorily reflect cognitive proximities. Thus, we use industry classification to compare the knowledge bases of VC investors and startups. Our dataset contains three-digit industry codes (Global Industry Classification Standard (GICS) codes) that distinguish 24 industries. We suppose that startups belonging to the same three-digit industry have very similar knowledge bases. We 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 cospecialization according to the following formula:

$$\textit{cognitive proximity between investors}_{T-1} = 1 - \left(AV_{j=1\ldots24}\left(SE^{j}_{i=1\ldots N}\left(\frac{\sum_{t=1}^{T-1} n_{ijt}}{\sum_{t=1}^{T-1} N_{it}} \right)\right)\right)$$

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

$$\textit{cognitive proximity between startup and investors}_{T-1} = AV_{i=1\ldots N}\left(\frac{\sum_{t=1}^{T-1} n_{ikt}}{\sum_{t=1}^{T-1} N_{it}} \right)$$

where $i = 1 \ldots N$ are the investors in the financing round (deal), $j = 1, \ldots, 24$ is the industry sector (three-digit GICS code), t is the index of the day ($t = 1$ is the first day in which 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 $T - 1$, $SE^{j}_{i=1\ldots N}$ is the standard error across investors of investment rates in sector j, $AV_{j=1\ldots24}$ is the averaging operator across sectors, and $AV_{i=1\ldots N}$ is the averaging operator across investors.

3.3.2 Geographic and 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 that of the startup they are funding in that deal. For each deal, we compute the index of geographic–institutional proximity between investors as follows:

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

$$Geographic\ proximity\ between\ investors = 1 - \frac{\begin{array}{c}Number\ of\ different\ states\ (countries)\\ of investors\ of\ the\ deal\end{array}}{Number\ of\ investors\ of\ the\ deal}$$

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

$$\begin{array}{c}Geographic\ proximity\ between\\ the\ startup\ and\ its\ investors\end{array} = \frac{\begin{array}{c}Number\ of\ investors\ in\ the\ deal\ from\\ the\ same\ state\ (country) as\ that\ of\ the\ startup\end{array}}{Number\ of\ investors\ of\ the\ deal}$$

The variable *Geographic proximity between investors* 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. Therefore, we define this variable only when there is more than one investor in the deal, meaning that the estimates that include the variable *Geographic proximity between investors* consider only 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 of reducing the sample to the cases of syndicated VC deals.

3.3.3 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 for 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 address trust and control problems. However, the larger the syndicate is, the greater the risk of loss of control and the reduction in trust, i.e., the lower the organizational proximity of the syndication. Accordingly, we create an inverted organizational proximity measure for VC deals defined as follows[9]:

$$Organizational\ proximity = number\ of\ investors\ in\ the\ syndicate$$

3.3.4 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 the following:

[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 to make sure that *orgaprox* captures a pure effect of the size of the syndicate not confounded with the size of the investment.

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

where 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 is documented.

We add suffixes to the variables when they are modified as follows: the suffix *_r1* means that the variable is measured at the last funding round before the event considered as the dependent variable, the suffix *_pct* means that the figure is in percentages, and the suffix *_sqr* means that 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 startup success are size, sector, and location, which are introduced here in the form of categorical dummies. The location of a startup is identified by the dummies *NorthAmerica*, for the US and Canada, *Europe* for European countries (including the UK), and *Asia* for Asian locations. Other areas are in the reference category[10]. 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 or 501 (see Appendix Table 4); all the other sectors are in the reference category[11]. We introduce a three-modal categorical variable based on the number of employees (*Workforce size*) to account for the size of the startup. We also introduce the amount of capital raised in the VC deal prior to the event (*Deal amount*). For *Workforce size* and *Deal amount*, the choice of a categorical rather than a quantitative specification is driven by the desire to obtain comparable hazard ratios, but 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. The first variable is a measure of VC investors' experience (*Investor experience*), which is equal to the average (across investors) number of companies in which the members of the VC syndicate have invested prior to 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 *Investor supportiveness*, which is equal

[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 Variable definitions and descriptive statistics

Variable		Definition	Obs.	Mean	Std. dev.	Min.	Max.
Events:	*Later-stage funding*	Dummy variable equal to 1 when the startup benefits from a new VC funding round	78,082	0.33	0.47	0	1
	IPO	Dummy variable equal to 1 when the startup goes public	78,082	0.02	0.15	0	1
	M&A	Dummy variable equal to 1 when the startup is merged or acquired	78,082	0.09	0.28	0	1
Cognitive proximity between investors		Time-varying index of cospecialization between the investors of the startup	63,810	0.80	0.10	0.6	1
Cognitive proximity between the startup and its investors		Time-varying index of cospecialization between the startup and its investors	63,810	0.27	0.23	0	1
Geographic proximity between investors		Time-varying index of geographic-institutional proximity between the investors of the startup	41,079	0.28	0.25	0	0.92
Geographic proximity between the startup and its investors		Time-varying index of geographic-institutional proximity of the startup with its investors	71,593	0.46	0.42	0	1
Organizational proximity		Time-varying size of the VC syndicate	78,080	2.41	2.00	1	15
Social proximity		Average share of investors' company portfolio that went public (time varying)	63,810	0.13	0.16	0	1
Control variables:	*Workforce size*	Ranking of startups' size based on the number of employees: = 1 if the startup belongs to the first tercile, = 2 if it belongs to the second tercile, and = 3 if it belongs to the third tercile	69,473	2.03	0.81	1	3
	Deal amount	Ranking of startups' size based on the amount of capital raised in the considered VC deal: = 1 if the startup belongs to the first tercile, = 2 if it belongs to the second tercile, and = 3 if it belongs to the third tercile	62,422	1.99	0.83	1	3
	NorthAmerica	Dummy = 1 if the startup is based in Canada or the US	78,092	0.64	0.48	0	1

Table 1 (continued)

Variable		Definition	Obs.	Mean	Std. dev.	Min.	Max.
Events:	*Later-stage funding*	Dummy variable equal to 1 when the startup benefits from a new VC funding round	78,082	0.33	0.47	0	1
	Europe	Dummy = 1 if the startup is based in Europe, including the UK	78,082	0.27	0.44	0	1
	Asia	Dummy = 1 if the startup is based in Asia	78,082	0.06	0.23	0	1
	ExpansionUS	Dummy = 1 if the US is in an expansion period according the NBER business cycle dating committee	78,082	0.88	0.33	0	1
	High tech	Dummy = 1 if the startup belongs to a high-tech sector (time invariant)	78,082	0.69	0.46	0	1
	Investor experience	Average number of startups the investors of the syndicate have invested in before the considered deal	71,741	0.28	0.84	0	13.61
	Investor supportiveness	Ratio of the average number of deals in which investors have previously participated to the average number of companies in which they have invested	63,585	112.31	36.84	0	357.68

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 1 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.

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 hazards test are either stratified or specified with a time-varying coefficient (Table 2)[12]. The tables do not present coefficients but rather hazard ratios (and their significance), that is, the percentage change in the likelihood 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 *Cognitive proximity*, *Geographic proximity*, *Organizational proximity*, and *Social proximity* have a significant impact on at least one of the three dependent variables. Thus, none of the proximity dimensions appear to be irrelevant, which is in line with Hypothesis 1a. In an integrated proximity approach using all five proximity dimensions[13], we still find that three of the five proximities (geographic, organizational, and social proximities) have a significant impact on the likelihood of later-stage financing, two of them (cognitive and social proximities) have a significant impact on the probability of an IPO, and three of them (geographic, organizational, and social proximities) have a significant impact on the odds of an M&A. However, the effects of the proximity variables turn out to be rather weak: the strongest hazard ratio in this first series of estimates is 0.868147, meaning that a one-unit increase in the corresponding proximity measure reduces the IPO probability by 13.2%[14]. Since the standard error of *Cognitive proximity between investors* is 0.10, this is not a large magnitude effect.

[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 residual test for the proportional hazards hypothesis. The results of these preliminary estimates are available upon request. When the proportional hazards hypothesis is not relevant for a covariate, we implement two types of solutions: if the covariate is qualitative, then it becomes a stratification variable in the subsequent stratified Cox estimations, using a different baseline hazard for each stratum, and if the covariate is quantitative, then 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 *Geographic proximity between investors_pct* and *Geographic proximity between investors_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 10,000 observations (the nonsyndicated cases where this variable cannot be defined).

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

[14] This situation can also be interpreted in the opposite way: one supplementary unit of cognitive distance between VC investors raises the probability of an IPO by 13.2%.

Table 2 Estimation of the time before the event, stratified regressions corrected for tied failures

Covariates	Events		
	Later-stage funding	IPO	M&A
*Cognitive proximity between investors*_r1_pct	0.995516	0.868147*	1.060459
	(0.016)	(0.056)	(0.037)
*Cognitive proximity between investors*_r1_pct_sqr	1.000040	1.000945*	0.999657
	(0.000)	(0.000)	(0.000)
*Cognitive proximity between the startup and its investors*_r1_pct	1.001115	0.980649**	1.000680
	(0.001)	(0.004)	(0.003)
*Cognitive proximity between the startup and its investors*_r1_pct_sqr	0.999982	1.000151*	0.999996
	(0.000)	(0.000)	(0.000)
*Geographic proximity between the startup and its investors*_r1_pct	1.002729**	0.995571	1.003663*
	(0.001)	(0.003)	(0.002)
*Geographic proximity between the startup and its investors*_r1_pct_sqr	0.999980**	1.000039	0.999973
	(0.000)	(0.000)	(0.000)
*Organizational proximity*_r1 (*op_r1*)	0.993399**	1.006944	0.909361**
	(0.002)	(0.004)	(0.019)
*Organizational proximity*_r1_sqr (*op_r1_sqr*)	0.999930	1.000275	1.004421*
	(0.000)	(0.000)	(0.002)
*Social proximity*_r1_pct (*sp_r1_pct*)	1.000370*	1.006673**	1.016991**
	(0.000)	(0.001)	(0.003)
*Social proximity*_r1_pct_sqr (*sp_r1_pct_sqr*)	0.999996	0.999656**	0.999764**
	(0.000)	(0.000)	(0.000)
Workforce size (ws)		2.152693**	
		(0.117)	
*Deal amount*_r1	1.120158**	0.996890	1.033690
	(0.011)	(0.040)	(0.021)

Table 2 (continued)

Covariates	Events		
	Later-stage funding	IPO	M&A
NorthAmerica (na)		0.889839	
		(0.172)	
Europe (E)	0.947211	1.139237	0.968491
	(0.040)	(0.233)	(0.096)
Asia (A)	0.957949	1.934172**	0.400193**
	(0.060)	(0.410)	(0.084)
ExpansionUS (eUS)	0.909712**		0.985842
	(0.018)		(0.045)
*Investor supportiveness*_r1	0.999912	0.999909	1.000221
	(0.000)	(0.001)	(0.000)
*Investor experience*_r1 (*ir_r1*)	1.000032**	0.999976**	0.999875**
	(0.000)	(0.000)	(0.000)
Strata variables	*High tech, na, ws*	*High tech, eUS*	*ws, na, high tech*
Time-varying covariates	*op_r1, op_r1_sqr, sp_r1_pct, sp_r1_pct_sqr*	*op_r1, op_r1_sqr, sp_r1_pct, ir_r1*	*none*
Function for time-varying covariates	ln(_t)	ln(_t)	
Number of observations	32,378	32,378	32,378
Number of subjects	14,503	13,409	14,503
Wald χ^2	377.32	944.79	159.61
SE method	Robust cluster	Cluster	Robust
Estimation method	Efron	Efron	Efron

** $p < .01$, and *$p < .05$

The results also corroborate Hypothesis 1b: the likelihood of later-stage funding, an event requiring trust from investors, is significantly influenced only by those proximities that play mainly a trust-building role (geographic, organizational, and social proximities). 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, 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 later-stage funding, is also supported by the significant and inferior-to-one hazard ratio of the variable *Organizational proximity* in the first column estimation. Finally, we see in Table 2 that when a proximity variable and its squared value both are significant, it is always with an inverse effect for the square, thus empirically validating Hypothesis 1d. This finding complements the results of Tian et al. (2020), who find 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 very weak in magnitude.

At this stage, cognitive proximity has a significant effect only 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 probability of an IPO by 1.9% (hazard ratio of 0.980649). Thus, Hypothesis 2b is validated empirically, but Hypothesis 2a is not.

Compared to other studies, our positive and significant first-order impact of geographic proximity on the odds of obtaining 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 of a startup being the target of an M&A (by approximately 0.37%). Our results complement those of Checkley et al. (2010), who find 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 kinds of events, namely, later-stage funding, IPO exits, and M&A exits. Note, however, that the amplitude of this impact 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 probabilities of startups obtaining later-stage funding and 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 those of most previous studies and complement such studies 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 five proximity dimensions together in our estimates.

Table 3 Estimation of time before the event, competing risk model

Covariate	Events	
	IPO	M&A
*Cognitive proximity between investors*_r1_pct	0.848797*	1.087291*
	(0.056)	(0.039)
*Cognitive proximity between investors*_r1_pct_sqr	1.001070*	0.999498*
	(0.000)	(0.000)
*Cognitive proximity between the startup and its investors*_r1_pct	0.981276**	1.002892
	(0.005)	(0.003)
*Cognitive proximity between the startup and its investors*_r1_pct_sqr	1.000140*	0.999982
	(0.000)	(0.000)
*Geographic proximity between the startup and its investors*_r1_pct	0.993664*	1.004121*
	(0.003)	(0.002)
*Geographic proximity between the startup and its investors*_r1_pct_sqr	1.000053	0.999965*
	(0.000)	(0.000)
*Organizational proximity*_r1 (*op_r1*)	1.007874	0.909577**
	(0.005)	(0.020)
*Organizational proximity*_r1_sqr (*op_r1_sqr*)	1.000230	1.002762
	(0.000)	(0.002)
*Social proximity*_r1_pct (*sp_r1_pct*)	1.006056**	1.011290**
	(0.001)	(0.003)
*Social proximity*_r1_pct_sqr (*sp_r1_pct_sqr*)	0.999714**	0.999763**
	(0.000)	(0.000)
ExpansionUS (eUS)	4.711696**	0.887216*
	(0.816)	(0.042)
Workforce size (ws)	2.490702**	0.810197**
	(0.139)	(0.018)
*Deal amount*_r1	0.970276	1.009531
	(0.040)	(0.021)
NorthAmerica (na)	0.819775	1.308121**
	(0.162)	(0.123)
Europe (E)	1.182489	0.948787
	(0.246)	(0.093)
Asia (A)	2.114189**	0.287741**
	(0.459)	(0.059)
High tech	1.116553	0.957805
	(0.076)	(0.036)
*Investor supportiveness*_r1	0.999715	1.000257
	(0.001)	(0.000)
*Investor experience*_r1 (*ir_r1*)	0.999978*	0.999887**
	(0.000)	(0.000)
Time-varying covariates	*op_r1, op_r1_sqr*, *sp_r1_pct, ir_r1*	None

Table 3 (continued)

Covariate	Events	
	IPO	M&A
Function used for time-varying covariates	ln(_t)	None
Number of observations	32,378	32,372
Number of subjects	13,409	13,407
Wald χ^2	1,149.21	362.79
SE method	Robust cluster	Robust
Competing event(s)	Exittype== 2 3	Exittype== 1 3

** $p < .01$, and * $p < .05$

Finally, and unsurprisingly, the control variables have effects depending on the type of event considered. Regarding the conditional probability of a startup accessing a new financing round, size, in terms of the amount invested, or *Deal amount*, has a positive impact. In terms of the number of employees, *Workforce size* also strongly increases the probability (by approximately 115%) of a startup going public. Localization in Asia significantly increases the probability of a startup going public and significantly decreases the probability of it being merged or acquired. The control variable for investor support is never significant, but the control variable for experience, *Investor experience*, is significant, with a positive effect on the odds of later-stage financing and a negative effect on the odds of going public or being merged or acquired. The business cycle dummy is a stratification variable in the IPO regression and is not significant in the M&A estimation; it has a significant negative impact in the later-stage funding estimation.

5 Robustness check: Dealing with competing events

In the previous estimates, we do not consider 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 later-stage funding does not prohibit a subsequent M&A or IPO, an M&A prevents a subsequent IPO, and vice versa. Unfortunately, in the stratified Cox model, competing events are treated as censored: when they occur, the likelihood is computed as if the competitor events can still occur after the observation period. This hypothesis is incorrect since competing events of an event can no longer occur once the latter occurs. Competing risk survival models modify the computed likelihoods appropriately.

We therefore run additional competing risk regressions based on the method of Fine and Gray (1999). The results are shown in Table 3. These findings are consistent with the conclusions from the stratified Cox model presented in Section 4, with only two differences regarding the proximity variables of interest. First, geographic proximity now has a significant negative impact on the likelihood of a startup going public, and second, cognitive proximity now has the expected significant positive impact on the likelihood of a startup undergoing an M&A, providing empirical validation for Hypothesis 2a.

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 a startup going public and a negative effect on the probability of a startup being merged or acquired. Worldwide, 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 a startup's location in North America now has a significant and positive impact on its likelihood of being merged or acquired.

6 Conclusions

To study the effects of VC relationship structures on the fate of VC-backed startups, we adopt an integrative and dynamic approach to 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 depend 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 VC proximity relations on the fate of startups, we consider not only the proximities between investors coinvesting in a startup but also the proximities between these investors and the startups they finance. We introduce time-varying measures of the five forms of proximity proposed in the proximity literature (Boschma 2005a) and propose and test six hypotheses on a sample of 27,810 startups observed over 33 years in 68 countries. The following hypotheses are proposed: (1a) in an integrated empirical approach where all five proximity dimensions are considered, they all significantly influence the fate of VC-backed startups; (1b) trust-related proximity dimensions, namely, geographic, organizational, and social proximities influence the likelihood of a startup's success in later-stage fundraising, while cognitive proximity also influences the probability of IPO and M&A exits; (1c) the larger the size of VC syndicate funding a startup is, the lower the probability of this startup receiving later-stage funding; (1d) the effects of the proximity variables on the likelihood of startups' late-stage funding, IPO, or M&A reverse themselves beyond certain thresholds; (2a) cognitive proximity between VC investors and between investors and investees positively influence the likelihood of a startup being merged or acquired; and (2b) cognitive distance between VC investors and between investors and investees positively influence the likelihood of a startup going public. We use Cox proportional hazards models, stratified and adjusted for tied failures, to test these hypotheses and check the robustness of these methods with maximum likelihood competing risk estimates. The empirical results obtained provide evidence in support of all six hypotheses.

As emphasized in our literature review, we are not the first to study the impact of proximities in VC deals. Several empirical studies show the influence of geographic, social, or institutional proximities on VC-backed startups' innovation, performance, successful exit events, and ability to attract VC funds or cross-border VC investments. There are also studies that show the influence of some cognitive biases, but we find only one study using a measure of cognitive proximity defined as knowledge base overlap akin to the one we use in this study (Awounou N'dri and Boufaden 2020). Our main contribution to this empirical literature is that we integrate the five proximity dimensions together and do so with time-varying proximity measures. To our knowledge, we are also the first authors 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 approach allows us to show that cognitive proximity is correlated with startups' strategic choice between IPO and M&A, which is also a new result in the literature.

These empirical findings have several practical implications. First, they support the claim of proximity scholars that too much proximity does not always have positive effects. The facts that proximity effects are not linear and can be positive or negative depending on the event experienced by the startups stem from the tradeoffs between mutual understanding and lock-ins and between the benefits of cooperation and the costs of rivalry. Thus, VC syndicates must find a balance between investors that are too similar and those that are too dissimilar. Second, in contexts where inputting new ideas is crucial for startups, cognitive differences may be more desirable than cognitive proximities, as is also found by Awounou N'dri and Boufaden (2020). Our study adds that this situation 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 is 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 the founder–managers of venture-backed startups. For those planning an IPO, it is important to limit cognitive similarity in the final round of financing. For those who prefer an M&A exit, it is important to strengthen cognitive similarity.

There are several limitations to this study that require further research. First, the measure of geographic–institutional proximity that we use can be split to separate the institutional and geographic dimensions and to compute the latter much more precisely than at the state/country level. However, this approach requires 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 fund managers and between them and startup managers, but it is certainly more a matter of quality, than quantity, of interaction. For this reason, we interpret our variable as an indicator of organizational distance rather than as an indicator of organizational proximity, emphasizing that when the syndicate is large, coordination and control are more complex, which means that the degree of organizational proximity of the syndicate is lower. This suggests testing a more qualitative organizational proximity indicator derived from detailed information on the organizational structures of the VC funds composing VC syndicates.

Appendix

Table 4 Startup distribution across industrial sectors (GICS codes)

Industry	Percentage	Observations
101: Energy equipment, oil gas, and consumable fuels	0.70	545
151: Construction materials, chemicals, containers, metals, and mining and forest products	1.45	1130
201: Aerospace and defense construction and engineering industrial conglomerates, machinery, and electrical equipment	1.40	1089
202: Commercial and professional services	6.62	5168
203: Transportation infrastructures, air freight airlines, marine, road, and rail	0.28	218
251: Automobiles and components	0.22	169
252: Household durables, leisure products, leisure goods, textiles, apparel, and luxury goods	1.98	1545
253: Hotels, restaurants, leisure and education services	3.80	2967
254: Media broadcasting, movies, and entertainment, cable and satellite advertising and publishing	6.45	5036
255: Retailing and distributors	4.98	3890
301: Food and staples retailing	0.19	150
302: Beverages and agricultural products	0.79	620
303: Household products and personal products	0.37	288
351: Health care equipment and services	8.81	6875
352: Pharmaceuticals, biotechnology, life sciences, and tools	13.24	10,333
401: Banks, thrifts and mortgages	0.46	356
402: Diversified financial services	0.60	467
403: Insurance	0.24	186
404: Real estate investment, trust management, and development	0.47	365
451: IT internet and software services	28.53	22,266
452: Technology, hardware, communications equipment, electronic components	11.54	9003
453: Semiconductors	0.40	314
501: Telecommunication services	5.27	4114
551: Gas, water, electric, and renewable energy utilities	1.21	947
TOTAL	100.00	78,041

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Declarations

Conflict of interest The authors have no financial or proprietary interests in any material discussed in this article.

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