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Family Venture Capital

ABSTRACT

This study sheds light on a hitherto neglected type of family business by examining the investment strategies of family-managed venture capital funds (family VCs) raised by VC firms worldwide. The findings reveal that family VCs are more likely than their non-family counterparts to pursue a local strategy, investing in geographically proximate startups and syndicating with local investors. The family VCs' propensity to pursue the local strategy is heightened when the VC is eponymously named and when the family is actively involved in the decision-making process within the fund. Contrary to conventional notions of 'home bias,' the study shows that family VCs' local focus is underpinned by a calculated strategy rooted in their superior knowledge of local entrepreneurial ecosystems. While family and non-family VCs performance are similar, family VCs' local investments demonstrate a markedly higher likelihood of yielding successful exits compared to the local investments of their non-family counterparts. These findings suggest that family VCs can be a valuable source of capital for local startups seeking to grow and succeed.

1. INTRODUCTION

In 1997, Miriam Rivera and Clint Korver married and co-founded Outcomes Software, an enterprise software company. However, after a few years, Miriam Rivera left the company to join Google when prospective Series A investors refused to fund a husband/wife team. Later, the couple decided to work together again and co-founded another firm in 2008. Their daughter, Serena Rivera-Korver, has since joined the firm. Given that family firms are widespread globally (La Porta et al. 1999), these cases would probably not be surprising at first. However, what might surprise us is the fact that the second firm they co-founded in 2008 is not the typical family business operating in a traditional industry like their first firm, but rather a venture capital firm whose name was, and still is, ULU Ventures. At the outset, they faced substantial difficulties in raising money from limited partners (LPs) as "*institutional investors weren't yet ready for a married investment team*". [1] However, they proved that family VCs could work, and so far, they have successfully raised and managed three funds, ranging from $3.5M to $138M. This is just an example of the many VC funds managed by families worldwide. For example, Enygma Ventures was founded in South Africa by husband-and-wife Jacob and Sarah Dusek. They have raised and currently manage a $100m fund to invest in women-led businesses in Sub-Saharan Africa. Similarly, in Australia, the two brothers Ben and Toby Heap founded H2 Ventures and raised a $180m fund to invest in Fintech and AI startups.

If we are aware of the relevance of traditional corporations run by a family, we are probably not used to thinking of family-managed VC funds. Indeed, the extant literature has mostly studied family businesses in traditional industries or with listed equity shares (e.g., Villalonga and Amit, 2010). Given the relevance of family firms in the world economy (La Porta et al., 1999), scholars have tried to understand how the peculiarities of family firms affect their strategies (e.g., Chrisman and Patel, 2012; Feldman et al., 2014), goals (e.g., Miller et al., 2010; Zellweger et al., 2013), and performance (e.g., Anderson and Reeb, 2003; Belenzon et al., 2016). However, while recent studies have explored family involvement in private equity through the lens of family offices

1 See "https://uluventures.com/why-a-vc-marriage-is-not-like-a-unicorn/

(Block et al., 2019; Schickinger et al., 2022; Manigart and Khosravi, 2023) and investments through the corporate venture capital units of family firms (Amore et al., 2021), the dynamics of family-managed independent VC funds have remained underexplored. This research endeavor aims to fill this void by investigating how the family's social capital influences the investment strategies, objectives, and performance outcomes of family-managed venture capital funds.

Traditional financial theories advocate for investments when the net present value of a project is positive (Brealey and Myers, 1996). However, the inherent uncertainties associated with startups (Stinchcombe, 1965; Macmillan et al., 1985), coupled with the challenges of accurately assessing their prospects (Amit et al., 1990; Matusik and Fitza, 2012), have prompted scholars to consider the impact of soft factors, such as social similarity and shared ethnicity, in mitigating information asymmetries between startups and investors. These soft factors can influence VC firms' selection of companies for investment (Claes and Vissa, 2020) and the chances of a successful exit, yielding sometimes inconclusive findings regarding the performance outcomes (see, for instance, Hegde and Tumlinson, 2014; Bengtsson and Hsu, 2015). Among these soft factors, the social capital of investors plays a prominent role in the VC literature (e.g., Balachandran and Hernandez, 2021). Social relationships provide a valuable mechanism for reducing uncertainties in the VC context, facilitating investments in startups (Batjargal and Liu, 2004; Balachandran and Hernandez, 2021), and fostering syndication among investors (Sorenson and Stuart, 2001; Chung et al., 2000).

Arregle et al. (2007) and many others have suggested that family firms possess a unique form of social capital that fundamentally differs from that of non-family firms as it is a function of the family's network and legacy relationships (Anderson et al., 2005). Indeed, extant research shows that family firms tend to have extensive kinship networks (Bertrand and Schoar, 2006), which they can leverage to pursue economic and non-economic goals (Gomez-Mejia et al., 2001; Chrisman et al., 2012; Zellweger et al., 2012; Leitterstorf and Rau, 2014). As people's closest family members generally reside locally (Berger and Luckmann, 1967), families tend to be particularly anchored in their local environment, and so does their family firm (Bird and Wennberg, 2014; Lumpkin and Bacq, 2022). Additionally, they are often closely monitored by local stakeholders (Berrone et al., 2010) and committed to them (e.g., Baù et al., 2019).

Building on these arguments, I propose that family VCs, with their enhanced local embeddedness, have stronger ties to local stakeholders (Cooke, 2007; Nell and Ambos, 2013) and a vested interest in contributing to the economic development of their local community (Miller and Le Breton-Miller, 2005; Lumpkin and Bacq, 2022). Consequently, I anticipate that these distinctive attributes will lead family VCs to display a greater inclination to invest in local startups and syndicate with local investors, thus increasing their propensity to adopt a "local strategy". This inclination toward a local strategy is expected to be particularly pronounced when the family is actively involved in the strategic decision-making of the VC and when the latter bears the name of the family as the immediate recognition of the family's involvement is likely to significantly enhance their engagement with local startups and partners.

Subsequently, this research delves into the repercussions of this local strategy on the performance outcomes of family VCs. The outcomes of this local strategy are theoretically ambiguous. On one hand, family VCs' local embeddedness may give them superior insights into local players (Cooke, 2007; Nell and Ambos, 2013), including promising startups within their region and opportunities for collaboration with local investors. This could potentially enhance their ability to identify the most promising startups and access lucrative deals identified by other local investors. On the other hand, they might be investing in (syndicating with) local firms because of a home bias typical of family firms (Baschieri et al., 2017), which has been shown to lead to suboptimal investment decisions (Lin and Viswanathan, 2016).

This research contributes to the existing literature in three significant ways. Firstly, it extends prior research on venture investing, which has predominantly explored how the strategies and performance of VC firms are shaped by the characteristics of the investing entity and its employees. Factors such as venture capitalists' values (Matusik et al., 2008), social capital (Batjargal and Liu, 2004; Balanchadran and Hernandez, 2021), homophily (Hegde and Tumlinson, 2014; Claes and Vissa, 2020), and the characteristics of their family (Calder-Wang and Gompers, 2021) have been examined for their influence on venture capitalists' strategies and performance outcomes. Building upon this foundation, this study investigates the impact of family control on VC funds, an aspect that has hitherto received scant attention, shedding light on how family influence shapes the strategy and performance of these funds.

Secondly, this research extends the literature about family firms by revealing a substantial presence of family-managed venture capital funds in the VC ecosystem. It represents the first endeavor to comprehensively document the significant role that families play in the venture capital landscape by directly raising and managing VC funds. Furthermore, this study contributes to the existing knowledge of family firms by empirically demonstrating that the strategies of family VCs are markedly influenced by their local embeddedness and unique network.

Lastly, this research underscores the potential value of local embeddedness, corroborating prior literature (e.g., Amore and Bennedsen, 2013; Nell and Ambos, 2013). If, on average, family VCs perform at par with non-family VCs, they exhibit superior performance relative to non-family VCs when they go local. In essence, while investments in (syndication with) geographically proximate startups (investors) enhance the prospects of successful exits for both family and non-family VCs, the former derive significantly greater benefits from such local investments.

2. BACKGROUND AND THEORETICAL ARGUMENTS

2.1 An Overview of Families in Entrepreneurial Finance: Family Offices and CVCs

While the research at the intersection between family firms and entrepreneurial finance is scant, a limited number of papers has studied family offices (e.g., Wessel et al., 2014; Block et al., 2019; Schickinger et al., 2022; Manigart & Khosravi, 2023) and CVC units of family businesses (e.g., Amore et al., 2021).

A family office constitutes an organizational entity entrusted with the day-to-day management and administration of the combined assets and business interests of one or more families. Its overarching mission centers on the preservation of familial wealth for both current and future generations (Wessel et al., 2014). Historically, family offices assumed responsibility for diverse administrative tasks, encompassing traditional financial investments, accounting, tax planning, property management, succession planning, and legal affairs. More recently, family offices have emerged as participants in the VC landscape. It is important to note that family offices fundamentally differ from conventional VC firms. Unlike VC firms that raise capital from institutional investors, family offices manage the wealth of affluent families or individuals, providing them with considerable latitude in selecting industries and companies for investment. This freedom from rigid mandates allows family offices to navigate investments without constraints related to predetermined sectors and criteria. Moreover, family offices benefit from extended investment horizons in comparison to traditional VC funds, enabling them to support startups that may require more time to achieve success while better aligning with the objectives of entrepreneurs. Additionally, Block et al. (2019) showed that the investment criteria used in family offices prioritize startups' profitability while giving lower weights to revenue growth vis-à-vis traditional VC firms. These findings are consistent with the evidence provided by Wessel et al. (2014), suggesting that family offices, differently from VC firms, are often conservative and risk-averse and thus more reluctant to pursue high-risk investments Finally, family offices differ in the degree of family involvement in their management. While some family offices are under the direct supervision of family members, the majority are professionally managed, entrusting the operational aspects to experts in the field (e.g., Walerud Ventures, is managed by husband and wife Bengt and Jane Walerud, and their daughter Caroline Walerud, while Oprah Winfrey Management, Oprah Winfrey's family office, is managed by Renata Erlikhman).

In contrast, despite an extensive body of literature exploring corporate venture capital (CVC) investments, which involve established corporations acquiring minority equity stakes in young ventures, the role of family businesses as active CVC investors has not been comprehensively examined. This gap in research is somewhat surprising, given the significance of the CVC market, which constitutes approximately 10% of the broader VC industry (Drover et al., 2017), and the prevalence of family businesses around the world (La Porta et al., 1999). To date, the investigation by Amore et al. (2021) stands as a notable exception, as it examined the CVC investments of U.S. listed firms, revealing that roughly one-third of these investments were completed by family firms. While (family) CVCs may, in some instances, seek profitable investments akin to traditional VC firms, the primary motivation behind most CVC investments is strategic. These investments aim to provide the parent company with insights into emerging technologies, access to complementary products, and entry into new markets over the long term (Dushnitsky and Lenox, 2006; Benson and Ziedonis, 2009; Keil et al., 2009). Notably, there exists substantial diversity in the structural configurations of CVC units (Hill et al., 2009). On one end of the spectrum, certain CVC units function as independent venture capital funds, maintaining clear structural separation from their parent corporation. They oversee a dedicated capital pool, which may also include funds raised externally, and exercise full autonomy over investment decisions. On the other hand, some CVC units are integrated within specific business units and seek approval and funding on a deal-by-deal basis. The former structural model generally exhibits stronger performance in achieving financial objectives, whereas the latter is often associated with strategic advantages. Structural differences also influence investment horizons, with units lacking dedicated funds not bound by the typical 10-year investment horizons of VC funds. Furthermore, CVC units may vary in terms of human resources. Some units comprise long-term corporate employees, while others engage professional venture capitalists. Although family members may engage in the daily activities of CVC units controlled by their family firms, decision-making is typically delegated to professionals in the field. A concrete example of a family business actively engaging in CVC investments is Nordstrom, a fourth-generation family business that has completed ten CVC investments between 2000 and 2022. Pitchbook data indicates that while members of the Nordstrom family directly oversaw M&A operations, none of the CVC investments were directly completed by family members

2.2 The Family VC

Although further scholarly inquiry into family offices and CVC entities affiliated with family businesses is necessary, this paper does not aim to advance our understanding of either of these two entities. Instead, it aims to introduce the existence of a previously overlooked category within the realm of family enterprises, referred to herein as family VCs (FVCs). The latter represents a distinct subset of venture capital funds, notable for their substantial familial involvement in management. It is important to emphasize that FVCs differ significantly from both the CVC units of family firms and conventional family offices.

Primarily, these distinctions manifest in terms of their fundamental raison d'être. Analogous to their generic venture capital counterparts, FVCs invest in nascent enterprises to generate returns for their LPs. In stark contrast, CVCs tethered to family businesses, while not precluding financial objectives, predominantly prioritize the acquisition of strategic advantages that accrue to the family firm over the long term. Similarly, family offices, while indeed oriented toward generating returns for the family, are primarily concerned with managing and preserving the wealth of a high-net-worth family or individual

Secondly, disparities surface concerning the extent to which the family is actively shaping the decision-making process. By definition, FVCs are characterized by substantive familial involvement. In contrast, when examining family offices and, to an even greater extent, CVC units of family enterprises, family members are rarely active participants in investment decision-making.

Thirdly, these entities diverge when the provenance of the capital under their stewardship is scrutinized. FVCs raise financial resources from institutional investors (LPs). In contradistinction, CVC divisions of family businesses may either solicit funds from LPs or harness the internal resources of the family firm. Conversely, family offices do not customarily solicit external funds from LPs but rather engage in the fiduciary management and administration of the assets and wealth of the family or high-net-worth individuals.

Fourthly, differences arise when considering their investment horizons. Family VCs generally have a horizon of 10+2 years. Conversely, contingent upon whether the CVC arm of a family enterprise is invested via an autonomous fund sourced from external investors or funneled through an internal unit within the family enterprise, the temporal orientation may mirror the conventional VC funds' 10+2 year horizon or be unbound by temporal limitations. Unlike family VCs, family offices maintain a protracted investment horizon extending beyond a single generation, eschewing the exigency of divesting from their investments within the 10+2 year time frame.

Lastly, divergences emerge in their investment approach. Family VCs evince a pronounced appetite for risk associated with early-stage enterprises and pioneering technologies, driven by the aim of engendering substantial financial returns for their LPs. In contradistinction, CVC entities affiliated with family enterprises frequently fixate upon strategic alignment with the core business, seeking synergistic opportunities and long-term benefits that support the family firm in the long run, in addition to seeking financial returns. In stark contrast, family offices typically prioritize stability and risk management over aggressive growth and high-risk investments as their ultimate aim is to safeguard capital and ensure a steady income stream. In summation, the salient divergences between FVCs, CVC units of family businesses, and traditional family offices are succinctly reported in Table 1.

INSERT TABLE 1 HERE

2.3 Theory and Hypothesis

The significance of social capital within the domain of the venture capital industry has garnered considerable attention within academic discourse, as well as among industry practitioners. Scholars have contributed to this discourse, with studies such as those conducted by Hsu (2007) and Balachandran and Hernandez (2021). These investigations have shed light on how a venture capitalist's network impacts critical aspects of VC strategies, including the selection of syndicate partners and startups, ultimately influencing the success of these investments. In parallel with scholarly recognition, industry practitioners, such as Hector Mason, who serves as the General Partner (GP) of Episode 1, emphasize the paramount role of social capital within the VC ecosystem. Mr. Mason articulates the centrality of interpersonal relationships and networks by asserting that "*Venture capital is almost entirely people-driven… If you look at the investments we've made at Episode1, the majority come from personal referrals. This is no coincidence. People who know us well, know what we like and therefore pass us pre-vetted (by them) deals which they think we should look at.*" [2] Mr. Mason's perspective underscores the foundational premise that venture capital fundamentally revolves around interpersonal relationships and encapsulates the core idea that a venture capitalist's network and relationships play a fundamental role in shaping their investment strategies and outcomes.

It is essential to recognize that while these networks exert considerable influence, they often exhibit a pronounced local character (Sorenson & Stuart, 2001, 2008). This localization reflects a distinctive aspect of the VC landscape, where the proximity and depth of relationships within specific regional entrepreneurial and investment ecosystems hold significant sway over investment

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2 See "https://mason-hfb.medium.com/why-and-how-to-build-a-network-in-venture-capital-dd179e28db4f"

decisions. Even if VC investments across the national border have seen a significant increasing trend in the latest years (Chemmanur et al., 2016), the predominantly localized nature of information exchange within these regional networks (Balachandran and Hernandez; 2021), heighten venture capitalists' inclination to syndicate with local investors and direct their investments toward local startups (Sorenson and Stuart, 2008; Cumming & Dai 2010). Importantly, this localized investment orientation has generally been associated with superior financial performance within the VC industry, as substantiated by the findings of Cumming and Dai (2010), Zhang and Gu (2021), and Chemmanur et al. (2016)

The preceding discussion underscores the salient role of social capital and localized networks in the venture capital industry. However, venture capitalists do not uniformly exhibit the same level of embeddedness within their respective territories. Variations in their levels of embeddedness within local networks may significantly influence their propensity to invest locally. The concept of embeddedness, as advanced by Granovetter (2018), encapsulates the idea that individuals and organizations do not make decisions in isolation but within networks of social relations that shape their choices and interactions (Aldrich & Cliff, 2003).

Within the realm of family firms, extant literature has emphasized their unique endowments in terms of social capital (Arregle et al., 2007), strong attachment to their local communities (Zellweger et al., 2013; Bird and Wennberg, 2014), and a pronounced commitment to contributing to the economic development of their community (Miller and Le Breton-Miller, 2005; Campopiano et al., 2014; Lumpkin and Bacq, 2022). As a result, family firms tend to be more deeply embedded within their local networks compared to their non-family counterparts (e.g., Berrone et al., 2010; Baù et al., 2019).[3]

Extant research conducted on firms operating in traditional industries has studied the impact of local embeddedness on various facets of business operations, including contributions to local businesses (Smulowitz et al., 2020), innovation (Huggins and Thompson, 2014), venture creation (Davidsson and Honig, 2003), firm growth (Dahl and Sorenson, 2012), access to localized knowledge (Baù et al. 2019), and the establishment of robust connections with local stakeholders such as clients, suppliers, and the community (Cooke, 2007; Nell and Ambos, 2013). In the context of venture capital, where reliance on social mechanisms and informal relationships plays a critical role in mitigating the substantial uncertainties inherent to VC activities (Shane and Cable, 2002; Wuebker et al., 2015; Balachandran and Hernandez, 2021), local embeddedness is poised to significantly shape the investment strategies and performance of family VCs.

The central argument of my theory posits that family VCs, due to their heightened local embeddedness, are better positioned to access more and higher quality non-public information about local startups, thus ameliorating information asymmetries that frequently deter VC investments (Amit et al., 1990). Information asymmetries in the VC context can be exacerbated by startup founders' inclination to provide incomplete information to potential investors as a

3 The bond linking family firms and their territory is exemplified by Gruppo Bertoldi, an Italian investment firm managed by the two brothers Gianluca and Giacomo Bertoldi claiming "*We are a family venture capital, with a longstanding commitment to the progress and growth of our region*". Although Gruppo Bertoldi does not conform to the conventional model of venture capital firms that raise capital from limited partners (and consequently, its venture capital activities fall outside the scope of my data sample), this exemplar vividly underscores the profound attachment that family firms maintain to their geographical roots. See "https://www.linkedin.com/company/bertoldi-holding-srl/about/."

precaution against the potential misappropriation of their ideas (Kim et al., 2019). Atanasov et al. (2012) have demonstrated that reputable VCs are more likely to behave ethically toward founders, indicating that reputational mechanisms can play a vital role in reducing the likelihood of opportunism ex-ante. Therefore, the family's reputation within their community might instill greater confidence in geographically proximate founders, leading to reduced hesitancy in disclosing sensitive information. Consequently, family VCs should be in a better position vis-à-vis non-family VCs to mitigate the information asymmetries affecting local startups, making local investments an optimal choice for rational investors.

Family firms have been the subject of extensive research, revealing a multifaceted set of motivations and objectives. Notably, the literature on family firms, exemplified by studies conducted by Gomez-Mejia et al. (2007), Chrisman et al. (2012), and Zellweger et al. (2012), has consistently shown that family businesses often exhibit a dual commitment to both economic and social objectives. While economic prosperity remains a primary goal, these firms recognize their unique position within the community and their potential to contribute to local well-being. The concept of local embeddedness, as explored by Acquaah (2012) and Bird and Wennberg (2014), offers insights into the mechanisms through which family firms manifest their social commitment. Local embeddedness signifies a deep-rooted presence within the community, characterized by active engagement with local stakeholders, residents, and institutions. This engagement extends beyond business transactions to include initiatives that align with the creation of wealth and positive social returns for the community. These contributions may involve job creation, support for local charities and nonprofits, educational initiatives, or investments in local infrastructure. In essence, family firms view themselves as not just economic entities but as integral components of the communities in which they operate.

Drawing from this rich literature on family firms, it becomes evident that family VCs should also be imbued with a sense of responsibility towards their local communities. Their local embeddedness positions them as stewards of their territory. Consequently, when family VCs evaluate investment opportunities, they may consider not only the potential financial returns but also the positive social impact on their community. This dual commitment to economic and social objectives suggests that family VCs might be more inclined to invest in geographically proximate startups. A critical implication of this perspective is that the quality threshold required for family VCs to invest in local startups may be lower than that needed for distant ventures. As a result, family VCs may be more open to local investments, thereby increasing the likelihood of channelling their resources into startups located within their immediate vicinity.

In summary, the local embeddedness of family VCs emerges as a dual catalyst. On one hand, it equips them with an enriched reservoir of information regarding local startups. On the other hand, it ignites a genuine desire to actively participate in and foster the growth of their immediate geographic domain. Consequently, this heightened local embeddedness not only enhances their access to superior information about local startups but also fuels their motivation to invest in geographically proximate startups.

The selection of syndicate partners is also a very important decision that can profoundly influence investment outcomes (Manigart et al., 2006). Beyond the mere sharing of risks, syndicate partners also pool their managerial expertise and financial resources (Brander et al., 2002). This collaborative endeavour creates a web of mutual interdependence among syndicate partners (Meuleman et al., 2010). Effective syndication hinges on aligning the competencies and motivations of participating VCs with the specific needs of the startup they intend to support, while adverse selection looms as a lurking peril when VCs claim competencies and objectives they do not possess (Meuleman et al., 2010). Building upon the previously established theoretical framework, which underscores the rich local knowledge base and profound community connections cultivated by family VCs, we could expect family VCs not only to excel in obtaining information on local startups but also to possess a superior knowledge of local investors. This superior information, nurtured through expansive local networks and deep-rooted embeddedness, acts as a potent remedy to counteract the information asymmetries often associated with syndication among investors. Furthermore, the superior connections with local investors should not only reduce the risk of adverse selection but also foster an environment conducive to forming partnerships. As evidenced in prior research, VCs exhibit a proclivity for collaborating with partners with whom they share relational bonds, as the latter fosters trust and mitigate the risk and uncertainty inherent in inter-organizational exchanges (Meuleman et al., 2010; Sorenson and Stuart, 2008). Consequently, family VCs' inclination to engage in syndication with local VCs goes beyond the act of merely inviting other investors to participate in a deal. It is also driven by reciprocal invitations extended by other local investors with whom family VCs maintain strong and enduring connections. Moreover, expectations and obligations built into strong local ties might constrain the choice of family VCs that might feel the obligation to join a syndicated partnership in which other local investors are taking part and invite other local investors to join them in an investment they are planning to make even if they lack the complementary skills required to support the startup. To summarize the previous discussion I propose the following:

Hypothesis (H1): *Family VCs are more inclined than non-family VCs to adopt a "local strategy," characterized by a higher propensity to (1) invest in local startups and (2) engage in syndication with local investors*.

3. DATA

3.1 Selection of VC funds

To conduct the empirical analyses for this paper, the data collection process primarily involved the identification of venture capital funds and their respective teams. Pitchbook, a widely recognized and comprehensive database in the field of entrepreneurial finance, was utilized for this purpose. Pitchbook has consistently been employed by entrepreneurial finance and private equity scholars (e.g., Degeorge et al., 2016; Block et al., 2019; Yao and O'Neil, 2022), as well as by professional investors. A significant advantage of Pitchbook, which distinguishes it from other datasets, lies in its ability to provide detailed information at the fund level.

Specifically, utilizing the Pitchbook database allowed for the identification of all VC funds (i.e., funds categorized as "Venture Capital" in the fundclass variable) raised by VC firms (i.e., investors categorized as "Venture Capital" in the primaryinvestortype variable) worldwide. This categorization ensured that the funds included in the dataset exclusively encompassed traditional VC funds raised by VC firms. Consequently, a clear demarcation was established between traditional venture capitalists and other variants, such as Corporate Venture Capital, Government Venture Capital, and family offices. As noted in Kinger Hans et al. (2023), the nature of the entity behind another one can significantly shape the motivations, internal structure, and incentives of the actors of the latter. The same concept applies when considering the entities behind the VC funds. As a matter of fact, the entity to which the fund belongs holds significant implications for the strategies and objectives pursued by the fund. For instance, CVCs may invest with a long-term vision to strategically benefit their parent company, whereas GVCs may focus on promoting economic development within their geographical domain. Therefore, it was imperative to restrict the analysis to VC funds raised exclusively by VC firms to eliminate potential confounding effects arising from the diverse motivations of different fund-raising entities. Given the finite lifespan of VC funds of typically 10 years (e.g., DeSantola et al., 2023), further validation was conducted to confirm that the entities included in the dataset indeed represented genuine VC funds. This was accomplished by examining the maturity of the funds at the time the deals included in the dataset were completed. Remarkably, an overwhelming 99.7% of the deals in the dataset were executed by funds that were no older than 10 years, affirming that the entities under examination in this paper indeed align with the conventional definition of VC funds.

3.2 Identification of family VCs

The central empirical challenge encountered in this study pertained to the identification of family VCs. As previously elucidated, family VCs are a distinct subset of VC funds characterized by substantial familial involvement in their management. Consistent with this definition, two complementary criteria were employed to identify family VCs. First, a VC was considered a family VC if a relative of the founder actively participated in the management and decision-making of the fund, or if the fund was co-founded by family members. Alternatively, a VC was classified as a family VC if family members collectively constituted a substantial portion of the fund's team, accounting for a quarter or more of the team. Recognizing that the 25% threshold for identifying family VCs is somewhat arbitrary, the robustness of the findings was assessed by considering different thresholds. Following prior literature (e.g., Amore et al. 2014), family connections were determined via surname affinity. It is important to acknowledge, however, that the use of surnames to infer family relationships has its limitations. Namely, two individuals may share a surname without any actual biological relationship. This concern is particularly salient in regions where numerous individuals unrelated by blood share common surnames.[4] In such cases, reliance on surname affinity alone could lead to erroneous categorization of a venture capital (VC) fund as a family-managed VC. To address this concern, VC funds located in countries where issues related to shared surnames among non-related individuals are prevalent were excluded from the analysis. Specifically, VC funds based in China, Hong Kong, Korea, India, Singapore, and Taiwan were omitted from the dataset due to the heightened risk of surname-based misclassification in these regions. Furthermore, recognizing that individuals with common Asian surnames may be present in countries beyond the aforementioned ones, an additional precautionary step was taken. In particular, the 50 most frequently occurring Asian surnames as reported in the Pitchbook database were identified.[5] In cases where a VC fund was labeled as family-controlled because of one of these surnames, that fund was also excluded from the analysis. Another concern might be that when the VC fund is managed by two spouses, I was able to classify the fund as a family VC only

4 For example, in China 5 surnames (Wang, Li, Zhang, Liu, and Chen) are shared by more than 430 million people (30% of China's population), and almost 86% of the Chinese population shares just 100 surnames.

5 On top of the 5 most common Chinese surnames mentioned above, other surnames included in the list include Kim, Wu, Singh, Gupta, Kumar, Aggarwal, and Huang. Robustness tests were conducted by removing the top 100 surnames. Results are robust to this different specification.

when one of the two took the surname of the spouse (or when a child of the couple sharing the surname of one of the two is actively involved in the management of the fund). While I might slightly underestimate the family VC phenomenon, given that 79% (5%) of women (men) change their surname after marriage, while 6% hyphenate their name with that of the spouse, I should be able to identify at least 90% of the funds managed by spouses as family VCs.[6] I have also manually looked for instances of VC funds managed by spouses who did not take the surname of the spouse and I was able to identify the couple mentioned in the introduction of this paper formed by Miriam Rivera and Clint Korver (ULU Ventures). Additionally, funds for which Pitchbook did not report information on the management team, or where only one manager was reported were excluded since in these cases, there was insufficient information available in Pitchbook to assess whether a VC qualified as a family VC.

Although the approach used in this paper is consistent with recent papers that have delved into familial relationships among managers (e.g., Parise, 2023), it is worth noting that a substantial portion of prior research in the field has traditionally relied upon family ownership as a primary criterion for categorizing and studying family firms. While this approach holds merit when examining traditional corporations, it becomes less suitable when applied to the unique peculiarities of VC funds. VC funds, unlike their corporate counterparts, exhibit distinct ownership and capital structures. Indeed, VC funds typically do not have shareholders in the same way that traditional corporations do. Limited partners are the primary investors in a VC fund. However,

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6 See “https://www.forbes.com/sites/kimelsesser/2023/09/07/8-in-10-women-married-to-men-still-take-husbands-last-name-according-to-new-survey/?sh=99986af428f9”

limited partners are not shareholders in the traditional sense but rather investors in the fund. Although looking at whether the LPs of the VC funds are family-owned might be an interesting future research avenue (although it would raise important empirical challenges as it would require identifying whether the different types of entities acting as LPs of a certain fund such as foundations, endowments, or corporate pension funds are family-owned/controlled entities), in this paper I have decided to focus on the management of the VC funds for three main reasons. Firstly, the fund managers play a critical role in making investment decisions, conducting due diligence, and providing guidance and support to portfolio companies. Their expertise and networks directly impact the fund's investment strategies and thus its performance. Consequently, it is important to study the fund managers as they are the ones responsible for the day-to-day operations and investment choices. Secondly, while LPs are crucial for providing capital, they usually delegate investment decisions to the fund managers. LPs, as investors, tend to limit their involvement in the everyday functioning and investment strategies of the fund. As a result, fund managers retain a high degree of autonomy to make investment decisions based on their expertise and beliefs. Thirdly, LPs primarily exert influence by selecting which VC funds to invest in. Their influence is indirect and occurs primarily at the fund selection stage rather than in the day-to-day operations of the fund. While LPs can monitor the activities of the managers, the way in which they can influence the decisions taken by the fund managers is much more limited when compared with the influence shareholders of traditional corporations can exert. If, for example, the shareholders of a traditional corporation can easily replace the CEO, the LPs of a VC fund typically do not have the ability to directly replace the GP. In sum, when examining the distinct realm of VC funds, the study of fund management emerges as more appropriate than the consideration of its investors.

The preeminent role of fund managers in shaping investment strategies, the limited direct involvement of LPs in operational matters, and the influence of LPs primarily confined to fund selection all underscore the need for this shift in focus. However, since family VCs might attract capital from different types of LPs, in the regression analyses I will control for this heterogeneity to make sure that the results presented in the paper do not stem from different types of LPs backing the funds.

Extensive research within the field of family business has tried to assess the impact of heightened family involvement in the decision-making process on the strategic choices pursued by family firms (e.g., Chua et al., 1999; Zahra, 2003). Nevertheless, when examining family firms operating in traditional industries, quantifying the precise extent of family influence on decision-making can be challenging. Consequently, the existing literature has frequently resorted to employing proxies, such as the count of family members occupying managerial roles within the firm (e.g., Chrisman et al., 2012). The venture capital setting, however, offers a unique opportunity to explore the degree to which family participation in the decision-making process shapes the strategies of family firms. Leveraging Pitchbook data, I harnessed insights into the lead partners responsible for investment decisions within VC funds. Through an analysis of the proportion of investment rounds led by family members, I distinguished between family VCs where family members predominantly wield influence over investment choices, and those where non-family professionals assume a more prominent role. Specifically, when family members collectively led more investment rounds than the most active non-family decision-maker within the fund, the family was considered highly involved in the decision-making process. On the flip side, if a non-family member took the lead on more deals than the family members, it indicated that the family played a less prominent role in the decision-making process. This distinction allows for a nuanced exploration of the dynamics at play within family VCs, shedding light on the pivotal role of familial influence in shaping strategic directions.

3.3 Dataset construction

Once the VC funds have been identified, I merged each fund with the corresponding VC deals completed between January 2000 and December 2022. To make sure that only VC deals were included in the dataset, only investments classified as “Venture Capital” in the dealclass variable were retained. Data suggests that family VCs in the time frame considered have taken part in 5.2% of the financing rounds included in my dataset, participating in deals collectively amounting to $110B. Following the approach used by prior papers (e.g., Nahata, 2008; Liu and Maula, 2016), I used the investment by a focal VC fund in a startup (i.e., the VC fund-startup dyad) as a unit of observation. In particular, when a VC fund invested twice or more in the same startup only the first investment has been retained.[7] Geographic coordinates for both funds, startups, and syndicate partners, were obtained using the OpenStreetMap. Geographical distances were computed employing the "geodist" command in Stata. Deals lacking information related to critical variables such as the geographic location of both the fund and startup, investment year, fund vintage year, and fund size were excluded. In the appendix, I explain in detail the steps taken to identify family VCs and construct the final dataset.

7 In untabulated analyses I tested the robustness of the findings to the inclusion of all VC deals (i.e., without restricting to the first investment round completed by a VC fund in a certain startup), obtaining very similar results.

3.4 Descriptive statistics

The final sample includes 127,841 VC deals received by 56,342 unique startups (7.1% of which have been supported at least once by a family VC). As previously mentioned, each VC fund-portfolio company pair is unique, even though the VC may have participated in multiple rounds of financing (Nahata, 2008). Table 2 presents summary statistics for the main variables used in the analyses. In Panel A, I present a breakdown of summary statistics at the VC fund-startup level. As shown, 3.6% of the deals were completed by a family VC. Furthermore, Panel A highlights that 27% of deals were aimed at supporting startups within 25 km of the investing VC fund. On average, each deal involves one syndicate partner located within this 25-kilometer radius.[8] Remarkably, approximately 19% of the syndicate partners are geographically situated within the same 25-kilometer radius of the focal VC fund.[9] Additionally, 15% of the VC deals executed have been directed towards supporting startups within this 25-kilometer radius and have involved syndication with at least 25% of the syndicate partners located within the same geographic proximity. On average, the fund maturity of the fund at the time of the investment is equal to two years, and the average age of the startups at the time of the deal is three years.

Panel B reports information at the fund level. The average fund size amounts to $171.8 million, with a median value of $73.4 million. On average, fund managers have led 6.5 VC deals prior to

8 To compute the number of geographically proximate syndicate partners I considered all investors that joined the deal. Thus, that variable is counting not only the number of funds within 25km but also the number of other investors (such as accelerators, incubators, angels, etc.) within 25km.

9 The denominator here is represented by the number of syndicate partners with available information on their location. The results presented in the paper are similar when using the number of syndicate partners at the denominator.

their involvement with the VC fund. 3.2% of the VC funds are eponymous. To identify eponymous funds, I draw from Belenzon et al. (2017) and use a string-matching algorithm to identify whether the last name of a VC fund manager is part of the fund's name or of the entity that raised the fund. If an individual has more than one surname (or his surname is composed of multiple words), I consider the fund as an eponymous fund if contains in its name at least one of those surnames. Moving forward, Panel B also provides insights into the limited partners (LPs) associated with the VC funds in my dataset. Approximately 24% of these funds have at least one fund of funds as an LP, as reported in Pitchbook. Additionally, 18.9% (or 18.5%) of the funds count public or corporate pension funds among their LPs. Panel C offers insights into the founding teams of startups that received VC financing in the dataset (the information pertaining to the founding teams is unavailable for approximately 6,000 startups in the dataset). The analysis indicates that, on average, a founding team consists of 2.6 individuals. Furthermore, around 30% (25%) of the startups were established by founders who possess an MBA (have prior entrepreneurial experience), as documented in Pitchbook records. Finally, approximately 38% of the startups have at least one founder who attended a university ranked among the top 30 universities according to the inaugural version of the QS Ranking, published in 2004. [10]

Table 3 presents the results of t-tests, elucidating the principal distinctions between family and non-family VCs at two distinct levels: the fund-startups level (Panel A) and the fund level (Panel

10 See https://www.universityrankings.ch/results/QS/2004

B). The findings disclose noteworthy disparities in investment patterns between these two categories of VCs, while only limited differences in the characteristics of these funds.

In Panel A, it is observed that family VCs exhibit a greater propensity, by 6.2 percentage points, to invest in startups located within a 25-kilometer radius. Furthermore, the average deal completed by family VCs involves a higher number of syndicate partners within the same 25-kilometer radius. Family VCs are also 6 percentage points more inclined to engage in local deals, denoting investments in startups situated within 25 kilometers, which are syndicated with at least 25% of their syndicate partners originating from the same 25-kilometer radius. Turning to Panel B, the most salient difference between family and non-family VCs refers to their naming. Indeed, family VCs are roughly 300% more likely to be eponymously named. However, family VCs do not demonstrate statistically significant differences from their non-family counterparts with respect to fund size, the experience of their management teams, or the entrepreneurial intensity of the geographic areas in which they operate. The latter metric assumes significance, as one might raise concerns that family VCs are more predisposed to local investments due to their geographical location in inherently more entrepreneurial regions. Such a presumption implies that family VCs might be drawn to local investments because of a greater supply of startups within their geographical vicinity. To alleviate such concerns, a metric for the entrepreneurial intensity of the areas housing the VC funds in the dataset has been constructed. This entails the creation of a panel for each city housing VC funds in the dataset, indicating the total number of VC financing rounds raised by all startups within a 25-kilometer radius in the preceding three years. [11] Subsequently, this variable has been standardized annually to ensure an average of zero and a standard deviation of one within each year. Panel B of Table 3, however, illustrates that family VCs, at the vintage year of their respective funds, are situated in regions characterized by a comparable level of entrepreneurial intensity as that observed in the areas of non-family VCs. Furthermore, only limited differences emerge when examining the composition of the LPs. Perhaps unsurprisingly, family VCs exhibit a modestly higher likelihood, by three percentage points of securing family offices as their LPs. Conversely, family VCs are marginally less likely, by 4 percentage points, to have governmental entities as their LPs. However, aside from these two marginal differences, the LPs supporting family and non-family VCs do not display statistically significant differences. These observations underscore the notion that while family VCs are more likely to be eponymously named, they are not much different from non-family VCs when considering other characteristics such as the experience of the team, the location, the size of the fund, and the source of the money they manage.

4. RESULTS

Hypothesis 1 posits that family VCs are more inclined to adopt a "local strategy," characterized by investments in startups situated in close geographic proximity and syndication with local investors. To empirically assess whether family VCs invest in local startups, I use as a dependent variable a binary indicator variable, taking a value of one when the VC fund and the target startup

11 The results are not affected by the use of other time frames such as 5 years.

are located within a radius of less than 25 kilometers, and zero otherwise. All specifications of Table 4 include control variables for the investment year and the industry in which the startup operates. In Column 2 of Table 4, I introduce additional controls to account for specific characteristics of the VC funds that may influence their propensity to invest in geographically proximate startups. Specifically, I include controls for the maturity of the fund at the time of the investment, the fund size, and the VC experience level of the fund's management team. Considering the maturity of the fund allows us to factor in the potential differences in investment behavior that may arise due to the age of the fund. The maturity of a VC fund can significantly influence its investment decisions as older funds may have different investment strategies and priorities compared to newer funds (Barrot, 2016). By controlling for the fund's maturity, we can isolate the impact of family control on the localization strategy while accounting for the potential effects of the fund's life stage. The size of a VC fund can also shape its investment behavior. Larger funds may have more resources at their disposal, enabling them to pursue a broader range of investment opportunities, including those outside their immediate geographic vicinity (Amore et al., 2023). Similarly, more experienced managers generally possess a more extensive knowledge base (Cumming and Dai, 2010), which might enhance their capacity to assess opportunities in distant regions characterized by higher information asymmetries (Hsu, 2004), thereby increasing their inclination to invest in more distant ventures. Previous research has identified three pivotal factors as significant determinants of a firm strategy and performance. These factors include financial capital, human capital, and social capital (Clough et al., 2019). In my analysis, I am controlling for two of these factors, namely VC financial capital and VC human capital. Using these controls should better isolate the unique influence of family VC social capital.

Recognizing the possibility that certain VC funds might exhibit a heightened propensity to invest locally due to their geographic location, I introduce fund city fixed effects in Column 3. The inclusion of this control ensures that the findings are not explained by the geographical distribution of VC funds. In essence, the inclusion of fund city fixed effects allows us to isolate the impact of family control while holding constant the city in which the fund is headquartered. Lastly, in Column 4, I further control for the composition of the fund's LPs. This control is implemented by incorporating the LP dummies detailed in Table 2. It is worth noting that the dataset contains certain funds for which Pitchbook does not provide information regarding their LPs. To address this data limitation, I group these funds into a separate category represented by a dummy variable. Results are robust to the exclusion of such funds. Robust standard errors are clustered at the fund level. As shown, according to the most complete specification of Table 4, family VCs are 6.3 percentage points more likely to invest in geographically proximate startups. The estimated effect is not only statistically significant but also economically so. Indeed, as the mean value of the DV is equal to 0.27, we can conclude that family VCs are 23.3% more likely to invest in local startups.

Importantly, this effect is robust to other distance thresholds such as the same exact city, 10 or 50 kilometers, as well as to the use of a continuous variable representing the logarithm of one plus the distance in kilometers between the fund and the startup. The results of these robustness tests are presented in the appendix (see Table A1). Importantly, family VCs do not conform to the conventional definition of local or domestic VCs as posited in prior literature, which typically considers local or domestic VCs as those investing within the same country (e.g., Mäkelä and Maula, 2006; Liu and Maula, 2016; Devigne et al., 2016). Instead, family VCs are more discerningly inclined to invest in startups that are genuinely geographically proximate. This is substantiated by the findings presented in Column 5 of Table A1, which reveal that family VCs are not inherently predisposed to invest in startups based solely in the same country. Their preference is solely directed towards geographically proximate startups. This underscores the nuanced nature of their investment strategy, which prioritizes startups in immediate proximity due to superior information access rather than mere geographical closeness. Indeed, the analysis presented in Column 4 of Table A1 reveals that family VCs exhibit a propensity to invest in startups that are 46% closer. However, it is crucial to underscore that this effect is not indicative of a mere inclination toward investing in startups being on average closer. Rather, this outcome is primarily driven by their distinct preference for truly local startups. Indeed, when the analysis is reexamined with the exclusion of startups within a 25-kilometer radius (Column 6 of Table A1), a critical shift in the results becomes evident. Specifically, the estimated coefficient associated with the family VC dummy variable becomes statistically insignificant. This outcome underscores the fact that family VCs are not simply drawn to investments in ventures that are closer in proximity; rather, their focus is distinctly centered on startups that are exceptionally, and unequivocally, local.

To ensure the robustness of the findings, I subject the classification of family VCs to various operationalizations in Table A4, given the arbitrary nature of the criterion used. In Column 1 of Table A2, I consider a VC fund as a family VC if it has at least two managers who are family related. I also employ different percentage thresholds for the share of family fund managers in Columns 2 (10%), 3 (20%), and 4 (25%). In Column 5, I introduce a continuous variable representing the proportion of fund managers from the same family.[12] As shown, results are robust to these different operationalizations.

Hypothesis 1 also posited that family VCs should be more inclined to syndicate with other geographically proximate investors. To test this, I computed the number of syndicate partners within 25 kilometers. This sum does not include only other funds that invested in the startup with the VC fund under examination, but also other investors such as, for example, accelerators, incubators, and angel investors, that took part in the investment round. The specification used to test the VC fund inclination to syndicate with geographically proximate investors is similar to the one presented in Table 4. However, since the dependent variable is a count variable, I employed a Poisson model to account for the counting format of the DV. The results, as presented in Column 4 of Table 4 (utilizing the same set of control variables as outlined in Column 4 of Table 4), reveal that family VCs, on average, syndicate with approximately 0.23 more local syndicate partners compared to their non-family counterparts. To provide context, considering that the mean value of the dependent variable equals 0.97, this implies that the average syndicate partnership involving family VCs' investments incorporates 23.7% more local investors. It is noteworthy that this estimated effect closely aligns with the previously calculated effect concerning their propensity to invest in local startups, which stood at 23.3%.

A potential concern arises with regard to whether this effect is solely attributable to the family VCs' inclination to invest in local startups. In other words, it might be argued that family VCs

12 In the regressions presented in Table A4, the criterion regarding the relative of the founder was removed. However, results are similar if I also include that criterion to identify family VCs.

syndicate with more local partners primarily due to their deliberate strategy of investing in geographically proximate startups. However, it is important to note that controlling for investments in local startups may not be a suitable control variable. This is attributed to the fact that the choice to invest locally constitutes a strategic decision on the part of family VCs, and investments in local startups may serve as a mediating factor in the relationship between syndication with local investors and family VCs. In other words, investment in local startups may be the mechanism through which family VCs have more local syndicate partners. However, to address this concern and demonstrate that the effect extends beyond their proclivity to syndicate with local partners purely because of their investments in local startups, Column 5 of Table 5 includes a control variable indicating whether the VC deal was aimed at supporting a geographically proximate startup (i.e., a startup within 25 km of the investing fund). The results, as shown, remain robust even after accounting for this additional variable, thereby suggesting that family VCs are not merely syndicating with more local partners because of their inclination to invest in geographically proximate startups. Another concern might be that they are syndicating with more local partners only because they are joining larger syndicate partnerships. To ease such concern, in Column 6 I replicate Column 4 and add a control for the number of syndicate partners above 25 kilometers. Controlling for the number of syndicate partners above 25 km is a better way to address the concern that family VCs are syndicating with more local partners only because they are joining larger syndicate partnerships vis-à-vis controlling for the raw number of syndicate partners. This is because it will avoid counting the same VCs both in the dependent variable (the count of syndicate partners within 25 km) and in the control variable.[13] As shown in Column 6, the estimated coefficient on the family VC dummy exhibits only a minor fluctuation following the introduction of the aforementioned control variable. This outcome indicates that family VCs do not appear to engage in syndication with a higher number of local syndicate partners solely due to their involvement in larger syndicate partnerships.

As previously done, I also test the robustness of my findings using different dependent variables. In particular, I used alternative distance thresholds, including the count of syndicate partners located within the same city, those positioned within a 10-kilometer radius, and those within a 50-kilometer radius. Additionally, I introduced a continuous variable denoting the logarithm of one plus the distance in kilometers between the VC fund and its nearest syndicate partner. The results, as depicted in Table A3, remain robust across these alternative specifications. Of particular note is the intriguing finding that even if the average distance between family VCs and their nearest syndicate partners is approximately 40% shorter (Column 4 of Table A2), the observed effect remains entirely driven by their proclivity to syndicate with extremely local partners. Indeed, when conducting a supplementary analysis that excludes syndicate partners located within a 25-kilometer radius (as presented in Column 5 of Table A2), the estimated coefficient associated with the family VC dummy becomes statistically insignificant. This underscores the conclusion that the observed syndication patterns among family VCs are predominantly attributable to their inclination to syndicate with extremely local partners, rather

13 The results are robust to the inclusion of the local syndicate partners in the control variable.

than those closer in proximity. Following the same approach used in Table A2, in Table A3 I test the robustness of the results using different measures to identify family VCs. As shown, the results are robust to alternative specifications.

In conclusion, I synthesized the two aforementioned strategies examined in this study, namely family venture capitalists' proclivity to invest in local startups and their tendency to syndicate with local partners. From this amalgamation, I derived a composite measure quantifying the degree to which family VCs exhibit a preference for concluding local deals. Specifically, I operationalized "local deals" as those investments oriented toward supporting startups situated within a 25-kilometer radius and characterized by the involvement of at least 25% of syndicate partners also located within this same geographical proximity. To test this, I use a specification analogous to the one presented in Table 4. As shown in Column 4 of Table 6, family VCs are 6.3 percentage points more likely to conclude local deals. Given a dependent variable mean of 0.15, the estimated coefficient implies that family VCs are 42% more likely to conclude local deals vis-à-vis non-family VCs. Collectively, these results provide support to Hypothesis 1 by providing strong evidence that family VCs are more likely to pursue a local strategy. I present the results of robustness tests for various operationalizations of the family VC dummy in Table A6.

One potential issue that merits consideration is whether the different geographical locations of family and non-family VCs may underlie the observed empirical outcomes. In order to address this concern, in Panel B of Table 3, I showed that family VCs are not based in more entrepreneurial cities vis-à-vis non-family VCs. Furthermore, in the regression analyses presented so far, I have used fund city fixed effects to ease such concerns. Using fixed effects for the city in the regression analyses, I controlled for unobservable city-specific characteristics that might affect investment decisions. However, while city fixed effects can control for time-invariant characteristics of cities, they may not capture all the nuances of local entrepreneurial ecosystems that can change over time. Entrepreneurial intensity can vary not only between cities but also within cities over time. Thus, to strengthen the reliability of the results, I made sure that all of the above findings hold when employing a matched sample of family and non-family VCs based on the entrepreneurial intensity of the area where they are based at the time of the deal. To construct this measure, I generated a panel dataset, encompassing all cities where the VCs in my dataset are headquartered. Within this framework, I devised a composite metric denoting the aggregate count of venture capital financing rounds secured by startups within a radius of 25 kilometers during the preceding three-year interval. [14] Subsequently, I standardized this variable on an annual basis, thereby centering it with a mean of zero and a standard deviation of one within each calendar year. Thus, the resultant metric serves as a reliable proxy for the entrepreneurial intensity of a given region at a given point in time. Critically, this approach effectively mitigates the influence of temporal variations in local entrepreneurial intensity on the empirical outcomes. Given that the number of deals executed by non-family VCs markedly exceeds those undertaken by their family VC counterparts, each deal completed by family VCs was matched with ten deals completed by the most closely resembling non-family VCs in terms of the entrepreneurial intensity of the area where they are based. This procedure effectively equates the entrepreneurial intensity of the area where family VCs are headquartered with that of the regions housing non-family VCs. Importantly, even after this match, the results reported in Table 7 corroborate the findings of Tables 4,5 and 6. Furthermore, in the

14 The results are robust to the use of different time frames such as 5 years.

interest of further validation, an additional robustness test is reported in the appendix (Table A6). In this analysis, Columns 4 of Tables 4, 5, and 6 are replicated, with the distinction that fund city fixed effects are replaced with fund country fixed effects. Additionally, this specification adds the previously defined control variables to account for the entrepreneurial intensity of the geographical area housing the VC fund at the time of the deal. As shown, the empirical findings remain robust even under this alternative specification.

4.1 The impact of family involvement in decision-making and eponymy

Extensive research within the domain of family business has long sought to understand how heightened family involvement in the decision-making process shapes the strategies adopted by family enterprises (e.g., Chua et al., 1999; Zahra, 2003). This paragraph seeks to establish whether the family VC's proclivity towards the local strategy is contingent upon the extent of family members' active involvement in decision-making. Secondly, this paragraph aims to leverage the unique venture capital setting to contribute fresh insights to the body of literature on family firms by showing that mere family presence in managerial roles may not be sufficient to significantly influence their strategic choices.

Hypothesis 1 posited that family VCs exhibit a predilection for pursuing local strategies. If the family is the driving force behind this strategy, then we should expect this inclination to be amplified when family members not only are managers of the family VC but also play an active role in shaping critical decisions within the VC fund. Unfortunately, when studying traditional corporations, it might be quite challenging to understand the extent to which the family is actively involved in the decision-making process. However, the venture capital arena offers an ideal setting for assessing the implications of heightened familial engagement in strategic decision-making on the behavioral patterns of family firms. Leveraging comprehensive data from Pitchbook, this analysis harnessed insights into the lead partners responsible for investment decisions within VC funds. Pitchbook data facilitated the classification of family VCs into two distinct categories: those marked by limited family involvement in decision-making and those where the family assumes a more central role. Specifically, when family members collectively led more investment rounds as lead partners than the most active non-family decision-maker within the fund, the family was considered highly involved in the decision-making process. In Table 8, the regression analyses mirror those presented in Column 4 of Table 4 (Column 1 of Table 8), Column 4 of Table 5 (Column 2 of Table 8), and Column 4 of Table 6 (Column 3 of Table 8). However, the "*Family VC*" variable has been replaced by two discrete binary variables. The first, termed "*Family VC – High Involvement*," assumes a value of one if the VC is family-managed and the family constitutes the primary decision-making of the fund. Conversely, the second variable, designated "*Family VC – Low Involvement*," assumes a value of one if the VC is family-managed but the family's role in decision-making is less pivotal. As shown in Table 8, family VCs characterized by a more passive familial role exhibit behaviors analogous to their non-family VC counterparts. Notably, the estimated coefficients, though positive, do not attain statistical significance. Conversely, when the family assumes an active role in decision-making processes, family VCs display a heightened inclination toward the pursuit of local strategies. Specifically, family VCs in which the family actively participates in decision-making processes are observed to be 29.2% more predisposed to invest in local startups and engage in syndication with 27.9% more local partners. These cumulative findings substantiate the contention that it is indeed the family's leadership and involvement that guide family VCs toward the adoption of localized strategies. Significantly, these empirical findings contribute substantively to the broader discourse on family firms, underscoring the proposition that the mere inclusion of family members within the managerial hierarchy may not suffice to exert a discernible influence on the strategic orientations of such firms. Instead, active and substantive involvement of family members in the decision-making process emerges as the pivotal determinant that shapes the strategic choices embraced by family enterprises.

Next, I analyze the impact of eponymy. Founders must decide how to name their firm. This decision is an important and visible one that can significantly affect the subsequent success of the firm. One of the options available to the funders is to give their own name to the company. The extant academic literature has shown that eponymous firms tend to achieve superior performance (Belenzon et al., 2017) and grow at a slower pace (Belenzon et al., 2020). In the context of family VCs, eponymy should strengthen the relationship between the family and their territory. A family VC with a name closely associated with the local community may have built a strong reputation and trust within that community over time. Local entrepreneurs and businesses may be more familiar and comfortable with a VC firm that bears a recognizable local name. This reputation and trust can facilitate deal-making and collaboration with local startups and partners. Furthermore, since the relationship between the family VC and the family is immediate when the family VC is eponymously named, the family is more easily recognizable when they support local startups and this might enhance the non-monetary benefits arising from their local investments. Consequently, we might expect eponymously named family VCs to be more likely to pursue a local strategy. In Table 9, the regression analyses mirror those presented in Column 4 of Table 3 (Column 1 of Table 9), Column 4 of Table 4 (Column 2 of Table 9), and Column 4 of Table 5 (Column 3 of Table 9).

However, the "*Family VC*" variable has been replaced by two discrete binary variables. The first, termed "*Family VC – Eponymous*" is a dummy with a value of one if the family VC is eponymously named, while "*Family VC – Non-Eponymous*" is a dummy with a value of one if the family VC is not eponymously named. As expected, the results presented in Table 9 suggest that the family VCs are more likely to pursue a local strategy when they are eponymously named.

4.2 Exploiting transitions from non-family to family VC

Assessing causality in family business research is a difficult task. Nevertheless, to strengthen the reliability of the results, I made sure that the findings hold when employing a matched sample of family and non-family VCs (Table 7). Moreover, investigating the heterogeneity behind the average findings I find stronger results when the family VC is led by the family (Table 8) and when the family VC is eponymously named (Table 9). To further progress toward the establishment of causality, I exploit shifts in the family involvement across consecutive funds raised by the same VC firm. This approach draws inspiration from extant literature on family firms operating within traditional industries, where transitions from non-family to family leadership (or vice versa) have been identified as pivotal events that shaped family firms' strategies and performance (e.g., Amore et al., 2021). In the context of venture capital, this analysis capitalizes on VC firms that manage multiple sequential funds to understand how transitions in the family management in the funds within the same VC firm shape the strategies pursued by these funds. Notably, while most VC firms have a clear dichotomy of either exclusively raising family-managed VC funds or non-family-managed VC funds, a subset of VC firms has ventured into both realms. In light of this, I have retained all VC deals executed by VC funds raised by firms that have raised both family and non-family VCs. To discern causal relationships, I have employed the non-family-managed VC fund(s) raised by the same VC firm as counterfactual(s) for the family VC fund(s) raised by the same firm, thereby enabling a comparison of the different strategic choices associated with varying management structures. Since a limited number of VC funds were concurrently raised by multiple firms, rendering the counterfactual in such instances less clear, I have excluded deals completed by VC funds raised by more than one firm. The choice of dependent variables aligns with those employed in previous analyses, specifically encompassing the binary indicator denoting proximity (within 25 kilometers) between the VC fund and the startup (Columns 1-3 of Table 10), the count of local syndicate partners (Columns 4-6 of Table 10), and a binary indicator having a value of one for investments syndicated with at least 25% of the syndicate partners within 25 kilometers and aimed at supporting startups within a 25-kilometer radius (Columns 7-9 of Table 10). The main explicatory variables are those previously presented. However, in all specifications, I have also included VC firm fixed effects to control for unobservable characteristics specific to each VC firm such as, for example, its culture, and investment philosophy. It is noteworthy that when a VC firm raises one or more family-managed VC fund(s), a potential variation in the overall characteristics of the VC firm, and consequently of the VC funds used as counterfactual might occur. However, under such circumstances, the estimated coefficients associated with the family VC variable are anticipated to exhibit a bias leaning toward zero. In simpler terms, this implies that we may inadvertently underestimate the impact of transitioning from a non-family VC to a family VC. The empirical results, as presented in Table 9, largely corroborate prior findings. They underscore the predisposition of family VCs to pursue a local strategy, particularly in instances where family members actively partake in the decision-making processes and where the VC firm bears an eponymous name. While this empirical evidence may not be devoid of imperfections, it constitutes a significant step toward attenuating some of the most obvious endogeneity concerns.

4.3 Post-Hoc Analyses: Is the Local Strategy a Good Strategy?

Hypothesis 1 posited that family VCs would exhibit a greater propensity to adopt a local investment strategy, driven by their heightened local embeddedness. Nevertheless, while preceding analyses have indeed demonstrated that family VCs are inclined towards local strategies, a fundamental question remains: is this local orientation a rational strategy, capitalizing on their superior information about the local entrepreneurial ecosystem, or rather a consequence of their home bias? Theoretically, the performance implications of family VCs' local strategies are ambiguous.

On one hand, family VCs, when investing in local startups, may leverage their local embeddedness (Bird and Wennberg, 2014) to access non-public information about these startups and secure preferential access, thereby diminishing information asymmetries concerning local startups and identifying the most promising ones. Similarly, in the context of syndicating with local investors, family VCs' local embeddedness may enable them access to superior information about local investors, thereby mitigating information asymmetries with potential local partners and facilitating inter-organizational exchange due to heightened reciprocal trust (Meuleman et al., 2010; Sorenson and Stuart, 2008). Furthermore, their robust relationships with other local investors may result in family VCs being invited to participate by other local investors in their best deals.

On the other hand, as previously discussed, family firms' desire to contribute to the economic development of their community (Miller and Le Breton Miller, 2005; Campopiano et al., 2014;

Lumpkin and Bacq, 2022), coupled with their goal of maintaining and preserving a strong reputation and positive relationships with community stakeholders (Zellweger and Nason, 2008; Cennamo et al., 2012), might endanger a home bias (Baschieri et al., 2017). This bias might lower the investment quality threshold for local startups (investment partners), potentially resulting in suboptimal investment outcomes (Lin and Viswanathan, 2016). Additionally, the expectations and obligations inherent in strong local ties might further constrain family VCs' choices. Their deep entrenchment within the local network may lead them to invest in (syndicate with) local startups (investment partners) of lower quality (or join lower quality deals when the invitation comes from local investors), reflecting the paradox of over-embeddedness elucidated by Uzzi (1996). Indeed, owing to the close-knit local kinship network characteristic of family firms, family VCs might opt to syndicate with other local investors with whom they share strong ties, even if such local investors lack the requisite skills to effectively support the startups being financed.

To discern the rationale behind family VCs' investments in local startups (syndicating with local investors), I examine the performance outcomes associated with geographic proximity. If family VCs are acting as rational agents, strategically capitalizing on their superior information concerning these startups (investors), one would anticipate that family VCs' investments would yield greater success when the startup (syndicate partner) is geographically proximate. Conversely, if family VCs' investments in local startups (syndicating with local investors) are primarily driven by their "home bias", such investments might yield comparatively lower levels of success.

Following the literature (e.g., Gompers et al., 2009; Dushnitsky and Shapira, 2010; Gaba and Dokko, 2015), I focus on the occurrence of an IPO or trade sale as a measure of a successful exit. Following Nahata (2008), I restrict the sample to deals completed by December 2018. Since I observe the exit outcomes until May 2023, this methodology provides a minimum of 4.5 years for a successful exit to occur. This approach is also consistent with the findings reported by Cumming and Binti Johan (2008) and Mason and Harrison (2002) who documented those successful exits often occur within 3-4 years after the initial investment. In the analyses reported in Table 11, the main explicatory variable is a dummy with a value of one if the VC firm successfully exited from the investment in the startup (i.e., exited through an IPO or M&A); zero elsewhere. The explicatory variables are those included in Column 4 of Table 4. As shown, in Column 1, on average family VCs perform as well as non-family VCs. As shown in Column 2, the extent to which the family is involved in the decision-making does not significantly shape the performance outcomes. However, eponymously named family VCs tend to achieve superior performance both relative to non-eponymously named family VCs and non-family VCs. This evidence is consistent with Belonzon et al. (2017) who, studying corporations operating in traditional industries found that eponymous firms tend to perform better than non-eponymous ones.

Turning to Column 1 of Table 12, I assess whether investments in local startups by family VCs reflect rational choices or are influenced by their local bias. In line with existing literature (e.g., Cumming and Dai, 2010; Jääskeläinen and Maula, 2014), I find that investments in local startups are generally associated with higher success rates. However, my focus is on discerning whether going local is beneficial for family VCs. To investigate this, I introduce an interaction term between the family VC dummy and the indicator for investing in local startups. The estimated coefficient on this interaction term should indicate the average differential impact on the chances of experiencing a successful exit for family VCs versus non-family VCs when investing in local startups. The results presented in Table 12 indicate that both family and non-family VCs benefit from investing locally. However, family VCs derive substantially greater benefits from their local investments, as evidenced by the interaction term's estimated coefficient, which is positive and approximately five times larger than the one on the “Local Startup” one. These findings hold even when controlling for investment characteristics in Column 2 (i.e., number of syndicate partners and startup age) and startup team attributes in Column 3 (i.e., education, prior entrepreneurial experience, and team size). In Column 3, the sample size decreases due to the unavailability of founding team information for some startups in Pitchbook. In sum, the evidence reported in Table 12 suggests that family VCs' preference for investing in local startups is not solely attributable to home bias but rather to their access to and utilization of superior information about local startup opportunities.

I employ a similar approach to assess the rationality of syndicating with local investors. To investigate this strategy, I introduce an interaction between the family VC indicator and the proportion of local investors involved in the deal. To calculate this share, I consider not only the count of other funds operating within a 25-kilometer radius but also account for other investor types participating in the same deal, including accelerators, incubators, corporations, and others. The denominator comprises the total number of syndicate partners for whom Pitchbook has location information. The variable has a value of zero when the deal was not syndicated. The findings remain consistent when I use the total count of syndicate partners as the denominator, which includes investors with missing location information. In untabulated analyses, I further scrutinize the robustness of these results by employing alternative measures, such as a binary variable indicating whether 25% of the syndicate partners are located within 25 kilometers, as well as a continuous variable representing the count of syndicate partners within this radius. These additional analyses yield similar results. As shown in Table 13, while syndicating with a higher proportion of local partners yields benefits for both family and non-family VCs, the latter group derives significantly greater advantages from this strategic choice. This finding further underscores the notion that the decision of family VCs to invest locally is a rational strategy.

Finally, I probe whether engaging in local deals—specifically, investments in local startups that syndicate with local partners—is indeed a rational strategy. To explore this, in Table 14 I introduce an interaction between the family VC indicator and a binary variable, taking on a value of one if the VC fund invested in a startup within a 25-kilometer radius while syndicating with at least 25% of the syndicate partners located within the same radius. Once again, the results indicate that while participating in local deals benefits all investors, family VCs enjoy a notable advantage from this approach. In the analyses concerning the performance implications of the local strategy, Following Nahata (2008), I considered a follow-up period of 4.5 years for exit events. This decision was based on prior research indicating that successful exits often occur within 3-4 years after the initial investment (e.g., Cumming and Binti Johan, 2008; Mason and Harrison, 2002). However, certain startups may require more time to achieve a successful exit. To address this concern and provide a more comprehensive perspective, I conduct a robustness test (Table A7) where I replicate the analyses concerning the performance implications of the local strategy while restricting the dataset to deals completed by December 2014. This adjustment ensures a minimum follow-up period of 9 years and 6 months for VCs to experience a successful exit (considering that the dataset was downloaded in June 2023). As VC funds typically have a lifetime of around 10 years, this extended follow-up period should encompass almost all exit events. In Column 1 of Table A7, I replicate Column 3 of Table 13 by considering only deals completed up to December

2014. Similarly, in Column 2 (3) of Table A7, I replicate Columns 3 of Table 14 and 15 following the same approach. As shown in Table A7, results are robust to this alternative specification.

Collectively, these findings strongly suggest that family VCs are rational investors. They are more likely to invest in local startups and syndicate with local partners because they have more information on the local entrepreneurial ecosystem. When family VCs invest in local startups or partner with local investors, they do so strategically, leveraging their local knowledge and relationships to their advantage. This approach consistently leads to better outcomes, as evidenced by a higher likelihood of successful exits. While both family and non-family VCs benefit from local investments, family VCs excel in this strategy. Their superior performance underscores their rational decision-making and reinforces the idea that they possess unique insights into their local entrepreneurial ecosystems. Family VCs, given their deep-rooted presence in the local ecosystem, tend to foster robust relationships with the local community, fellow investors, and entrepreneurs alike. These well-established connections inherently elevate their capacity to source local deals effectively. In a complementary manner, family VCs' extensive familiarity with the nuances of the local entrepreneurial landscape equips them with a unique and superior ability to screen and assess local opportunities. This combination of robust local networks and a profound understanding of the region's dynamics positions family VCs to excel in the local investment landscape, potentially leading to superior performance when they focus on local investments.

5. CONCLUSION

Traditionally, family firms have been associated with more traditional industries, but the emergence of family-managed VC funds like ULU Ventures, Enygma Ventures, and H2 Ventures presents a remarkable shift in this narrative. These VC funds, led by family teams, have successfully raised substantial capital, and are actively contributing to the growth of startups. This study has bridged the gap between the two distinct fields of family firms and venture capital. It has shown that the influence of families in the venture capital landscape transcends the confines of CVC entities associated with family businesses (Amore et al., 2021) and family offices (e.g., Block et al., 2019; Manigart and Khosravi, 2023). It extends to a distinctive category of venture capital funds which I label family VCs. Family VCs are venture capital funds akin to traditional venture capital funds that stand out for their pronounced familial involvement in fund management. The findings of this research underscore that family VCs are integral players in the venture capital arena, while also shedding light on their distinctive investment approach.

Drawing upon global Pitchbook data covering VC investments from 2000 to 2022, this study has contributed several novel insights to the existing literature. Firstly, it has shown that family VCs, having supported 7.1% of the startups in the sample, are significant players in the VC arena. Secondly, the research has highlighted the remarkable influence of local embeddedness on the investment strategies of family VCs, indicating a clear preference for investing in geographically proximate startups and forming syndicates with investors from the same region. Importantly, family VCs are different from domestic VCs that invest in startups based in the same country (e.g., Mäkelä and Maula, 2006; Liu and Maula, 2016; Devigne et al., 2016). Instead, family VCs are more discerningly inclined to invest in startups that are genuinely geographically proximate. Furthermore, this propensity for local investment was found to be particularly pronounced when family members held a substantial role in the fund decision-making and when the VC fund was eponymously named. In examining the performance implications of this local strategy, the study has uncovered that family VCs' inclination toward local investments is not a mere result of home bias but rather a rational strategy aimed at capitalizing on their superior knowledge of the local entrepreneurial ecosystem. Indeed, while local investments are generally associated with enhanced performance for both family and non-family VCs, it is family VCs who reap the most substantial benefits when embracing a local focus.

This paper represents the first attempt to study family VCs. Future papers might want to explore many other interesting aspects such as other characteristics of the families that might shape their investment strategies and performance. For example, it might be interesting to understand the extent to which personal motivations confer private emotional benefits to family VCs. It is worth noting also, that in this paper I focused on VC funds raised by VC firms. However, there are also other players in the VC arena characterized by a substantial family involvement that goes beyond CVCs controlled by a family firm, family offices, and the family VCs studied in this paper. As a matter of fact, there are many other different types of investors active in the VC arena being family-managed such as accelerators (e.g., Pax Momentum managed by the Hanson family), PE (e.g., Northwood Ventures managed by the Schiff family), impact investors (e.g., TD Veen managed by Veen family), real estate (e.g., The Durst Organization managed by the Durst family), and banks (e.g., Banca Sella managed by the Sella family). Studying these entities might be an interesting avenue for future research.

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Table 1

	Family VCs	Family Offices	CVC arms of Family Firms
Primary Purpose	Their primary purpose is to invest in startups and early-stage companies with the goal of generating financial returns. Their mission centers around identifying the most promising startups, nurturing them, and experiencing successful exits.	Primarily concerned with managing and preserving the wealth of a high-net-worth family or individual. Their mission is to oversee various assets, including investments in diverse asset classes such as stocks, real estate, and alternative investments (including VC investments).	While they might invest in startups to generate financial returns, their main focus is to leverage startup investments to generate long-term strategic advantages for the family firm in the long run.
Fundraising	Raise capital from LPs. The latter provide the necessary capital for investments, and the family manages these funds with the aim of achieving strong investment returns.	Typically, do not raise funds from external investors like LPs. Instead, they manage the wealth and assets of a single family or a select group of closely related families. Their focus is on wealth preservation and long-term financial stability.	Unlike Family VCs, CVCs controlled by family firms may not raise money from external Limited Partners (LPs) and may utilize the resources of the family business to finance investments.
Management	Managed by members of the same family. This means that family members are actively involved in the decision-making processes, the daily operations of the fund, and its investment strategies.	May or may not be family managed. While some family offices are directly managed by family members, others hire professional managers, advisors, and experts to handle the day-to-day management of their financial affairs. The level of family involvement can vary widely.	These CVCs may not be managed by family members but by professionals with expertise in venture capital and strategic investments.
Investment Horizon	Have a predefined investment horizon, often around 10 (+2) years. They must exit their investments within this timeframe.	Often have a longer investment horizon, which extends beyond a single generation. They aim to protect and grow family wealth for the benefit of current and future generations.	These CVCs may not have a dedicated fund structure and, as a result, may not be bound by the traditional 10-year investment horizon. They may have a more flexible approach, aligning with the strategic objectives of the family firm.
Investment Approach	Oriented toward achieving high returns and realizing capital gains. They are willing to take risks associated with early-stage companies and innovative technologies to generate substantial financial rewards.	While they may invest in a wide range of assets, including equities and real estate, their primary objective is to preserve capital and generate consistent income. They typically prioritize stability and risk management over aggressive growth and high-risk investments.	The primary focus of CVCs controlled by family firms is often on strategic alignment with the core business, seeking synergies and long-term benefits for the family firm in addition to financial returns.

Table 2. Summary Statistics

	Obs.	Mean	s.d.	Median
Panel A. Fund-Startup Level Characteristics				
Family VC	127,841	0.036	0.185	0
Family VC – High Involvement	127,253	0.026	0.160	0
Family VC – Low Involvement	127,253	0.010	0.098	0
Local Startup	127,841	0.270	0.444	0
N. Local Syndicate Partners	127,841	0.966	1.613	0
% Local Syndicate Partners	127,841	0.192	0.286	0
Local Syndicate Partnership	127,841	0.175	0.380	0
Local Deal	127,841	0.150	0.357	0
Fund maturity	127,841	1.987	1.853	2
N. Syndicate Partners	127,841	5.141	4.878	4
Startup Age	125,767	3.612	3.203	3
Successful Exit	127,841	0.291	0.454	0
Panel B. VC Fund Characteristics				
Eponymy	5,644	0.032	0.200	0
Fund Size	5,644	171.8	584.3	73.4
Fund Team Experience	5,644	6.461	10.49	3
Entrepreneurial Intensity Area	5,644	1.307	1.643	0.80
Bank LP	5,644	0.064	0.245	0
Corporate LP	5,644	0.095	0.293	0
Corporate Pension Fund LP	5,644	0.185	0.388	0
Direct Investment LP	5,644	0.084	0.277	0
Economic Development Agency LP	5,644	0.049	0.216	0
Endowment LP	5,644	0.112	0.315	0
Family Office LP	5,644	0.025	0.157	0
Foundation LP	5,644	0.172	0.378	0
Fund of Funds LP	5,644	0.239	0.427	0
Government LP	5,644	0.066	0.248	0
High-Net-Worth Individual LP	5,644	0.029	0.167	0
Insurance LP	5,644	0.103	0.304	0
Investment Advisor LP	5,644	0.023	0.148	0
Money Management Firm LP	5,644	0.047	0.212	0
Other LP	5,644	0.014	0.119	0
Private Investment Fund LP	5,644	0.021	0.142	0
Public Pension Fund LP	5,644	0.189	0.391	0
Sovereign Walth Fund LP	5,644	0.041	0.199	0
Union Pension Fund LP	5,644	0.048	0.214	0
Wealth Management Firm LP	5,644	0.029	0.166	0
Panel C. Startup Characteristics				
Family Backed	56,342	0.071	0.256	0
MBA	50,390	0.297	0.457	0
Serial Founder	50,390	0.252	0.434	0
Elite Education	50,390	0.384	0.486	0
Founding Team Size	50,390	2.637	1.396	2

Panel A presents summary statistics at the VC fund-Startup level. *"Family VC*" is a binary indicator taking the value of 1 if the venture capital fund exhibits significant familial involvement in its management, which is defined as either having family members make up at least 25% of the fund managers or having a relative of the founder serving as a fund manager. Otherwise, it takes a value of 0. "*Family VC – High Involvement*" is a binary indicator taking the value of 1 if VC fund is a family VC, as previously defined, and family members are significantly engaged in the fund's decision-making process. Family members are considered significantly involved in the decision-making process if they have collectively led more deals as lead partners of the fund than (or at least as many as) the most active non-family member within the fund. It takes a value of 0 otherwise. "*Family VC – Low Involvement*" is a binary indicator taking the value of 1 if the VC fund is a family VC, as previously defined, but family members are not significantly involved in the fund's decision-making process. Otherwise, it takes a value of 0. "*Local Startup*" is a binary variable taking the value of 1 if the VC fund's headquarters is located within 25 kilometers of the startup, and 0 otherwise. "*N. Local Syndicate Partners*" represents the count of syndicate partners (including both other funds and other types of investors) located within 25 kilometers of the VC fund. "*% Local Syndicate Partners*" indicates the proportion of syndicate partners within 25 kilometers out of the total number of syndicate partners for which location information is available. "*Local Syndicate Partnership*" is a binary indicator taking the value of 1 if at least 25% of syndicate partners, for which location information is available, are based within 25 kilometers of the VC fund. Otherwise, it takes a value of 0. "*Local Deal*" is a binary variable taking the value of 1 if the VC fund's headquarters are within 25 kilometers of the startup and at least 25% of syndicate partners with available location information are within the same 25-kilometer radius. It takes a value of 0 otherwise. "*Fund Maturity*" represents the number of years that have passed since the fund's vintage year. This variable has been winsorized at the 1 percent level. "*N. Syndicate Partners*" is the count of syndicate partners involved in the deal, with winsorization applied at the 1 percent level. "*Startup Age*" indicates the age of the startup in years at the time of the deal, with winsorization applied at the 1 percent level. "*Successful Exit*" is a binary variable taking the value of 1 if the VC firm successfully exited its investment in the startup through an IPO or trade sale. Otherwise, it takes a value of 0. Panel B presents summary statistics at the VC fund level. *"Eponymy*" is an indicator variable taking the value of 1 if the last name of a VC fund manager is part of the fund's name or of the entity that raised the fund. It takes a value of 0 otherwise. "*Fund Size*" denotes the monetary size of the fund in millions of dollars. "*Fund Team Experience*" is the cumulative number of deals completed as lead partners by the fund managers before the vintage year of the fund. "*Entrepreneurial Intensity Area*" is a proxy for the entrepreneurial intensity of the area where the VC fund is based. To gauge the entrepreneurial activity level in the vicinity of the VC fund's location, a panel was constructed for each city housing the VC funds in the dataset. This panel records the total number of VC financing rounds secured by startups within a 25-kilometer radius over the preceding three years. To ensure comparability, this variable has been standardized annually, yielding an average of zero and a standard deviation of one within each year. The value presented in the table represents the entrepreneurial intensity of the area where the VC fund is situated as of its vintage year. Furthermore, Panel B provides additional information about the LP composition of the VC funds. It reports many indicator variables assuming a value of 1 if the VC fund has a particular type of limited partner (LP). For example, "*Bank LP*" takes on the value 1 if at least one bank is among the LPs of the VC fund; otherwise, it assumes a value of 0. Panel C presents summary statistics at the startup level. "*Family Backed*" is an indicator variable taking a value of 1 if the startup received support from at least one family VC. Otherwise, it takes a value of 0. "*MBA*" is an indicator variable taking the value of one if at least one of the startup's founders holds an MBA degree; otherwise, it assumes a value of 0. "*Serial Founder*" is an indicator variable taking the value 1 if at least one of the startup's founders has previously founded other startups before initiating the current one. Otherwise, it takes on a value of 0. "*Elite Education*" is an indicator variable taking the value of one if at least one of the founders of the startup attended a university ranked among the top 30 universities according to the inaugural version of the QS Ranking, published in 2004. "*Founding Team Size*" counts the number of founders associated with the startup.

Table 3. Differences Family VCs Vs. Non-Family VCs

Panel A. Fund-Startup Level	Family VC	Non-Family VC	Difference: Family VC-Non Family VC
Local Startup	0.330	0.268	0.062
			(0.007)
N. Local Syndicate Partners	1.260	0.954	0.305
			(0.024)
% Local Syndicate Partners	0.218	0.191	0.026
			(0.004)
Local Syndicate Partnership	0.206	0.174	0.033
			(0.005)
Local Deal	0.208	0.148	0.060
			(0.005)
Fund maturity	1.840	1.992	-0.153
			(0.028)
N. Syndicate Partners	5.693	5.120	0.573
			(0.074)
Startup Age	3.423	3.619	-0.196
			(0.049)
Successful Exit	0.307	0.290	0.017
			(0.007)

Panel B. VC Fund Level	Family VC	Non-Family VC	Difference: Family VC-Non Family VC
Eponymy	0.115	0.029	0.086
			(0.014)
Fund Size	141.755	172.72	-30.965
			(46.172)
Fund Team Experience	6.958	6.446	0.512
			(0.829)
Entrepreneurial Intensity Area	1.455	1.302	0.153
			(0.130)
Bank LP	0.060	0.064	-0.004
			(0.019)
Corporate LP	0.097	0.095	0.002
			(0.023)
Corporate Pension Fund LP	0.140	0.186	-0.046
			(0.030)
Direct Investment LP	0.067	0.084	-0.018
			(0.022)
Economic Development Agency LP	0.043	0.050	-0.007
			(0.017)
Endowment LP	0.085	0.113	-0.028
			(0.025)
Family Office LP	0.054	0.025	0.030
			(0.013)
Foundation LP	0.164	0.173	-0.009
			(0.030)
Fund of Funds LP	0.200	0.240	-0.041
			(0.034)
Government LP	0.024	0.067	-0.043
			(0.019)
High-Net-Worth Individual LP	0.030	0.029	0.002
			(0.013)
Insurance LP	0.097	0.103	-0.006
			(0.024)
Investment Advisor LP	0.012	0.023	-0.011
			(0.011)
Money Management Firm LP	0.054	0.047	0.007
			(0.017)
Other LP	0.006	0.015	-0.009
			(0.009)
Private Investment Fund LP	0.024	0.021	0.004
			(0.011)
Public Pension Fund LP	0.206	0.188	0.018
			(0.031)
Sovereign Walth Fund LP	0.024	0.042	-0.018
			(0.015)
Union Pension Fund LP	0.043	0.048	-0.006
			(0.017)
Wealth Management Firm LP	0.036	0.029	0.008
			(0.013)

Table 4. Local Startups

Dependent variable:	Local Startup	Local Startup	Local Startup	Local Startup
	(1)	(2)	(3)	(4)
Family VC	0.058***	0.063***	0.058***	0.063***
	(0.021)	(0.020)	(0.016)	(0.017)
Fund Maturity		-0.003	-0.001	-0.001
		(0.002)	(0.001)	(0.001)
Fund Size		-0.012***	-0.014***	-0.017***
		(0.003)	(0.003)	(0.003)
Fund Team Experience		-0.029***	-0.005	-0.006
		(0.005)	(0.004)	(0.004)
Observations	127,841	127,841	127,841	127,841
Investment Year Dummies	Yes	Yes	Yes	Yes
Startup Industry Dummies	Yes	Yes	Yes	Yes
Fund City Dummies	No	No	Yes	Yes
LP Types Dummies	No	No	No	Yes

This table reports the results of OLS regressions. "*Local Startup*" is a binary variable taking the value of 1 if the VC fund's headquarters is located within 25 kilometers of the startup, and 0 otherwise. "*Family VC*" is a binary indicator taking the value of 1 if the venture capital fund exhibits significant familial involvement in its management, which is defined as either having family members make up at least 25% of the fund managers or having a relative of the founder serving as a fund manager. Otherwise, it takes a value of 0. "*Fund Maturity*" represents the number of years that have passed since the fund's vintage year. This variable has been winsorized at the 1 percent level. "*Fund Size*" is the natural logarithm of one plus the monetary size of the fund in millions of dollars. "*Fund Team Experience*" is the natural logarithm of one plus the cumulative number of deals completed as lead partners by the fund managers before the vintage year of the fund. All specifications include investment year and startup industry fixed effects. In Columns 3 and 4, I extend the model by introducing fixed effects specific to the city where the fund is located. Furthermore, in Column 4, I introduce a set of dummy variables indicating the presence of certain types of Limited Partners as outlined in Panel B of Table 2. Funds with missing info on their LPs are grouped into a missing LP dummy. Robust standard errors clustered at the VC fund level are reported in parentheses.

Table 5. Local Syndicate Partners

Dependent variable:	N. Local Syndicate Partners	N. Local Syndicate Partners	N. Local Syndicate Partners	N. Local Syndicate Partners	N. Local Syndicate Partners	N. Local Syndicate Partners
	(1)	(2)	(3)	(4)	(5)	(6)
Family VC	0.259***	0.249***	0.211***	0.228***	0.175***	0.201***
	(0.084)	(0.083)	(0.057)	(0.057)	(0.048)	(0.056)
Fund Maturity		-0.015**	-0.007	-0.005	-0.004	-0.004
		(0.007)	(0.005)	(0.005)	(0.005)	(0.005)
Fund Size		-0.005	-0.027***	-0.022**	-0.012	-0.028***
		(0.013)	(0.010)	(0.010)	(0.009)	(0.010)
Fund Team Experience		0.041*	0.006	0.012	0.013	0.009
		(0.024)	(0.017)	(0.018)	(0.015)	(0.017)
Local Startup					0.770***	
					(0.015)	
N. Non-Local Syndicate Partner						0.040***
						(0.002)
Observations	127,841	127,841	127,841	127,841	127,841	127,841
Investment Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Startup Industry Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Fund City Dummies	No	No	Yes	Yes	Yes	Yes
LP Types Dummies	No	No	No	Yes	Yes	Yes

This table reports the results of Poisson regressions. "*N. Local Syndicate Partners*" represents the count of syndicate partners (including both other funds and other types of investors) located within 25 kilometers of the VC fund. "*Family VC*" is a binary indicator taking the value of 1 if the venture capital fund exhibits significant familial involvement in its management, which is defined as either having family members make up at least 25% of the fund managers or having a relative of the founder serving as a fund manager. Otherwise, it takes a value of 0. "*Fund Maturity*" represents the number of years that have passed since the fund's vintage year. This variable has been winsorized at the 1 percent level. "*Fund Size*" is the natural logarithm of one plus the monetary size of the fund in millions of dollars. "*Fund Team Experience*" is the natural logarithm of one plus the cumulative number of deals completed as lead partners by the fund managers before the vintage year of the fund. All specifications include investment year and startup industry fixed effects. In Columns 3-6, I extend the model by introducing fixed effects specific to the city where the fund is located. Furthermore, in Columns 4-6, I introduce a set of dummy variables indicating the presence of certain types of Limited Partners as outlined in Panel B of Table 2. In Column 5 I add "*Local Startup*", a binary variable taking the value of 1 if the VC fund's headquarters is located within 25 kilometers of the startup, and 0 otherwise. In Column 6 I add "*N. Non-Local Syndicate Partner*", the count of syndicate partners distant more than 25 km away from the city where the fund is based. Robust standard errors clustered at the VC fund level are reported in parentheses.

Table 6. Local Deal

Dependent variable:	Local Deal	Local Deal	Local Deal	Local Deal
	(1)	(2)	(3)	(4)
Family VC	0.058***	0.063***	0.058***	0.063***
	(0.021)	(0.020)	(0.016)	(0.017)
Fund Maturity		-0.003	-0.001	-0.001
		(0.002)	(0.001)	(0.001)
Fund Size		-0.012***	-0.014***	-0.017***
		(0.003)	(0.003)	(0.003)
Fund Team Experience		-0.029***	-0.005	-0.006
		(0.005)	(0.004)	(0.004)
Observations	127,841	127,841	127,841	127,841
Investment Year Dummies	Yes	Yes	Yes	Yes
Startup Industry Dummies	Yes	Yes	Yes	Yes
Fund City Dummies	No	No	Yes	Yes
LP Types Dummies	No	No	No	Yes

This table reports the results of OLS regressions. "*Local Deal*" is a binary variable taking the value of 1 if the VC fund's headquarters are within 25 kilometers of the startup and at least 25% of syndicate partners with available location information are within the same 25-kilometer radius. It takes a value of 0 otherwise. "*Family VC*" is a binary indicator taking the value of 1 if the venture capital fund exhibits significant familial involvement in its management, which is defined as either having family members make up at least 25% of the fund managers or having a relative of the founder serving as a fund manager. Otherwise, it takes a value of 0. "*Fund Maturity*" represents the number of years that have passed since the fund's vintage year. This variable has been winsorized at the 1 percent level. "*Fund Size*" is the natural logarithm of one plus the monetary size of the fund in millions of dollars. "*Fund Team Experience*" is the natural logarithm of one plus the cumulative number of deals completed as lead partners by the fund managers before the vintage year of the fund. All specifications include investment year and startup industry fixed effects. In Columns 3 and 4, I extend the model by introducing fixed effects specific to the city where the fund is located. Furthermore, in Column 4, I introduce a set of dummy variables indicating the presence of certain types of Limited Partners as outlined in Panel B of Table 2. Funds with missing info on their LPs are grouped into a missing LP dummy. Robust standard errors clustered at the VC fund level are reported in parentheses.

Table 7. Matching

Panel A. Matching

	Family VC	Non-Family VC	Difference Family - Non-Family
Local Startup	0.330	0.274	0.056***
			(0.015)
N. Local Syndicate Partners	1.260	1.004	0.256***
			(0.037)
Local Deal	0.208	0.157	0.051***
			(0.007)

Deals completed by family VCs are matched with those completed by non-family VCs by means of one-to-ten propensity score matching on the entrepreneurial intensity of the area where the VC funds are based at the time of the deal. This procedure effectively equates the entrepreneurial intensity of the cities where family and non-family VCs are based.

Table 8. Family Involvement and Local Strategy

Dependent variable:	Local Startup	N. Local Syndicate Partners	Local Deal
	(1)	(2)	(3)
Family VC – High Involvement	0.079***	0.269***	0.065***
	(0.019)	(0.061)	(0.017)
Family VC – Low Involvement	0.019	0.090	0.027
	(0.027)	(0.123)	(0.022)
Fund Maturity	-0.001	-0.005	-0.001
	(0.001)	(0.005)	(0.001)
Fund Size	-0.017***	-0.023**	-0.010***
	(0.003)	(0.010)	(0.002)
Fund Team Experience	-0.006	0.017	-0.002
	(0.004)	(0.018)	(0.003)
Observations	127,253	127,253	127,253
Investment Year Dummies	Yes	Yes	Yes
Startup Industry Dummies	Yes	Yes	Yes
Fund City Dummies	Yes	Yes	Yes
LP Types Dummies	Yes	Yes	Yes

This table reports the results of OLS (Columns 1 and 3) and Poisson (Column 2) regressions. "*Local Startup*" is a binary variable taking the value of 1 if the VC fund's headquarters is located within 25 kilometers of the startup, and 0 otherwise. "*N. Local Syndicate Partners*" represents the count of syndicate partners (including both other funds and other types of investors) located within 25 kilometers of the VC fund. "*Local Deal*" is a binary variable taking the value of 1 if the VC fund's headquarters are within 25 kilometers of the startup and at least 25% of syndicate partners with available location information are within the same 25-kilometer radius. It takes a value of 0 otherwise. "*Family VC – High Involvement*" is a binary indicator taking the value of 1 if the VC fund is a family VC, as previously defined, and family members are significantly engaged in the fund's decision-making process. Family members are considered significantly involved in the decision-making process if they have collectively led more deals as lead partners of the fund than (or at least as many as) the most active non-family member within the fund. It takes a value of 0 otherwise. "*Family VC – Low Involvement*" is a binary indicator taking the value of 1 if the VC fund is a family VC, as previously defined, but family members are not significantly involved in the fund's decision-making process. Otherwise, it takes a value of 0. "*Fund Maturity*" represents the number of years that have passed since the fund's vintage year. This variable has been winsorized at the 1 percent level. "*Fund Size*" is the natural logarithm of one plus the monetary size of the fund in millions of dollars. "*Fund Team Experience*" is the natural logarithm of one plus the cumulative number of deals completed as lead partners by the fund managers before the vintage year of the fund. All specifications include investment year, startup industry, and fund city fixed effects Furthermore, in all columns I include dummy variables indicating the presence of certain types of Limited Partners as outlined in Panel B of Table 2. Funds with missing info on their LPs are grouped into a missing LP dummy. Robust standard errors clustered at the VC fund level are reported in parentheses.

Table 9. Eponymy and Local Strategy

Dependent variable:	Local Startup	N. Local Syndicate Partners	Local Deal
	(1)	(2)	(3)
Family VC – Eponymous	0.160***	0.416***	0.130***
	(0.035)	(0.069)	(0.037)
Family VC – Non-Eponymous	0.035**	0.151**	0.033**
	(0.017)	(0.070)	(0.013)
Fund Maturity	-0.001	-0.005	-0.001
	(0.001)	(0.005)	(0.001)
Fund Size	-0.017***	-0.023**	-0.010***
	(0.003)	(0.010)	(0.002)
Fund Team Experience	-0.006	0.011	-0.002
	(0.004)	(0.018)	(0.003)
Observations	127,841	127,841	127,841
Investment Year Dummies	Yes	Yes	Yes
Startup Industry Dummies	Yes	Yes	Yes
Fund City Dummies	Yes	Yes	Yes
LP Types Dummies	Yes	Yes	Yes

This table reports the results of OLS (Columns 1 and 3) and Poisson (Column 2) regressions. "*Local Startup*" is a binary variable taking the value of 1 if the VC fund's headquarters is located within 25 kilometers of the startup, and 0 otherwise. "*N. Local Syndicate Partners*" represents the count of syndicate partners (including both other funds and other types of investors) located within 25 kilometers of the VC fund. "*Local Deal*" is a binary variable taking the value of 1 if the VC fund's headquarters are within 25 kilometers of the startup and at least 25% of syndicate partners with available location information are within the same 25-kilometer radius. It takes a value of 0 otherwise. "*Family VC – Eponymous*" is a binary indicator taking the value of 1 if the VC fund is a family VC, as previously defined, and the VC is eponymously named. It takes a value of 0 otherwise. "*Family VC – Non-Eponymous*" is a binary indicator taking the value of 1 if the VC fund is a family VC, as previously defined, but the VC is not eponymously named. Otherwise, it takes a value of 0. "*Fund Maturity*" represents the number of years that have passed since the fund's vintage year. This variable has been winsorized at the 1 percent level. "*Fund Size*" is the natural logarithm of one plus the monetary size of the fund in millions of dollars. "*Fund Team Experience*" is the natural logarithm of one plus the cumulative number of deals completed as lead partners by the fund managers before the vintage year of the fund. All specifications include investment year, startup industry, and fund city fixed effects Furthermore, in all columns I include dummy variables indicating the presence of certain types of Limited Partners as outlined in Panel B of Table 2. Funds with missing info on their LPs are grouped into a missing LP dummy. Robust standard errors clustered at the VC fund level are reported in parentheses.

Table 10. Transition from Non-Family to Family VCs within VC firms

Dependent variable:	Local Startups			N. Local Syndicate Partners			Local Deal		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Family VC	0.046**			0.068			0.034**		
	(0.018)			(0.051)			(0.015)		
Family VC – High Involvement		0.080***			0.140**			0.064***	
		(0.020)			(0.061)			(0.017)	
Family VC – Low Involvement		-0.002			-0.094			-0.007	
		(0.024)			(0.066)			(0.018)	
Family VC – Eponymous			0.077***			0.178***			0.041
			(0.028)			(0.067)			(0.033)
Family VC – Non-Eponymous			0.038*			0.021			0.032*
			(0.022)			(0.063)			(0.017)
Fund Maturity	0.000	0.000	0.001	0.000	-0.001	0.003	0.002	0.002	0.002
	(0.004)	(0.004)	(0.004)	(0.014)	(0.013)	(0.014)	(0.003)	(0.003)	(0.003)
Fund Size	-0.012	-0.011	-0.013	-0.027	-0.020	-0.028	-0.005	-0.004	-0.005
	(0.008)	(0.008)	(0.009)	(0.024)	(0.023)	(0.023)	(0.007)	(0.007)	(0.007)
Fund Team Experience	0.016	0.013	0.018	0.054	0.053	0.067	0.009	0.006	0.010
	(0.016)	(0.016)	(0.016)	(0.044)	(0.043)	(0.045)	(0.012)	(0.012)	(0.012)
Observations	8,800	8,796	8,800	8,789	8,785	8,789	8,800	8,796	8,800
VC Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Investment Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Startup Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fund City FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

The description of this Table is presented below

This table reports the results of OLS (Columns 1-3 and 7-9) and Poisson (Columns 4-6) regressions. "*Local Startup*" is a binary variable taking the value of 1 if the VC fund's headquarters is located within 25 kilometers of the startup, and 0 otherwise. "*N. Local Syndicate Partners*" represents the count of syndicate partners (including both other funds and other types of investors) located within 25 kilometers of the VC fund. "*Local Deal*" is a binary variable taking the value of 1 if the VC fund's headquarters are within 25 kilometers of the startup and at least 25% of syndicate partners with available location information are within the same 25-kilometer radius. It takes a value of 0 otherwise. "*Family VC*" is a binary indicator taking the value of 1 if the venture capital fund exhibits significant familial involvement in its management, which is defined as either having family members make up at least 25% of the fund managers or having a relative of the founder serving as a fund manager. Otherwise, it takes a value of 0. "*Family VC – High Involvement*" is a binary indicator taking the value of 1 if the VC fund is a family VC, as previously defined, and family members are significantly engaged in the fund's decision-making process. Family members are considered significantly involved in the decision-making process if they have collectively led more deals as lead partners of the fund than (or at least as many as) the most active non-family member within the fund. It takes a value of 0 otherwise. "*Family VC – Low Involvement*" is a binary indicator taking the value of 1 if the VC fund is a family VC, as previously defined, but family members are not significantly involved in the fund's decision-making process. Otherwise, it takes a value of 0. "*Family VC – Eponymous*" is a binary indicator taking the value of 1 if the VC fund is a family VC, as previously defined, and the VC is eponymously named. It takes a value of 0 otherwise. "*Family VC – Non-Eponymous*" is a binary indicator taking the value of 1 if the VC fund is a family VC, as previously defined, but the VC is not eponymously named. Otherwise, it takes a value of 0. "*Fund Maturity*" represents the number of years that have passed since the fund's vintage year. This variable has been winsorized at the 1 percent level. "*Fund Size*" is the natural logarithm of one plus the monetary size of the fund in millions of dollars. "*Fund Team Experience*" is the natural logarithm of one plus the cumulative number of deals completed as lead partners by the fund managers before the vintage year of the fund. All specifications include investment year, startup industry, and fund city fixed effects Furthermore, in all columns I include dummy variables indicating the presence of certain types of Limited Partners as outlined in Panel B of Table 2. Funds with missing info on their LPs are grouped into a missing LP dummy. Robust standard errors clustered at the VC fund level are reported in parentheses.

Table 11. Family VCs Performance

Dependent variable:	Successful Exit	Successful Exit	Successful Exit
	(1)	(2)	(3)
Family VC	0.002		
	(0.014)		
Family VC – High Involvement		-0.003	
		(0.020)	
Family VC – Low Involvement		0.013	
		(0.009)	
Family VC – Eponymous			0.027***
			(0.010)
Family VC – Non-Eponymous			-0.008
			(0.022)
Fund Maturity	0.001	0.001	0.001
	(0.001)	(0.001)	(0.001)
Fund Size	0.018***	0.018***	0.018***
	(0.003)	(0.003)	(0.003)
Fund Team Experience	0.002	0.003	0.002
	(0.002)	(0.002)	(0.002)
Observations	127,253	127,253	127,253
Investment Year Dummies	Yes	Yes	Yes
Startup Industry Dummies	Yes	Yes	Yes
Startup Country Dummies	Yes	Yes	Yes
Fund City Dummies	Yes	Yes	Yes
LP Types Dummies	Yes	Yes	Yes

This table reports the results of OLS regressions. "*Successful Exit*" is a binary variable taking the value of 1 if the VC successfully exited its investment in the startup through an IPO or trade sale. Otherwise, it takes a value of 0. *"Family VC*" is a binary indicator taking the value of 1 if the venture capital fund exhibits significant familial involvement in its management, which is defined as either having family members make up at least 25% of the fund managers or having a relative of the founder serving as a fund manager. Otherwise, it takes a value of 0. "*Family VC – High Involvement*" is a binary indicator taking the value of 1 if the VC fund is a family VC, as previously defined, and family members are significantly engaged in the fund's decision-making process. Family members are considered significantly involved in the decision-making process if they have collectively led more deals as lead partners of the fund than (or at least as many as) the most active non-family member within the fund. It takes a value of 0 otherwise. "*Family VC – Low Involvement*" is a binary indicator taking the value of 1 if the VC fund is a family VC, as previously defined, but family members are not significantly involved in the fund's decision-making process. Otherwise, it takes a value of 0. "*Family VC – Eponymous*" is a binary indicator taking the value of 1 if the VC fund is a family VC, as previously defined, and the VC is eponymously named. It takes a value of 0 otherwise. "*Family VC – Non-Eponymous*" is a binary indicator taking the value of 1 if the VC fund is a family VC, as previously defined, but the VC is not eponymously named. Otherwise, it takes a value of 0. "*Fund Maturity*" represents the number of years that have passed since the fund's vintage year. This variable has been winsorized at the 1 percent level. "*Fund Size*" is the natural logarithm of one plus the monetary size of the fund in millions of dollars. "*Fund Team Experience*" is the natural logarithm of one plus the cumulative number of deals completed as lead partners by the fund managers before the vintage year of the fund. All specifications include investment year, startup industry, fund city, and startup country fixed effects. Furthermore, in all columns, I include dummy variables indicating the presence of certain types of Limited Partners as outlined in Panel B of Table 2. Funds with missing info on their LPs are grouped into a missing LP dummy. Robust standard errors clustered at the startup country and VC fund level are reported in parentheses.

Table 12. The Performance Implications of Family VCs' Investments in Local Startups

Dependent variable:	Successful Exit	Successful Exit	Successful Exit
	(1)	(2)	(3)
Family VC	-0.012	-0.014	-0.010
	(0.016)	(0.016)	(0.015)
Local Startup	0.007*	0.012***	0.011***
	(0.004)	(0.003)	(0.004)
Family VC * Local Startup	0.036**	0.034**	0.030**
	(0.014)	(0.014)	(0.013)
Fund Maturity	0.001	0.001	0.001
	(0.001)	(0.001)	(0.001)
Fund Size	0.018***	0.017***	0.017***
	(0.003)	(0.003)	(0.003)
Fund Team Experience	0.002	0.002	0.001
	(0.002)	(0.002)	(0.002)
N. Syndicate Partners		0.005***	0.005***
		(0.001)	(0.000)
Startup Age		0.006***	0.006***
		(0.000)	(0.000)
Founding Team MBA			0.011**
			(0.006)
Founding Team Serial Founder			0.010***
			(0.003)
Founding Team Elite Education			0.017***
			(0.003)
Observations	81,483	81,483	73,540
Investment Year Dummies	Yes	Yes	Yes
Startup Industry Dummies	Yes	Yes	Yes
Startup Country Dummies	Yes	Yes	Yes
Fund City Dummies	Yes	Yes	Yes
LP Types Dummies	Yes	Yes	Yes
Founding Team Size Dummies	No	No	Yes

This table reports the results of OLS regressions. "*Successful Exit*" is a binary variable taking the value of 1 if the VC successfully exited its investment in the startup through an IPO or trade sale. Otherwise, it takes a value of 0. *"Family VC*" is a binary indicator taking the value of 1 if the venture capital fund exhibits significant familial involvement in its management, which is defined as either having family members make up at least 25% of the fund managers or having a relative of the founder serving as a fund manager. Otherwise, it takes a value of 0. "*Local Startup*" is a binary variable taking the value of 1 if the VC fund's headquarters is located within 25 kilometers of the startup, and 0 otherwise. "*Fund Maturity*" represents the number of years that have passed since the fund's vintage year. This variable has been winsorized at the 1 percent level. "*Fund Size*" is the natural logarithm of one plus the monetary size of the fund in millions of dollars. "*Fund Team Experience*" is the natural logarithm of one plus the cumulative number of deals completed as lead partners by the fund managers before the vintage year of the fund. All specifications include investment year, startup industry, fund city, and startup country fixed effects. Furthermore, in all columns, I include dummy variables indicating the presence of certain types of Limited Partners as outlined in Panel B of Table 2. Funds with missing info on their LPs are grouped into a missing LP dummy. In Column 2 I also control for "N. *Syndicate Partners*" *Startup Age*". The former is the count of syndicate partners involved in the deal, with winsorization applied at the 1 percent level. "*Startup Age*" indicates the age of the startup in years at the time of the deal, with winsorization applied at the 1 percent level. In Column 3, I control for the characteristics of the founding team by adding additional variables. "*MBA*" is an indicator variable taking the value of one if at least one of the startup's founders holds an MBA degree; otherwise, it assumes a value of 0. "*Serial Founder*" is an indicator variable taking the value 1 if at least one of the startup's founders has previously founded other startups before initiating the current one. Otherwise, it takes on a value of 0. "Elite Education" is an indicator variable taking the value of one if at least one of the founders of the startup attended a university ranked among the top 30 universities according to the inaugural version of the QS Ranking, published in 2004. "*Founding Team Size*" counts the number of founders associated with the startup. Robust standard errors clustered at the startup country and VC fund level are reported in parentheses.

Table 13. The Performance Implications of Family VCs' Syndication with Local Partners

Dependent variable:	Successful Exit	Successful Exit	Successful Exit
	(1)	(2)	(3)
Family VC	-0.009	-0.012	-0.011
	(0.013)	(0.013)	(0.010)
% Local Syndicate Partners	0.037***	0.039***	0.038***
	(0.007)	(0.008)	(0.010)
Family VC * % Local Syndicate Partners	0.039***	0.040***	0.044***
	(0.014)	(0.015)	(0.016)
Fund Maturity	0.001	0.001	0.000
	(0.001)	(0.001)	(0.001)
Fund Size	0.018***	0.017***	0.018***
	(0.003)	(0.003)	(0.003)
Fund Team Experience	0.002	0.002	0.001
	(0.002)	(0.002)	(0.002)
N. Syndicate Partners		0.005***	0.005***
		(0.001)	(0.000)
Startup Age		0.006***	0.006***
		(0.000)	(0.000)
Founding Team MBA			0.011**
			(0.006)
Founding Team Serial Founder			0.010***
			(0.003)
Founding Team Elite Education			0.017***
			(0.003)
Observations	81,483	81,483	73,540
Investment Year Dummies	Yes	Yes	Yes
Startup Industry Dummies	Yes	Yes	Yes
Startup Country Dummies	Yes	Yes	Yes
Fund City Dummies	Yes	Yes	Yes
LP Types Dummies	Yes	Yes	Yes
Founding Team Size Dummies	No	No	Yes

This table reports the results of OLS regressions. "*Successful Exit*" is a binary variable taking the value of 1 if the VC successfully exited its investment in the startup through an IPO or trade sale. Otherwise, it takes a value of 0. *"Family VC*" is a binary indicator taking the value of 1 if the venture capital fund exhibits significant familial involvement in its management, which is defined as either having family members make up at least 25% of the fund managers or having a relative of the founder serving as a fund manager. Otherwise, it takes a value of 0. "*% Local Syndicate Partners*" indicates the proportion of syndicate partners within 25 kilometers out of the total number of syndicate partners for which location information is available. "F*und Maturity*" represents the number of years that have passed since the fund's vintage year. This variable has been winsorized at the 1 percent level. "*Fund Size*" is the natural logarithm of one plus the monetary size of the fund in millions of dollars. "*Fund Team Experience*" is the natural logarithm of one plus the cumulative number of deals completed as lead partners by the fund managers before the vintage year of the fund. All specifications include investment year, startup industry, fund city, and startup country fixed effects. Furthermore, in all columns, I include dummy variables indicating the presence of certain types of Limited Partners as outlined in Panel B of Table 2. Funds with missing info on their LPs are grouped into a missing LP dummy. In Column 2 I also control for "*N. Syndicate Partners" Startup Age*". The former is the count of syndicate partners involved in the deal, with winsorization applied at the 1 percent level. "*Startup Age*" indicates the age of the startup in years at the time of the deal, with winsorization applied at the 1 percent level. In Column 3, I control for the characteristics of the founding team by adding additional variables. "*MBA*" is an indicator variable taking the value of one if at least one of the startup's founders holds an MBA degree; otherwise, it assumes a value of 0. "*Serial Founder*" is an indicator variable taking the value 1 if at least one of the startup's founders has previously founded other startups before initiating the current one. Otherwise, it takes on a value of 0. "*Elite Education*" is an indicator variable taking the value of one if at least one of the founders of the startup attended a university ranked among the top 30 universities according to the inaugural version of the QS Ranking, published in 2004. "*Founding Team Size*" counts the number of founders associated with the startup. Robust standard errors clustered at the startup country and VC fund level are reported in parentheses.

Table 14. The Performance Implications of Family VCs' Local Deals

Dependent variable:	Successful Exit	Successful Exit	Successful Exit
	(1)	(2)	(3)
Family VC	-0.013	-0.015	-0.013
	(0.014)	(0.014)	(0.013)
Local Deal	0.024***	0.025***	0.021***
	(0.003)	(0.004)	(0.005)
Family VC * Local Deal	0.055***	0.054***	0.056***
	(0.012)	(0.013)	(0.013)
Fund Maturity	0.001	0.001	0.001
	(0.001)	(0.001)	(0.001)
Fund Size	0.018***	0.017***	0.018***
	(0.003)	(0.003)	(0.003)
Fund Team Experience	0.002	0.002	0.001
	(0.002)	(0.002)	(0.002)
N. Syndicate Partners		0.005***	0.005***
		(0.001)	(0.000)
Startup Age		0.006***	0.006***
		(0.000)	(0.000)
Founding Team MBA			0.011**
			(0.006)
Founding Team Serial Founder			0.010***
			(0.003)
Founding Team Elite Education			0.017***
			(0.003)
Observations	81,483	81,483	73,540
Investment Year Dummies	Yes	Yes	Yes
Startup Industry Dummies	Yes	Yes	Yes
Startup Country Dummies	Yes	Yes	Yes
Fund City Dummies	Yes	Yes	Yes
LP Types Dummies	Yes	Yes	Yes
Founding Team Size Dummies	No	No	Yes

This table reports the results of OLS regressions. "*Successful Exit*" is a binary variable taking the value of 1 if the VC successfully exited its investment in the startup through an IPO or trade sale. Otherwise, it takes a value of 0. *"Family VC*" is a binary indicator taking the value of 1 if the venture capital fund exhibits significant familial involvement in its management, which is defined as either having family members make up at least 25% of the fund managers or having a relative of the founder serving as a fund manager. Otherwise, it takes a value of 0. *Local Deal*" is a binary variable taking the value of 1 if the VC fund's headquarters are within 25 kilometers of the startup and at least 25% of syndicate partners with available location information are within the same 25-kilometer radius. It takes a value of 0 otherwise. "*Fund Maturity*" represents the number of years that have passed since the fund's vintage year. This variable has been winsorized at the 1 percent level. "*Fund Size*" is the natural logarithm of one plus the monetary size of the fund in millions of dollars. "*Fund Team Experience*" is the natural logarithm of one plus the cumulative number of deals completed as lead partners by the fund managers before the vintage year of the fund. All specifications include investment year, startup industry, fund city, and startup country fixed effects. Furthermore, in all columns, I include dummy variables indicating the presence of certain types of Limited Partners as outlined in Panel B of Table 2. Funds with missing info on their LPs are grouped into a missing LP dummy. In Column 2 I also control for "*N. Syndicate Partners*" *Startup Age*". The former is the count of syndicate partners involved in the deal, with winsorization applied at the 1 percent level. "*Startup Age*" indicates the age of the startup in years at the time of the deal, with winsorization applied at the 1 percent level. In Column 3, I control for the characteristics of the founding team by adding additional variables. "*MBA*" is an indicator variable taking the value of one if at least one of the startup's founders holds an MBA degree; otherwise, it assumes a value of 0. "*Serial Founder*" is an indicator variable taking the value 1 if at least one of the startup's founders has previously founded other startups before initiating the current one. Otherwise, it takes on a value of 0. "*Elite Education*" is an indicator variable taking the value of one if at least one of the founders of the startup attended a university ranked among the top 30 universities according to the inaugural version of the QS Ranking, published in 2004.

"*Founding Team Size*" counts the number of founders associated with the startup. Robust standard errors clustered at the startup country and VC fund level are reported in parentheses.

APPENDIX

Table A1

Dependent variable:	Fund-Startup Same City	Fund-Startup within 10 Km	Fund-Startup within 50 Km	Ln (Km Fund-Startup)	Fund-Startups Same Country	Ln (Km Fund-Startup) Excluding Startups within 25 Km
	(1)	(2)	(3)	(4)	(5)	(6)
Family VC	0.052***	0.054***	0.068***	-0.462***	0.017	-0.022
	(0.014)	(0.015)	(0.018)	(0.136)	(0.018)	(0.072)
Fund Maturity	-0.001	-0.001	-0.001	0.007	0.001	-0.003
	(0.001)	(0.001)	(0.001)	(0.011)	(0.001)	(0.006)
Fund Size	-0.013***	-0.014***	-0.018***	0.149***	-0.014***	0.057***
	(0.003)	(0.003)	(0.003)	(0.026)	(0.004)	(0.014)
Fund Team Experience	-0.004	-0.005	-0.007	0.071**	-0.010**	0.035**
	(0.004)	(0.004)	(0.005)	(0.034)	(0.004)	(0.016)
Observations	127,841	127,841	127,841	127,839	127,841	93,257
Investment Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Startup Industry Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Fund City Dummies	Yes	Yes	Yes	Yes	Yes	Yes
LP Types Dummies	Yes	Yes	Yes	Yes	Yes	Yes

This table replicates the analyses reported in Column 4 of Table 4. However, different thresholds have been used to determine whether the VC fund and the startup are geographically proximate. In Column 1 the dependent variable is a binary variable taking the value of 1 if the VC fund's headquarters is located in the same city where the startup is based, and 0 otherwise. In Column 2 the dependent variable is a binary variable taking the value of 1 if the VC fund's headquarters is located within 10 kilometers of the startup, and 0 otherwise. In Column 3 the dependent variable is a binary variable taking the value of 1 if the VC fund's headquarters is located within 50 kilometers of the startup, and 0 otherwise. In Column 4 the dependent variable is the natural logarithm of one plus the distance in kilometers between the VC fund and the startup. In Column 5 the dependent variable is a binary variable taking the value of 1 if the VC fund and the startup are based in the same country, and 0 otherwise. In Column 6 the dependent variable is the natural logarithm of one plus the distance in kilometers between the VC fund and the startup. However, in Column 6 investments made in startups within 25 kilometers have been dropped.

Table A2

Dependent variable:	N. Syndicate partners same city	N. Syndicate partners within 10 Km	N. Syndicate partners within 50 Km	Ln (Km Fund-Closest syndicate partner)	Ln (Km Fund-Closest syndicate partner excluding those within 25 Km)
	(1)	(2)	(3)	(4)	(6)
Family VC	0.270***	0.238***	0.220***	-0.402***	-0.085
	(0.061)	(0.061)	(0.052)	(0.130)	(0.061)
Fund Maturity	-0.002	-0.003	-0.004	0.011	-0.001
	(0.007)	(0.006)	(0.005)	(0.011)	(0.005)
Fund Size	-0.027**	-0.023**	-0.008	0.105***	0.009
	(0.012)	(0.011)	(0.010)	(0.025)	(0.014)
Fund Team Experience	0.017	0.016	0.009	0.041	0.012
	(0.022)	(0.019)	(0.017)	(0.036)	(0.022)
Observations	125,719	126,695	127,841	113,561	104,810
Investment Year Dummies	Yes	Yes	Yes	Yes	Yes
Startup Industry Dummies	Yes	Yes	Yes	Yes	Yes
Fund City Dummies	Yes	Yes	Yes	Yes	Yes
LP Types Dummies	Yes	Yes	Yes	Yes	Yes

This table replicates the analyses reported in Column 4 of Table 5. However, different thresholds have been used to determine whether the VC fund and its syndicate partners are geographically proximate. In Column 1 the dependent variable is the count of syndicate partners (including both other funds and other types of investors) located in the same city of the VC fund. In Column 2 the dependent variable represents the count of syndicate partners (including both other funds and other types of investors) located within 10 kilometers of the VC fund. In Column 3 the dependent variable represents the count of syndicate partners (including both other funds and other types of investors) located within 50 kilometers of the VC fund. In Columns 4 and 5 the dependent variable is the natural logarithm of one plus the distance in kilometers between the VC fund and its closest syndicate partner. However, in Column 6 syndicate partners within 25 kilometers have been excluded.

Table A3

Dependent variable: Local Startup					
Threshold for FVC	At least 2 Family Members	10%	20%	25%	Continuous Share
	(1)	(2)	(3)	(4)	(5)
Family VC	0.055***	0.056***	0.057***	0.072***	0.112***
	(0.016)	(0.017)	(0.020)	(0.018)	(0.030)
Fund Maturity	-0.002	-0.002	-0.001	-0.001	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Fund Size	-0.017***	-0.017***	-0.017***	-0.017***	-0.017***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Fund Team Experience	-0.006	-0.006	-0.006	-0.006	-0.005
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Observations	127,744	127,744	127,800	127,841	127,744
Investment Year Dummies	Yes	Yes	Yes	Yes	Yes
Startup Industry Dummies	Yes	Yes	Yes	Yes	Yes
Fund City Dummies	Yes	Yes	Yes	Yes	Yes
LP Types Dummies	Yes	Yes	Yes	Yes	Yes

This table replicates the analyses reported in Column 4 of Table 4. However, different thresholds have been used to determine whether the VC fund is a family VC. Only the criterion based on the share of family members has been used. In Column 1 the VC fund is considered a family VC if there are at least two family members in the fund. In Column 2 the VC fund is considered a family VC if family members make up at least 10% of the fund managers. In Column 3 the VC fund is considered a family VC if family members make up at least 20% of the fund managers. In Column 4 the VC fund is considered a family VC if family members make up at least 25% of the fund managers. In Column 5 a continuous variable indicating the share of the fund managers belonging to the same family has been used as the main explicatory variable.

Table A4

Dependent variable: N. Local Syndicate Partners					
Threshold for FVC	At least 2 Family Members	10%	20%	25%	Continuous Measure
	(1)	(2)	(3)	(4)	(5)
Family VC	0.188***	0.185***	0.227***	0.250***	0.396***
	(0.051)	(0.052)	(0.059)	(0.058)	(0.113)
Fund Maturity	-0.006	-0.005	-0.005	-0.005	-0.005
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Fund Size	-0.023**	-0.023**	-0.022**	-0.022**	-0.022**
	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
Fund Team Experience	0.012	0.012	0.012	0.013	0.014
	(0.018)	(0.018)	(0.018)	(0.018)	(0.018)
Observations	127,744	127,744	127,800	127,841	127,744
Investment Year Dummies	Yes	Yes	Yes	Yes	Yes
Startup Industry Dummies	Yes	Yes	Yes	Yes	Yes
Fund City Dummies	Yes	Yes	Yes	Yes	Yes
LP Types Dummies	Yes	Yes	Yes	Yes	Yes

This table replicates the analyses reported in Column 4 of Table 5. However, different thresholds have been used to determine whether the VC fund is a family VC. Only the criterion based on the share of family members has been used. In Column 1 the VC fund is considered a family VC if there are at least two family members in the fund. In Column 2 the VC fund is considered a family VC if family members make up at least 10% of the fund managers. In Column 3 the VC fund is considered a family VC if family members make up at least 20% of the fund managers. In Column 4 the VC fund is considered a family VC if family members make up at least 25% of the fund managers. In Column 5 a continuous variable indicating the share of the fund managers belonging to the same family has been used as the main explicatory variable.

Table A5

Dependent variable: Local Deal					
Threshold for FVC	At least 2 Family Members	10%	20%	25%	Continuous Measure
	(1)	(2)	(3)	(4)	(5)
Family VC	0.048***	0.048***	0.053***	0.059***	0.088***
	(0.013)	(0.013)	(0.016)	(0.016)	(0.026)
Fund Maturity	-0.001	-0.001	-0.001	-0.001	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Fund Size	-0.011***	-0.011***	-0.010***	-0.010***	-0.010***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Fund Team Experience	-0.002	-0.002	-0.002	-0.002	-0.001
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Observations	127,744	127,744	127,800	127,841	127,744
Investment Year Dummies	Yes	Yes	Yes	Yes	Yes
Startup Industry Dummies	Yes	Yes	Yes	Yes	Yes
Fund City Dummies	Yes	Yes	Yes	Yes	Yes
LP Types Dummies	Yes	Yes	Yes	Yes	Yes

This table replicates the analyses reported in Column 4 of Table 6. However, different thresholds have been used to determine whether the VC fund is a family VC. Only the criterion based on the share of family members has been used. In Column 1 the VC fund is considered a family VC if there are at least two family members in the fund. In Column 2 the VC fund is considered a family VC if family members make up at least 10% of the fund managers. In Column 3 the VC fund is considered a family VC if family members make up at least 20% of the fund managers. In Column 4 the VC fund is considered a family VC if family members make up at least 25% of the fund managers. In Column 5 a continuous variable indicating the share of the fund managers belonging to the same family has been used as the main explicatory variable.

Table A6

Dependent variable:	Local Startup	N- Local Syndicate Partners	Local Deal
	(1)	(2)	(3)
Family VC	0.066***	0.270***	0.058***
	(0.017)	(0.057)	(0.014)
Fund Maturity	-0.002	-0.007	-0.001
	(0.001)	(0.005)	(0.001)
Fund Size	-0.023***	-0.014	-0.012***
	(0.003)	(0.010)	(0.002)
Fund Team Experience	-0.013***	0.015	-0.005*
	(0.004)	(0.016)	(0.003)
VC Area Entrepreneurial Intensity	0.026***	0.292***	0.025***
	(0.002)	(0.009)	(0.002)
Observations	127,841	127,841	127,841
Investment Year Dummies	Yes	Yes	Yes
Startup Industry Dummies	Yes	Yes	Yes
Fund Country Dummies	Yes	Yes	Yes
LP Types Dummies	Yes	Yes	Yes

This table replicates the analyses reported in Column 4 of Table 4 in Column 1, the analyses reported in Column 4 of Table 5 in Column 2, and the analyses reported in Column 4 of Table 6 in Column 3. However, the fund city fixed effects have been replaced with fund country fixed effects. Additionally, I am now including a control for the entrepreneurial intensity of the area where the VC fund is based by including the variable "Entrepreneurial Intensity Area". To gauge the entrepreneurial activity level in the vicinity of the VC fund's location, a panel was constructed for each city housing the VC funds in the dataset. This panel records the total number of VC financing rounds secured by startups within a 25-kilometer radius over the preceding three years. To ensure comparability, this variable has been standardized annually, yielding an average of zero and a standard deviation of one within each year. The control included in this table represents the entrepreneurial intensity of the area where the VC fund is based in the year when the deal was concluded.

Table A7

Dependent variable:	Successful Exit	Successful Exit	Successful Exit
	(1)	(2)	(3)
Family VC	0.004	0.001	0.001
	(0.014)	(0.012)	(0.012)
Local Startup	0.015**		
	(0.006)		
Family VC * Local Startup	0.046**		
	(0.019)		
% Local Syndicate Partners		0.038***	
		(0.013)	
Family VC * % Local Syndicate Partners		0.074***	
		(0.024)	
Local Deal			0.029***
			(0.008)
Family VC * Local Deal			0.071***
			(0.022)
Fund Maturity	0.002	0.002	0.002
	(0.002)	(0.002)	(0.002)
Fund Size	0.025***	0.025***	0.025***
	(0.003)	(0.003)	(0.003)
Fund Team Experience	0.002	0.002	0.002
	(0.003)	(0.003)	(0.003)
N. Syndicate Partners	0.008***	0.008***	0.007***
	(0.000)	(0.000)	(0.000)
Startup Age	0.003***	0.003***	0.003***
	(0.000)	(0.000)	(0.000)
Founding Team MBA	0.021***	0.021***	0.021***
	(0.007)	(0.007)	(0.007)
Founding Team Serial Founder	0.009*	0.010*	0.009*
	(0.005)	(0.005)	(0.005)
Founding Team Elite Education	0.016**	0.016***	0.016**
	(0.006)	(0.006)	(0.006)
Observations	40,706	40,706	40,706
Investment Year Dummies	Yes	Yes	Yes
Startup Industry Dummies	Yes	Yes	Yes
Startup Country Dummies	Yes	Yes	Yes
Fund City Dummies	Yes	Yes	Yes
LP Types Dummies	Yes	Yes	Yes
Founding Team Size Dummies	Yes	Yes	Yes

This table replicates the analyses reported in Column 3 of Table 12 in Column 1, the analyses reported in Column 3 of Table 13 in Column 2, and the analyses reported in Column 3 of Table 14 in Column 3. However, only deals completed by December 2014 have been retained.

Dataset construction

In this section, I will elucidate the method employed to identify family-managed Venture Capital funds for the purpose of this study, with the aim of facilitating replication and encouraging further research on this unexplored topic. I further elaborate on the steps taken to construct the final dataset. Below, I report step by step the procedure employed to identify family VCs and the data construction process:

1) Identification of VC Funds:

I relied on data from Pitchbook, a widely recognized source in the field of venture capital research. I retained all funds categorized as "Venture Capital" in the "FundCategory" variable, raised by entities labeled as "Venture Capital" in the "primaryinvestortype" variable. This step assures that the entities studied in this paper are indeed traditional venture capital funds.

2) Identification of Fund Managers:

To ascertain the individuals managing these VC funds, I merged the "Fund" dataset with the "FundTeamRelation". An important step involved the elimination of instances where Pitchbook reported the same individual twice for the same fund. Then, I retained only those funds for which Pitchbook provided information on at least two employees.

3) Identification of Family Connections:

Following established scholarly practices (Amore et al., 2014), I employed surname affinity as an indicator of family ties. While it is acknowledged that shared surnames do not always imply biological relationships, the relatively low number of VC fund managers (with an average of 4.4 individuals per fund) mitigates the probability of coincidental surname matches. However, it is essential to acknowledge potential sources of error. For instance, in countries like China, a few surnames are exceedingly common and shared by a substantial portion of the population. To address this concern, I excluded funds based in six countries where this issue is particularly relevant (China, Hong Kong, Korea, India, Singapore, and Taiwan).

Furthermore, I identified the 50 most common Asian surnames listed in Pitchbook, as individuals sharing very common Asian surnames are prevalent not only in Asia but also in other regions. If a VC fund was designated as a family VC solely due to one of these surnames, it was excluded from our analysis. I also conducted robustness tests by removing the top 100 Asian surnames, and the results were consistent with the findings presented in this paper. When the VC fund is managed by two spouses, I was able to classify the fund as a family VC only when one of the two took the surname of the spouse. While I might slightly underestimate the family VC phenomenon, given that 79% (5%) of women (men) change their surname after marriage, while 6% hyphenate their name with that of the spouse, I should be able to identify 90% of the funds managed by spouses. I have also manually looked for instances of VC funds managed by spouses who did not take the surname of the spouse and I was able to identify only the couple mentioned in the introduction of this paper formed by Miriam Rivera and Clint Korver (ULU Ventures).

4) Defining Family VCs:

For the classification of VC funds as "Family VCs," I employed a rigorous criterion that requires a substantial degree of familial involvement in fund management. Specifically, a VC fund was labeled as a Family VC if either a relative of the founder was involved in fund management or if family members collectively accounted for 25% or more of the fund management team. I rigorously tested the robustness of the findings by varying the threshold, removing the founder-related criterion, and employing a continuous variable to indicate the share of family members in the fund team. Importantly, the robustness tests consistently yielded results that align with the main findings reported in this paper.

5) Family's Involvement in Decision-Making

To gauge the extent to which family members are actively engaged in the decision-making process of VC funds, I utilized the information available in Pitchbook regarding the lead partners for specific investment deals. While it is worth noting that this data may not always be complete, I exploited the available data points to construct a meaningful metric. First, I calculated the share of investment deals completed by the fund where a family member served as the lead partner. This metric provides a direct measure of the family's involvement in leading investment decisions. In parallel, I identified the share of deals completed by other members of the fund team who are not part of the family. This provides a baseline for understanding the involvement of non-family members in investment decision-making. I have classified the family as highly involved in the fund management if, collectively, family members completed more deals than (or at least as many as) the most active non-family member within the fund. This classification criterion serves as a clear and robust indicator of family dominance in decision-making.

6) Entrepreneurial Intensity Fund Location

A concern might be that family funds are more likely to go local because they are based in more entrepreneurial areas. If this were true, they might be more likely to go local because of the larger supply of startups in their area. To ease such a concern, in the main analyses, I control for fund city fixed effects. However, I have also constructed a measure of the entrepreneurial intensity of the area where the funds are based. For each city where the VC funds in my dataset are based, I constructed a panel indicating the total number of VC financing rounds raised by all startups within 25 km in the previous three years. Then I standardized this variable by year so that it has an average of zero and a standard deviation of one within each year. Then I merged this variable to show that at the fund's vintage year family VCs are not based in more entrepreneurial cities. Furthermore, I also conduct robustness tests where I control for the entrepreneurial intensity of the city where the VC fund is based at the time of the deal

7) Dataset Construction

The dataset was constructed by merging each VC fund with its corresponding investment deals. Only VC deals (i.e., deals classified as "Venture Capital" by Pitchbook in the "DealCategory" variable were retained). In the primary analyses, all VC deals completed within the temporal span from 2000 to 2022 were retained. In pursuit of data quality and completeness, deals lacking information related to critical variables such as the geographic location of both the fund and startup, investment year, fund vintage year, and fund size were excluded. Singleton observations were also eliminated, ensuring uniformity in sample composition. Geographic coordinates for both funds, startups, and syndicate partners, were obtained using the OpenStreetMap. Geographical distances were computed employing the "geodist" command in Stata. To permit an adequate period for investors to potentially realize successful exits, the unit of observation was restricted to deals completed up until December 2018. Moreover, the sample was refined to encompass solely the initial investment undertaken by the VC fund in the startup, aligning with the methodology established by Nahata (2008) and existing conventions within prior research. Following prior research, an investment was deemed successful if the VC firm achieved an exit through either an initial public offering (IPO) or a trade sale resulting from its investment in the startup. As an additional robustness test, the sample was further constrained to encompass deals completed up to December 2015, providing investors with an extended timeframe to potentially realize successful exits and thereby fortifying the robustness of our findings.

Micro Venture Capital

November 27, 2023

Abstract

Research Summary: Recently, the venture capital (VC) industry has experienced the entry of several new capital providers. Using US data on investors and their portfolio startups from 2000 to 2022, we document the emergence of a new type of investors: the *micro VC*. Our analysis reveals that micro VCs have an idiosyncratic investment strategy, which differs from traditional VCs. Compared to these investors, micro VCs invest in riskier startups, that is, early-stage ventures initiated by less experienced founders; yet, micro VCs are less likely to syndicate, stage their investments, and replace the startup founders. Additionally, startups funded by micro VCs are less likely to experience successful exits than those backed by traditional VCs. These results can be traced to a mix of smaller capital endowments, less sophisticated limited partners, and lesser human capital of which micro VCs dispose, and that may induce them to spread their thin capital across many investments to maximize returns. Our analysis also uncovers important differences in the strategies pursued by micro VCs and business angels.

Managerial Summary: The venture capital (VC) industry is increasingly populated by a variety of investors with disparate characteristics and objectives. One such type of investors is represented by the so-called micro VC firms. These are VC firms which manage funds typically below $50 million and focused primarily on investing in founder-led startups. We leverage comprehensive VC data in the US to answer three questions: (1) Who leads micro VC firms? (2) How do micro VC firms invest? (3) How do startups backed by micro VC perform? We find that micro VC firms are often led by relatively inexperienced entrepreneurs with little VC experience, and these firms are supported by less sophisticated limited partners. Although micro VC firms invest in riskier startups, they are less engaged in syndication and investment staging than traditional VC firms. Finally, micro VC-backed startups have a lower probability of successful exit as compared to those backed by traditional VC firms. Collectively, our results suggest that micro VCs differ from traditional VCs beyond being "micro".

1 Introduction

Historically, the venture capital (VC) industry has been dominated by a relatively well-defined set of specialized investors. Yet, in recent years, several cash-rich entities other than traditional VC firms have become increasingly active in the startup ecosystem bringing diversity to the VC industry (Block et al., 2018; Drover et al., 2017; Wright et al., 2016). This phenomenon is driven by demand and supply mechanisms. On the demand side, scholars have documented a stark decrease in the cost of starting new ventures (Ewens et al., 2018b). Moreover, recent technological advances have offered new opportunities to individuals willing to start new companies (Dushnitsky and Matusik, 2019). As a result, the number and variety of startups demanding entrepreneurial finance have risen dramatically. On the supply side, the quests for higher returns and greater portfolio diversification have led various non-traditional VC investors to invest in startups (Kwon et al., 2020). Consequently, the whole VC industry has experienced a sizeable expansion: the amount of funds allocated to startups reached $580 billion in 2021; twenty times the amount invested in 2002 (The Economist, 2021). Despite a recent decline due to less favorable monetary policies worldwide, the VC industry remains the key provider of finance and support to new ventures.[1]

There is a vast literature on VC that spans strategy, entrepreneurship, and finance. Scholars in these fields have explored how venture capitalists (VCs) select portfolio firms, how they structure their investments (Ewens et al., 2022; Gompers et al., 2020; Kaplan and Strömberg, 2003; Tian, 2011), and how they contribute to new ventures' strategies (Blevins and Ragozzino, 2018; Forti et al., 2020) and financial performance (Conti and Graham, 2020; Dutta and Folta, 2016; Fitza et al., 2009; Hellmann and Puri, 2002). By contrast, we still know little about the investment strategies adopted by emerging entities other than traditional VCs. Recent undertakings in this area include the analysis of business angels (Lerner et al., 2018), mutual funds (Chernenko et al., 2021; Kwon et al., 2020), hedge funds (Aragon et al., 2018), and venture lenders (De Rassenfosse and Fischer, 2016).

[1] https://techcrunch.com/2023/03/14/y-combinator-late-stage-investing-interest-rates/.

We contribute to this literature by providing evidence of the emergence of a novel, and thus far unexplored, type of investors in entrepreneurial finance labeled as micro VCs. Investors self-identified as micro VCs (or classified as such by data providers like Crunchbase) have become increasingly popular in the startup ecosystem and, as we will show, tend to have idiosyncratic features compared to other investors. Given the relatively unknown nature of this phenomenon, we adopt an exploratory, descriptive analysis, which allows us to address the following questions: i) What are the main characteristics of micro VCs?, ii) Do micro VCs pursue different investment strategies compared to traditional VCs and business angels?, and iii) How do startups backed by micro VCs perform?

We employ fine-grained data on US investors and their startups from Crunchbase covering the period 2000-2022 and augmented these data with detailed investor-level information from PitchBook. These data reveal that, from 2010 to 2020, the number of deals by entities labeled as micro VCs increased by 219% (from a handful to several thousand). This trend mirrors the 200% increase in the number of deals by traditional VCs, and the 256% increase in the number of deals by business angels. As of 2020, the early-stage deals concluded by micro VCs represented 21% of the total early-stage deals.

Although investors labeled as micro VCs are smaller than traditional VCs in terms of fund size—our data reveals that the median size of a micro VC fund in our data is $25 million—our data indicate that they are often organized as partnerships and so are more alike traditional VCs than business angels. However, despite having this trait in common, our evidence points to important organizational differences between micro VCs and traditional VCs. First, micro VCs' limited partners (LPs) are predominantly foundations, wealthy individuals, and family offices. Second, these LPs have smaller assets under management than the LPs of traditional VCs, which are mostly private and public pension funds (arguably more sophisticated investors compared to those behind micro VCs). Third, micro VC top managers are more likely to be former entrepreneurs with little track record of success, whereas traditional VC top managers tend to be successful entrepreneurs or individuals with VC experience. These organizational differences are reflected in the fact that micro VCs are relatively more prone than traditional VCs to engage in 'spray and pray,' spreading their thinner capital across a relatively larger number of early-stage startups to maximize their shots on goal and, in general, their portfolio returns.

We show that these organizational differences and differences in strategic focus have important implications for the following investor choices: i) investing in geographically close startups; ii) investing in founders with a track record of success; iii) CEO replacement; iv) round size and syndication; and v) investment staging and co-investment with traditional VCs. First, we show that micro VCs invest in geographically closer startups than traditional VCs. Second, micro VCs are less likely to invest in previously successful entrepreneurs and less likely to professionalize their investees through the replacement of their CEOs than traditional VCs. Third, micro VCs invest in smaller rounds and are less likely to participate in syndicates, syndicate with other traditional VCs, and stage their investments. Finally, we provide some evidence suggesting that micro VCs do not specialize in making early-stage screening for later-stage traditional VCs relative to business angels and other traditional VCs. In fact, we produce correlations showing that focal rounds financed by micro VCs are less likely to be followed by rounds financed by other traditional VCs relative to focal rounds financed by business angels or traditional VCs. Taken together, these findings suggest that, in addition to possessing less financial capital than traditional VCs, micro VCs have fewer non-financial resources at their disposal, making it too costly for them to implement standard strategies to especially monitor portfolio startups. Therefore, micro VCs may find it optimal to engage in spray and pray, possibly investing in early-stage startups that require relatively little financial and non-financial capital. By doing so, they may overcome difficulties in finding appropriate co-investors for ex-post monitoring and avoid diluting control.

To bring our results full circle, we explore the implications for startup performance of the organizational and strategic differences we have uncovered between micro and traditional VCs. Our results indicate that startups supported by micro VCs experience a lower probability of exiting successfully than those backed by traditional VCs. This result, which persists after the inclusion of startup fixed effects to control for selection, suggests that the spray and pray strategy micro VCs pursue, and the related implications for the screening and monitoring of portfolio startups, have a reflection on the startups' exit outcomes.

Remarkably, we also observe significant differences between micro VCs and business angels. All else equal, micro VCs are less likely than business angels to invest in founders with previous successful entrepreneurial experience and to participate in syndicates, but more likely to replace the founders as the CEOs. These findings may be consistent with business angels taking their time and having more incentive to select their portfolio companies, including the founders, and finding potential co-investors to reduce risks.

The key takeaway of our study is that micro VCs have become a widespread phenomenon in the startup ecosystem with peculiar organizational characteristics and investment strategies. These distinct features are associated with a lower exit rate of micro VC portfolio companies relative to startups backed by traditional VCs.

2 Background and theoretical arguments

2.1 Entrepreneurial finance: An overview

Investing in startups is notoriously risky because of asymmetric information problems (Stuart et al., 1999). Typically, startups lack collateral and pursue early-stage projects whose technical and commercial feasibility is hard to evaluate for potential investors (Hochberg et al., 2018). While startups have traditionally struggled to attract capital through traditional channels, such as debt (Leland and Pyle, 1977), entrepreneurial finance has expanded in the past decades, at least partially filling the early ventures' funding gap (Dushnitsky and Matusik, 2019). The most widely studied types of entrepreneurial finance investors are traditional VC firms and, to a lesser extent, business angels, which provide capital and non-financial support to entrepreneurial ventures.

VC firms are typically organized as limited partnerships, where the general partners (GPs) raise funds from investors, the limited partners (LPs), and invest these funds in promising young firms (Gompers and Lerner, 2004). GPs are principally compensated through management fees, which are a percentage of the total capital invested in a fund, and are also entitled to a performance-based carried interest. They might receive additional benefits, such as restricted stock units or options if they prov ide valuable monitoring to their portfolio startups. Several of the most celebrated companies in the US and worldwide have been backed by VCs. Empirical evidence shows that, though VCs fund a relatively limited number of startups, the majority of startups that have gone public have received VC funding (Kaplan and Lerner, 2010). Moreover, VCs often outperform public equity markets in terms of financial returns (Harris et al., 2014).

Motivated by the success of the VC investment model, the entrepreneurial finance literature has extensively investigated VCs' investment strategies. Two key factors feature prominently in the literature, screening and monitoring. Screening refers to the ability of VCs to reduce asymmetric information problems by scrutinizing firms before investing in them (Sørensen, 2007). Monitoring refers to the VCs' ability to evaluate the viability of their portfolio firms as they invest in them and maximize their investees' probability of success through advice and other value-adding activities (Bernstein et al., 2016). To pursue screening and monitoring, VCs employ a variety of tools, such as syndication with other investors (Brander et al., 2002), investment staging (Gompers, 1995; Tian, 2011), corporate governance and leadership interventions (Amornsiripanitch et al., 2019; Conti and Graham, 2020; Hellmann and Puri, 2002), and contractual and compensation arrangements (Gompers et al., 2020; Kaplan and Strömberg, 2003).

In addition to VC firms, business angels are another important source of early-stage financing. Angel investing is organized around informal or semi-formal networks of wealthy individuals, often former entrepreneurs, who meet regularly to identify and pursue investments in new ventures (Kerr et al., 2014). While some scholars have advocated a model whereby startups first obtain angel financing and then transition to venture capital (Benjamin and Margulis, 2005), more recent studies have found evidence that these two kinds of investments are dynamic substitutes (Hellmann et al., 2021): startups that select into angel financing are less likely to obtain subsequent VC funding and vice-versa.

Whereas scholars have devoted attention to venture capitalists and, to a lesser extent, business angels, other types of investors have emerged in the past years and of which little is known. One such type of investors is micro VCs. While these investors are organized in limited partnerships similar to traditional VCs, we will show that micro VCs employ idiosyncratic investment strategies that, at least partially, differ from those of traditional VCs and business angels. In the following subsections, we will provide a theoretical discussion that will help us frame our empirical analysis.

2.2 Micro VC in the entrepreneurial finance landscape: Theoretical discussion

As we will show in the next sections, three main organizational characteristics appear to distinguish micro VCs from traditional VCs. First, micro VC funds are smaller than funds managed by traditional VCs. Second, the LPs of micro VCs are typically foundations, wealthy individuals, and family offices with fewer assets under management than the LPs of traditional VCs. Moreover, another organizational difference our data reveal is that while micro VCs are run by former founders with little track record of success, traditional VCs are managed by either former successful entrepreneurs or individuals with VC experience.[2]

The literature has highlighted a positive correlation between an investor's financial and non-financial capital (Sapienza and Gupta, 1994). Moreover, Lerner et al. (2007) have documented the heterogeneous performance of LPs, while Mittal (2022) has shown that underfunded LPs disproportionally match with general partners of lower quality, and this has significant implications for the performance of private equity funds. Finally, Zarutskie (2010) has shown that the experience of venture capital managers matters, and top managers with former VC experience or experience as successful entrepreneurs have better screening and monitoring skills.

Both financial and non-financial capital have been deemed fundamental factors for the

[2]Refer to Table A1 for a list of micro VC self-descriptions.

success of startups. Not only do investors' financial resources allow investee startups to develop their technologies and bring them to the market, investors' non-financial resources—encompassing experience, reputation, and network ties—guarantee better exit performance (Bertoni et al., 2011; Fitza et al., 2009; Gorman and Sahlman, 1989; Hsu and Ziedonis, 2013; Sapienza, 1992; Sapienza et al., 1996). Given the arguably smaller micro VCs' financial and non-financial capital, we might expect these investors to spread their thin financial and non-financial capital across a large number of startups to hedge risks and maximize shots on goals. Further, we might expect them to concentrate their efforts on screening and monitoring their startups' progress rather than professionalizing them, as this activity may require more capital. In what follows, we examine how micro VCs' organizational characteristics and hypothesized strategy focus may relate to the following more micro choices: 1) investing in geographically close startups; 2) investing in founders with a track record of success; 3) CEO replacement; 4) round size and syndication; and 5) investment staging and co-investment with traditional VCs.

Studies have shown that VCs can better screen and monitor their portfolio startups when both parties are geographically close (Bernstein et al., 2016; Sorenson, 2018). This is because geographic proximity increases the frequency of contact between startups and their investors, allowing the latter to assess the quality and progress of the former. Since micro VCs arguably possess less financial and non-financial capital, they could find it profitable to invest in a local network of companies they may know better and monitor at little cost. As a result, we expect that micro VCs will disproportionally invest in geographically close startups relative to traditional VCs.

Moving to the next strategy, the literature has shown that founders with successful entrepreneurial experience contribute to their startups by helping address problems of asymmetric information (as experience is often perceived as a signal for quality), providing fundamental contacts among investors and customers, and identifying and developing promising business ideas (Colombo and Grilli, 2005; Conti et al., 2013; Gompers et al., 2010; Kaplan et al., 2009). If micro VCs pursued a spray and pray strategy, they might invest in startups regardless of founder experience. However, these investors may derive high returns from targeting successful founders as the latter could at least partially offset the former's limited screening and monitoring capital. One aspect to consider, though, is that there is typically a positive assortative matching along the quality dimension between entrepreneurs and investors (Sørensen, 2007). In other words, the limited non-financial capital of micro VCs—including a potentially smaller network of CEO replacements—might prevent them from pairing with successful entrepreneurs. Overall, these arguments make the prediction here ambiguous: while micro VCs may derive high returns from investing in successful serial entrepreneurs, these entrepreneurs may not find it profitable to match with micro VCs.

Although the human capital of a startup's founding team has been deemed fundamental for attracting financing, the value of such capital has been shown to depreciate over time as founders might not be able to guide their venture through the more mature phases of product development and commercialization (Hendricks et al., 2019; Wasserman, 2003, 2017). As a result, the replacement of an initial founder as the CEO is one of the fundamental actions through which traditional VCs professionalize their investee startups (Chahine and Zhang, 2020; Conti and Graham, 2020; Ewens and Marx, 2018; Hellmann and Puri, 2002). While startups may derive large benefits from external CEOs, the limited non-financial capital at micro VCs' disposal and the fact that they could spread it across a large number of startups may induce them to retain the initial founders more frequently than traditional VCs.

Regarding the round strategies of micro VCs, the limited financial resources of these investors could lead them to invest in relatively smaller rounds. However, the overall size of a round may not be as small if micro VCs can participate in investment syndicates. These syndicates permit prospective investors to pool resources and may reduce the risks of investing in early-stage ventures (Nanda and Rhodes-Kropf, 2017). Additionally, they allow relatively less endowed investors to capitalize on the screening and monitoring capabilities of relatively more endowed investors (Brander et al., 2002; Casamatta and Haritchabalet, 2007). Relatedly, micro VCs' lesser monitoring capital may induce them to stage their investments relatively more, conditioning their investment decisions on the information that startups gradually reveal regarding the quality of their technologies and management team (Gompers, 1995; Tian, 2011). While syndication and investment staging would allow micro VCs to better screen and monitor their investments, micro VCs' small size may be an obstacle in finding suitable syndicate partners or financing a startup over multiple rounds. Therefore, these investors could specialize in investments that require little staging and syndication. Another possibility is that micro VCs concentrate their limited non-financial capital on screening early-stage startups for later-stage traditional VCs. This strategy may be consistent with studies showing that the returns from screening are higher than those from monitoring (Sørensen, 2007). A synthesis of our arguments is provided in Table 1.

⟨ Insert Table 1 about here ⟩

While we have compared micro VCs to traditional VCs, the arguments we have laid out provide insights into the potential differences between micro VCs and business angels. The main difference between micro VCs and angels is that the former are organized as limited partnerships and, therefore, are held accountable to LPs for the strategies they pursue. Moreover, since they raise funds from LPs, micro VCs are likely to dispose of larger financial capital than business angels, who invest personal resources. Therefore, it is possible that micro VCs display hybrid investment strategies relative to business angels and traditional VC funding. We refrain from developing specific predictions relative to differences in strategies between micro VCs and business angels, given the context of business angels is largely under-investigated. Despite this, in the empirical analysis, we will compare micro VCs to business angles to provide a more comprehensive overview of the micro VC phenomenon.

3 Data

We assembled a large dataset comprising information on the deals made by US micro VCs, traditional VCs, and business angels in new ventures. These data are available from

Crunchbase, a relatively new repository of startups and their investors increasingly used in academic research (Conti and Roche, 2021; Marx and Hsu, 2022; Ng and Stuart, 2022; Roche et al., 2020). Crunchbase records extensive information on startup financing rounds, participating investors, founding members, and industries. A substantial portion of the data is directly collected by Crunchbase staff, while the remaining share is crowdsourced and subsequently reviewed by Crunchbase. The advantage of Crunchbase relative to standard datasets on venture capital investment, such as VentureXpert and VentureSource, is that it provides a larger coverage of startups, including those companies that did not raise financing from traditional VCs, more accurate coverage of investors participating in startup rounds, as well all as a more precise record of the round amounts (Retterath and Braun, 2020; Roche et al., 2020).[3] We finally complement and extend the data from Crunchbase with data from PitchBook on the LPs of VC funds.

We focus on startups founded from 2000 onward because the coverage of startups by Crunchbase has been validated as most accurate in more recent years (Wu, 2016).[4] We restrict the analysis to deals made in US startups and their US investors because Crunchbase information is more precise for these companies and investor typologies. Furthermore, we limit the sample to companies that are at most ten years old by the time they raise their first financing round as older companies may not correspond to the standard definition of startups (Colombo and Shafi, 2016; Conti and Guzman, 2021; Cumming et al., 2017).[5] Finally, we excluded funding rounds received by startups after they went public or were acquired. We observe the deals for these startups until December 2020 and track their exit events until July 2022, the date of our last extraction of the Crunchbase dataset.[6]

[3] Several authors, including Tian (2011), and Gompers and Lerner (2004) have highlighted an over-reporting problem by VentureXpert whereby this dataset reports more financing rounds than actually occurred because Thomson frequently splits financing rounds. It is common that a single financing round is reported as several separate financing rounds by different VC firms on different (but proximate) dates.

[4] In Tables A3 to A6, exclude those deals that occurred before 2006 and the corresponding startups that raised those deals.

[5] As we show in the Appendix (Tables A7-A10), our results hold when we restrict the sample to companies that were at most five years old by the time they had raised their first round.

[6] In Table A11, we show that the results of our analyses remain qualitatively unchanged when we exclude investor-startups that received an investment from their investors after 2013.

Since we are interested in comparing the investment strategies of micro VCs relative to traditional VCs and business angels, we retain those financing deals made by a micro VC, a traditional VC, or a business angel. To categorize investors, we relied on the classification provided by Crunchbase, which we verified by employing information from PitchBook and other sources. We define micro VC as any investor that labeled itself as "micro venture capital" in Crunchbase. We exclude from the categorization those investors assigned multiple labels, such as "micro venture capital" and "accelerator," as these investors might not correspond to micro venture capital investors *strictu sensu*. Similarly, we define traditional VCs as any investor labeled "venture capital" in Crunchbase, and as business angels, those investors labeled "angel." Crunchbase mistakenly categorizes only a handful of government or corporate investors as (micro) venture capitalists. These investors, along with their associated deals, have been excluded. Our final dataset encompasses 120,802 deals made in 28,870 US startups by 12,973 investors. The number of deals made by micro VCs is 17,806, while the number of deals made by traditional VCs is 85,169, and the number of deals made by business angels is 17,827.

To verify the accuracy of our classification of micro VCs and ensure these investors' funds are indeed small, we used data on fund size from PitchBook. We employ this dataset, given that prior studies have highlighted the accuracy of the information it provides on fund characteristics (Retterath and Braun, 2020). For this test, we implemented a fuzzy matching algorithm to find the names of Crunchbase micro VCs in PitchBook. Having retained only those micro VCs for which we could find a compelling match in PitchBook, we collected information regarding these investors' fund sizes. Mirroring anecdotal evidence from interviews we conducted with European micro VCs, we found that 84% of the investors labeled in Crunchbases as micro VCs managed a fund no larger than \$50 million, which is the cutoff typically used to define micro VCs.[7] The average size of a micro VC fund

[7]We interviewed two micro VC partners, one employee at a micro VC fund, and the founder of a fund specialized in investing in micro VC funds, the majority of them from Europe.

is $42 million, and the median is $25 million.[8] For comparison, the average size of a traditional VC fund is $209 million, and the median is $81 million. We also found substantial correspondence between the fund size information provided by Crunchbase and that provided by PitchBook.[9] As a further validation test, we asked two research assistants to verify that investors reported in Crunchbase as micro VCs are so defined by other websites, such as LinkedIn, investor websites, CBInsights, and TechCrunch. Their analysis showed a 97% correspondence between Crunchbase's classification and the information reported from these several sources on the internet. Moreover, the research assistants analyzed a random sample of Crunchbase traditional VCs, finding that only 1% of them were micro VCs. The results of these tests reassure us that our definition of micro VCs correctly captures this category of investors.

Figure 1 reports the number of deals concluded by micro and traditional VCs during our sample period. As shown, the participation of micro VCs in startup deals rapidly increased beginning in 2010. During the 2010-2020 period, the number of deals by micro VCs increased by 219%, mirroring the 200% increase in the number of deals by traditional VCs and the 256% increase in the number of deals by business angels. By the end of the period, the proportion of total deals and early-stage deals made by micro VCs became 13% and 21%, respectively.

⟨ Insert Figure 1 about here ⟩

Figure 2 displays the distribution of deals by micro VCs, traditional VCs, and business angels across industries. As, on average, Crunchbase assigns three industry group keywords to each startup, for a total of 49 keywords, we regrouped these keywords into more aggregate

[8] Consistent with this evidence, Charles Hudson, Managing Partner of Micro VC Precursor Venture, once stated: "I think the difference between a $10 million fund and a $25 million fund is fairly trivial. Twenty-five to $50, it's a difference in scale but not in substance. You go from $50 to $100, you're doing different work" provides further confirmation that the $50 fund cutoff is meaningful for defining micro VCs. The quote was retrieved from: https://www.heavybit.com/library/podcasts/venture-confidential/ep-19-feat-charles-hudson-of-precursor-ventures on June 26, 2023.

[9] As a robustness check, we report in the Appendix the totality of our regression analyses, having excluded from the sample micro VCs managing funds larger than $50 million (Tables A12-A15). These analyses confirm and strengthen our main findings.

categories. These are: agriculture and forestry, biotechnology, communications, consumer-related industries, energy, financial services, hardware, healthcare, internet, manufacturing, software, transportation, and other. As shown, all the investors invest predominantly in startups active in the software sector. Business angels are less present in biotechnology and healthcare compared to the other investors, while traditional VCs are relatively less active in consumer-related industries. Micro VCs tend to mirror the sectorial strategies of traditional VCs.

⟨ Insert Figure 2 about here ⟩

Table 2 presents descriptive statistics for our sample.[10] As shown in Panel A, most startups (65%) are in California, Massachusetts, and New York. Thirty-three percent of the startups were initiated by at least one serial founder; that is, an individual who started at least one venture in the past. Moreover, 13% of the companies were initiated by at least one successful serial founder; that is, a serial founder whose previous startups experienced an acquisition or an initial public offering (IPO).[11] As in Conti and Graham (2020), we find that 65% of the startups have, as of July 2022, at least one of their original founders as their CEO.[12] This suggests that CEO replacement occurred in approximately 35% of the cases.

In Panel B, we report descriptive statistics at the round level. As shown, 33% of the rounds are seed, pre-seed, or angel rounds, and 23% are series A. The average size of a round is $17.8 million, while the fraction of syndicated rounds is 87%. Seventy percent of the investments were completed by traditional VCs, while micro VCs and angels each account for 15% of the investments.

In Panel C, we report descriptive statistics at the investor-startup level. Here, we show that investors participate in a startup's 1.5 funding rounds (also rounds raised after the year 2020 were counted), and the average distance between the investor and its investee startup is

[10] Correlation tables are reported in Table A2 of the Appendix.
[11] When considering these characteristics, the number of observations decreases because we could not find founder information for all of the startups in our sample.
[12] We excluded startups for which Crunchbase does not report the current CEO.

1,233 Km. In Panel D, we display investor-level information. The majority of investors are business angels (64%), followed by traditional VCs (32%) and micro VCs (4%). Although business angels represent the majority of investors, descriptive statistics in previous panels show that they participate in considerably fewer rounds relative to VCs and micro VCs.

As anticipated, we also collected information on the investors' organizational features, specifically focusing on the characteristics of their LPs and top management. We collected LP information from PitchBook. As reported, the average assets under management (AUM) of the investors' LPs are $35,314 billion (winsorized at the 5% level). Approximately 18% of the LPs are foundations, making it the largest LP group.[13] This LP type is followed by public pension and corporate pension funds. Panel E reports descriptives at the investor-fund level and shows that the average ratio of investments made to fund size is 1.7 (median=0.2), implying that investors, on average, make 1.7 investments per million dollars.

In Panel F, we present statistics at the investor-top-management level for traditional and micro VCs. The keywords we used to identify top managers (TMs) are board member, CEO, chairman, director, founder, GP, partner, president, principal, and VP. Here, we show that 31% of the investor TMs started a company (on average, TMs start a successful company that was either acquired or went IPO in 24% of the cases), while 33% worked for a traditional VC firm.[14]

⟨ Insert Table 2 about here ⟩

Micro VCs versus traditional VCs

Table 3 reports descriptive statistics, distinguishing between micro VCs and traditional VCs. These descriptives reveal fundamental differences between traditional and micro VCs, offering a first glance at micro VCs' distinct characteristics.

[13]Examples of foundations are the Rockefeller Foundation, the Ford Foundation, the Sherman Fairchild Foundation, the John D. and Catherine T. MacArthur Foundation, the Wellcome Trust, and the Andrew W. Mellon Foundation.

[14]If TMs are currently affiliated with a traditional VC, we measure VC experience by whether they have worked in a different VC than the one with which they are currently affiliated. We collected data on managers' entrepreneurial experience using Crunchbase and LinkedIn.

In Panel A, we show that the proportion of early-stage rounds (seed, pre-seed, and angel) in which micro VCs participate is significantly larger than that for traditional VCs. Conversely, we show that traditional VCs are relatively more active in series A rounds than micro VCs. Micro VCs are less likely than traditional VCs to participate in investor syndicates and are less likely to syndicate with other traditional VCs. Finally, the average size of the rounds in which micro VCs participate is smaller than that for traditional VCs.

In Panel B, we report that traditional VCs invest more rounds than micro VCs in their portfolio startups. Moreover, micro VCs invest in geographically closer startups than traditional VCs and in startups whose founders are relatively inexperienced; that is, founders with no entrepreneurial or successful entrepreneurial experience. To complement these findings, we show that the startups in which micro VCs invest are more likely to have one of their founders as the current CEO, indicating micro VCs appoint an external CEO less frequently than traditional VCs. Additionally, we show that startups backed by traditional VCs are more likely to exit via either an IPO or acquisition than startups backed by micro VCs.

In Panel C, we show that micro VCs and traditional VCs are both present in the traditional US entrepreneurial hubs, that is, California, New York, and Massachusetts. Moving to LP characteristics, these descriptives suggest considerable differences between micro VCs and traditional VCs. The LPs' average AUM is significantly larger for traditional than micro VCs, suggesting the former VCs are backed by LPs with deeper pockets than the latter VCs. Moreover, the share of LPs that are either corporate pension funds or public pension funds is larger for traditional VCs than micro VCs, whereas the percentage of foundation LPs and individual/family office LPs is greater for micro VCs. In Panel D, we show that micro VC funds make significantly more investments per million dollars than traditional VCs, suggesting that micro VCs employ a spray and pray strategy. Indeed, the average (median) number of deals completed by micro VCs per million dollars is 4.1 (0.6), while the average (median) number of deals completed by traditional VCs is 1.3 (0.18). These figures are consistent with the anecdotal evidence we gathered in interviews with European micro VCs

Finally, in Panel E, we show that micro VCs are more likely to be run by managers with entrepreneurial experience than traditional VCs. However, the share of founded successful startups is larger for top employees of traditional VCs than for those of micro VCs. Finally, the proportion of top employees with some traditional VC experience is higher among traditional VCs than micro VCs.

⟨ Insert Table 3 about here ⟩

Micro VCs versus business angels

Table 4 reports descriptive statistics, distinguishing between micro VCs and business angels. In Panel A, we show that the proportion of seed investments is larger for business angels than micro VCs, while micro VCs appear to specialize in series A rounds. Moreover, business angels are more likely to participate in syndicated rounds than micro VCs, although they are less likely to syndicate with traditional VCs than micro VCs.

Moving to Panel B, we show that business angels invest fewer rounds in their investee startups than micro VCs, and they invest in geographically close startups. Remarkably, the proportion of investments made in startups led by serial entrepreneurs is larger across angels than across micro VCs. Moreover, startups in which business angels invest are less likely to have an external CEO appointed than startups financed by micro VCs. Startups backed by micro VCs are more likely to experience an IPO or acquisition than startups in which business angels have invested.

Finally, in Panel C, we show that micro VCs and business angels select similar geographical locations in the US. Both investor categories appear to be mostly concentrated in California and New York.

⟨ Insert Table 4 about here ⟩

4 Investor strategies

4.1 Empirical methodology

In this section, we investigate whether and how micro VCs, traditional VCs, and business angels differ in the strategies discussed in Section 2. The first strategy we examine is whether investors invest in geographically close startups. The second is whether investors invest in startups initiated by successful serial founders, that is, founders whose prior startups experienced either an acquisition or an IPO. Related to the second strategy, the third strategy we analyze is whether investors invest in the professionalization of their investees by replacing their CEOs. To evaluate how these strategies may differ by investor type, we estimate the following equation at the investor-startup-pair level:

$$Y_{ij} = \alpha + \beta_1 MicroVC_{ij} + \beta_2 Angel_{ij} + \beta_3 Exp_{ij} + \phi + \rho + \psi + \varepsilon_{ij}, \quad (1)$$

where Y_{ij} is, alternatively: (1) an indicator for whether an investor i's portfolio startup j is in the lowest quartile of the distribution for the geographical distance from the investor[15]; (2) an indicator for whether a portfolio startup is initiated by at least one successful serial entrepreneur (i.e., an entrepreneur who successfully led at least one of their companies to either an IPO or acquisition); and (3) an indicator for whether the investor retains one of the founders as the CEO as of July 2022.

The regressors of interest are an indicator identifying micro VCs and an indicator identifying business angels investing in startup j, where the reference outcome is represented by traditional VC investors. Following prior studies (Gompers et al., 2008; Nanda and Rhodes-Kropf, 2017), we control for investor-deal experience with the number of deals an investor i made in the five years prior to investing for the first time in the focal startup j. By including this control, we want to assess whether any difference between micro VCs and traditional VCs or business

[15] Similar to Tian (2011), we prefer this specification rather than considering the continuous distance between an investor and its investee, given that such a distance is inevitably measured with noise, especially when either the investor or their portfolio startup are located in large cities. However, we obtain similar results when using the natural logarithm of the distance between an investor and its investee.

angels goes beyond the deal experience they have accumulated over time. In equation (1), ϕ is an investor-state-by-year fixed effect, and the year to which we refer is the year of an investor's first investment in its portfolio startup. This fixed effect absorbs the effect of changing market conditions—measured at the investor's state level—that may affect the overall availability of startups, successful founders, and potential replacements, and impact investor strategies. These macroeconomic trends change over time and are likely to have a differential impact by state. The ρ denotes an industry-group-by-year fixed effect (whereby the industries we refer to are those listed in Figure 2). This fixed effect absorbs potential technology shocks that may affect both the supply of startups and their founders and differentially constrain investor strategies. Again, these shocks may vary by company round year.[16] Moreover, ψ is a round-type fixed effect, and the round we refer to is the first round in which an investor invests in startup j. We consider three round types: early-stage (pre-seed, seed, and angel rounds), series A, and other rounds. We include ψ to absorb fixed differences across the first rounds in which investors participate.

In the second part of our empirical investigation of investor strategies, we assess differences between micro VCs, traditional VCs, and business angels relative to the characteristics of the round in which they participate and their propensity to invest more than one round in their investee startups. To evaluate investor differences in round characteristics, we estimate the following equation at the investor-round level:

$$Y_{ir} = \alpha + \beta_1 MicroVC_i + \beta_2 Angel_i + \beta_3 Exp_{ir} + \phi + \rho + \psi + \varepsilon_{ir}, \tag{2}$$

where Y_{ir} is alternatively defined as: (1) the natural logarithm of the size of an investor round r[17]; (2) an indicator for whether an investor i's round r is syndicated; and (3) an indicator for

[16] As shown in Tables A16-A18, the results remain invariant when we include year, state, and technology fixed effects separately without interactions.

[17] We opt for the natural logarithm, given that the distribution of a round size is highly skewed (Ewens et al., 2018a; Nanda and Rhodes-Kropf, 2017; Tian, 2011). Note that none of the available VC datasets collects reliable information on the amount each investor invests in a round. Hence, we follow the prior literature and proxy such an amount with the total round size (Conti et al., 2019; Nanda and Rhodes-Kropf, 2017; Tian, 2011).

whether an investor invests with a traditional VC investor in round r. The relevant regressors in this equation are an indicator of whether investor i is a micro VC and an indicator of whether investor i is a business angel. The reference outcome is one in which the round investment is carried out by a traditional VC. Again, we control for the deal experience of an investor with the number of deals investor i concluded in the five years prior to round r. We control for the same set of fixed effects as in Equation (1). Because Equation (2) is estimated at the investor-round rather than at the investor-startup level, ψ this time denotes round-type fixed effects and not fixed effects for the first round in which an investor invests in a startup. These fixed effects absorb fixed differences across rounds —namely, seed, series A, and more mature rounds—in which investors participate. Finally, we evaluate whether investors differentially engage in investment staging by estimating a variant of Equation (1). In this case, the outcome is an indicator of whether an investor invests two or more rounds in its portfolio startup.

4.2 Results

The results from estimating Equation (1) are reported in Table 5, where we cluster standard errors at the investor level. The unit of observation is the investor-startup pair. As displayed in column (1), both micro VCs and angels invest in relatively geographically closer startups than traditional VCs, although angels are more likely than micro VCs to invest in startups within the first quartile of the distribution for their distance from portfolio investors. These results are in line with the predictions outlined in Section 2 and with anecdotal evidence gleaned from our interviews. Moreover, they suggest that business angels rely more on local networks of companies than micro VCs.

Moving to column (2), here we show that micro VCs are less likely to invest in startups founded by successful serial entrepreneurs than traditional VCs. This result suggests that in doing spray and pray, micro VCs spread their thin capital across many startups regardless of the founders' human capital. We additionally find that micro VCs are 2.5 percentage points less likely than angels to invest in startups with successful serial founders (p-value of the difference: 0.00), while business angels are as likely as traditional VCs to invest in successful serial founders. When we shared these results with our interviewees, two of them suggested that business angels have a different business model. As they make fewer investments and they invest their own money, they carefully select each one of them.

Next, we consider the replacement of a founder CEO. The results reported in column (3) show that micro VCs are more likely to retain the founders of their portfolio startups as CEOs relative to traditional VCs. This confirms that the limited non-financial capital of which micro VCs dispose and the fact that they spread it across a large number of startups may lead them to retain the initial founders more frequently than traditional VCs. This is also in line with the fact that, according to our interviewees, micro VCs rarely take board seats in their portfolio companies or lead investment rounds. We additionally find that micro VCs are relatively more likely than business angels to replace the founders (p-value of the difference: 0.00).[18] According to one interviewee, business angels make more sporadic investments in startups than micro VCs. Therefore, they may be more selective with their investments and less keen to substitute the initial founders as they might have spent considerable effort choosing them. Another possibility might be that business angels hold fewer control rights and take board positions even less frequently than traditional VCs.

⟨ Insert Table 5 about here ⟩

Moving to the characteristics of an investor's round, the first three columns of Table 6 report the results from estimating Equation (2), having clustered standard errors at the investor level. Here, the unit of observation is the investor-round. As reported in column (1), all else equal, both micro VCs and business angels invest in smaller rounds than traditional VCs. There is no significant difference between micro VCs and business angels in their round size. Examining investor syndication in column (2), we show that, while micro VCs are four percentage points less likely to participate in syndicated rounds relative to traditional

[18]The number of observations changes from one column to the other depending on data availability. In Table A19, we reproduce the same analyses employing a common sample. The results remain invariant.

VCs, business angels are five percentage points more likely to do so. These results indicate that micro VCs tend not to share screening and monitoring efforts with other investors. Complementing these results, we observe in column (3) that both micro VCs and business angels are less likely to invest with traditional VCs relative to the reference outcome, *having controlled for round characteristics*. The totality of these results may suggest that micro VCs invest in startups whose capital requirements are relatively small—either because it may be difficult to find co-investors for ex-post monitoring or to avoid diluting control of their investments.

Finally, we examine an investor's propensity to engage in staging in column (4). Here, we show that both micro VCs and business angels are less likely than traditional VCs to engage in investor staging, although the magnitude of the effect is stronger for business angels (26 percentage points) than for micro VCs (10 percentage points). These results suggest that, on average, business angels and micro VCs specialize in one-time, early-stage (as indicated by the descriptives in Tables 3 and 4) investments relative to traditional VCs, and such specialization is relatively more prevalent among business angels than micro VCs.[19]

⟨ Insert Table 6 about here ⟩

As we mentioned in Section 2, a possible explanation for the correlational differences between micro and traditional VCs reported in Table 6 is that micro VCs direct their limited non-financial capital towards screening early-stage startups for later-stage traditional VCs rather than invest in ex-post monitoring for which they might have a comparative disadvantage. To shed light on this possibility, in column 1 of Table A21, we restrict the sample to US startups that raised more than one round with a micro VC, business angel, or traditional VC. We then estimate a model at the startup-round level for the likelihood that a startup raises a future round with a new traditional VC (that is, a traditional VC that did not invest in any of the prior rounds raised by the startup). As our here focus lies on gauging

[19] As shown in tables A19 and A20, the results discussed so far remain invariant when we utilize a common sample across the various models.

the likelihood of securing funding from new conventional venture capitalists, we also extend our consideration to investors located outside the United States in this analysis. We exclude a startup's last round as startups cannot raise the next round after the last. We control for round stage, investment-year by state and investment-year by technology fixed effects and impose robust standard errors. The results show that rounds raised from micro VCs are significantly less likely to be followed by rounds financed by traditional VCs relative to rounds initially raised from business angels and traditional VCs. Similarly, column 2 of the same table shows that rounds raised from micro VCs are significantly more likely to be followed by rounds financed by other micro VCs relative to rounds initially raised from business angels and traditional VCs. Overall, these associations suggest that micro VCs do not specialize in making early-stage screening for later-stage traditional VCs. Rather, they are consistent with micro VCs specializing in investments that require little capital and possibly less monitoring.

5 Portfolio startups' performance

5.1 Empirical methodology

Having highlighted differences between micro VCs, business angels, and traditional VCs relative to a number of fundamental screening and monitoring strategies, next we assess whether there are differences in performance across startups financed by these investors. For this purpose, we follow prior studies (Da Rin and Phalippou, 2017) and examine a variant of Equation (1), where the outcome of interest is an indicator of whether an investor's startup was acquired or went public by July 2022. To assess whether the strategies examined in the prior section are responsible, at least in part, for any performance differential we might observe across differentially-funded startups, we will additionally control for these strategies.

While the described equation allows us to assess whether investors' differential strategies translate into different performance outcomes of their portfolio startups, it does not allow us to distinguish screening from ex-post monitoring. In an attempt to shed some light on such a distinction, we build on Conti and Guzman (2021) and estimate the following within-startup equation:

$$Y_{jt} = \alpha + \beta_1 CumMicroVC_{jt} + \beta_2 CumVC_{jt} + \beta_3 CumAngel_{jt} \qquad (3)$$
$$+\phi_t + \rho_t + \lambda_t + \delta_j + \varepsilon_{jt},$$

where Y_{jt} is the cumulative likelihood that a startup j experiences a successful exit (IPO or acquisition) by year t. In practice, it is a (0/1) indicator that equals one if -as of a given year- a startup has experienced an IPO or an acquisition. We truncate this outcome after the year startup j experiences a successful exit. Among the regressors, $CumMicroVC_{jt}$ is a (0/1) indicator that becomes one starting from the year in which a micro VC invests in a given startup j. Similarly, $CumVC_{jt}$ and $CumAngel_{jt}$ are (0/1) indicators that become one starting from the year in which a traditional VC or a business angel invests, respectively, in a given startup j. ϕ_t is a startup's state-by-year fixed effect, while ρ_t is a startup's industry-by-year fixed effect, and λ_t is a fixed effect for the cumulative number of rounds a startup raises as of year t. Finally, δ_j is a fixed effect for startup j. ϕ_t and ρ_t control for trends that vary over time at the state and industry level, λ_t absorbs differences across startups in round characteristics, while δ_j absorbs fixed differences, including quality differences, across startups. Because we are including startup fixed effects that control as much as possible for the selection of portfolio startups by their investors, any difference between investor types should be, at least in part, ascribed to their monitoring capital.

5.2 Results

The results from estimating the performance of portfolio startups in a cross-section model are reported in Table 7. In column (1), we show that, all else equal, micro VCs and business angels have a negative impact on their startups' likelihood of experiencing a successful exit relative to traditional VCs. The negative effect is stronger in magnitude for business angels than for micro VC investors. Instead, investments completed by micro VCs are three percentage points less likely to translate into IPOs or acquisitions than investments completed by traditional VCs. This effect corresponds to a 9% decline in the outcome mean. Investments completed by business angels are five percentage points less likely to terminate into successful exists, equivalent to a 16% decline in the outcome mean. These preliminary findings suggest important differences in either the type of startups that micro VCs, traditional VCs, and business angels select or in these investors' monitoring strategies. These effects remain similar in column (2), where we condition the sample to the one for which we have the full set of strategy controls.

To assess the relevance of the investors' strategies, we control in column (3) of Table 7 for the totality of strategies we discussed in the prior section. The results mirror, in large part, the empirical findings of studies cited in Section 2. A startup's geographical closeness to an investor is positively correlated with exit performance, although the effect is not significantly different from zero at conventional levels. A closer inspection of this result reveals that the effect of geographical proximity is, in large part, absorbed by investor-state-by-year fixed effects, suggesting that, by investing in geographically close startups, investors are better able to screen local opportunities. We additionally find that investing in serial founders with successful experience is positively related to startup performance. Moreover, we show that retaining one of the original founders as the CEO is negatively related to startup performance. Further, our results point to a positive correlation between the funding amount a startup receives and its odds of being acquired or going IPO. Finally, we highlight a positive correlation between syndicating with a traditional VC and the likelihood that a portfolio startup exits successfully.

Remarkably, we show that, once we control for these strategies, the difference in exit performance between startups funded by micro VCs and startups funded by traditional VCs is no longer statistically significant. This suggests that the investor strategies we analyze fully explain the performance differences between startups funded by micro VCs and startups funded by traditional VCs. In contrast, the inclusion of the strategy controls we examined in the previous section does not fully explain the performance differential between angel-backed and VC-backed startups. Therefore, the differences in screening and monitoring practices between business angels and both types of VCs must go beyond the strategies we have analyzed.

⟨ Insert Table 7 about here ⟩

To bring our results full circle, we examine whether the strategies we have considered in this paper are helpful only for screening or also for monitoring. In column (1) of Table 8, we report the results from estimating Equation (3), having excluded startup fixed effects. With no controls for fixed differences across startups, we find that micro VCs and traditional VCs contribute to the performance of their startups, but the effect for traditional VCs—1.9 percentage points—is approximately four times as large as the effect for micro VCs—0.46 percentage points—and the difference is statistically significant. Remarkably, once we include startup fixed effects in the model displayed in column (2), the effect associated with micro VC investors drops to 0.2 percentage points (equivalent to a 57% decline) and becomes statistically insignificant. Conversely, although the effect associated with traditional VC investors declines by 79% to 0.4 percentage points, a larger decline than that observed for micro VCs, it remains statistically significant at conventional levels. Interestingly, regardless of the equation specification we estimate, business angels do not appear to contribute to the exit outcomes of their investee startups. [20]

Overall, our results suggest that micro VCs' limited resources induce these investors spread their thin financial, screening, and monitoring capital across a large number of investments to maximize the number of shots on goal. The limited financial and non-financial capital micro-VC-funded startups receive has repercussions on their ability to achieve a successful exit, are else equal.

⟨ Insert Table 8 about here ⟩

[20] This last result may be due to the fact that business angels are not as "impatient" as traditional and micro VCs and their startups may take longer to exit.

6 Discussion and conclusions

While the entrepreneurial finance literature has extensively studied the characteristics and strategies of traditional VCs, little is known about the new typologies of entrepreneurial investors that have emerged as a result of recent demand- and supply-side trends. This paper fills this gap by focusing on micro VCs, investors -we uncover- that typically manage funds smaller than \$50 million. We document that the number of deals made by micro VCs has experienced a stunning 256% increase in the past ten years, and their proportion, 13%, is now similar to that of business angels. These figures highlight the importance of exploring the micro VC phenomenon in depth.

The key finding of our study is that micro VCs differ from traditional VCs in several ways, besides managing relatively small funds. Their LPs are prevalently foundations, individuals, and small business offices with fewer assets under management relative to traditional VC LPs, which are predominantly private and public pension funds. Additionally, micro VC top managers are disproportionally individuals with entrepreneurial experience but little track record of success, while traditional VCs are led by individuals with successful entrepreneurial and VC experience. Consistent with these organizational differences, we provide descriptive evidence showing that micro VCs are relatively more prone than traditional VCs to engage in spray and pray, spreading their thinner capital across a relatively larger number of early-stage startups.

The organizational differences and differences in strategic focus we uncovered have implications for the following more micro investor choices: 1) investing in geographically close startups; 2) investing in founders with a track record of success; 3) CEO replacement; 4) round size and syndication; and 5) investment staging and co-investment with traditional VCs. Specifically, we find that, while relative to traditional VCs, micro VCs are more likely to invest in geographically close startups, a standard practice to reduce screening and monitoring costs, micro VCs are less likely to invest in ventures led by experienced founders and to professionalize these ventures through the replacement of the CEO. We also find that micro

VCs participate in smaller rounds and are less likely to syndicate and stage their investments. Moreover, we provide some evidence showing that micro VCs do not specialize in doing early-stage screening for later-stage traditional VCs relative to business angels and other traditional VCs. These findings suggest that micro VCs engaging in spray and pray possibly invest in early-stage startups that require little capital. By doing so, they may overcome difficulties in finding appropriate co-investors for ex-post monitoring and avoid diluting control.

Overall, these findings are consistent with anecdotal evidence gleaned from interviews with a small sample of European micro VCs. These investors drew a relatively disengaged portrayal of micro VCs: they invest small amounts in a large number of early-stage startups, do very little due diligence, their shareholder agreements are not sophisticated, they rarely take board seats or lead investments in their portfolio startups, and they seldom replace the founders as the CEOs.

The differences in the organization and investments of micro and traditional VCs are reflected in the differential performance of portfolio startups. By estimating *ad hoc* fixed effects models, we show that startups that receive micro VC funding have a lower likelihood of exiting via acquisition or IPO. As such, these results run counter to the findings in the private equity literature that smaller equity funds earn higher returns because of more selective investment decisions (Lopez-de Silanes et al., 2015). In contrast with these findings, our study suggests that economies of scale matter for the screening, monitoring, and professionalization of startups.

Having uncovered important differences between micro and traditional VCs, we compare micro VCs to business angels. Micro VCs' limited resources may make them pursue similar strategies as business angels, although two major differences between micro VCs and business angels are that the latter risk their own money when investing in a startup and invest in fewer startups. We find that micro VCs invest less in founders with previous successful entrepreneurial experience and are less likely to participate in syndicates but are more likely to replace startup founders with external CEOs. These findings may be consistent with business angels taking their time and having more incentives to select their portfolio startups, including their founders, and find potential co-investors to reduce risks.

Our results inform and extend the scant strategy and finance literature that has examined the characteristics of investors beyond traditional VCs. While this literature has examined business angels (Hellmann et al., 2021; Kerr et al., 2014), mutual funds (Chernenko et al., 2021; Kwon et al., 2020), hedge funds (Aragon et al., 2018), venture lenders (De Rassenfosse and Fischer, 2016), corporate venture capital (Dushnitsky and Lenox, 2006; Dushnitsky and Shaver, 2009) and crowdfunding platforms (Drover et al., 2017; Dushnitsky and Fitza, 2018), we contribute by investigating the investments undertaken by micro VCs. Our results suggest that relative to traditional VCs and business angels, micro VCs have distinct investment strategies that seem to reflect their peculiar organizational features.

We leveraged rich data at the investor and startup levels, which allowed us to provide a set of novel results to the literature. Our findings have direct implications for entrepreneurs seeking financial capital. We have shown that micro VCs are a distinct category of investors with their own organization and practices. These investors may be an optimal match for startups with relatively small capital requirements and wanting to maintain control over their operations.

Our study is subject to some limitations, such as the lack of fine-grained data to probe into the specific type of activities in which micro VCs engage and the lack of exogenous variations in micro VC funding to derive causality. Despite these limitations, our paper has provided important evidence on the micro VC phenomenon that offers guidance to practitioners interested in entrepreneurial finance and suggests several avenues for future research. For example, future studies could parse the causal impact of micro VC financing on startup outcomes. While we have adopted an inductive approach to assess how micro VCs matter for the screening and monitoring of startups, future research could employ more qualitative data on the activities that micro VCs undertake. Future research might also develop more precise theories on the functioning of micro VC that would represent a valuable contribution to the scant literature on the organization of non-traditional VCs. While we have explored the "average" characteristics of micro VCs and their "average" strategies, it would be important to dig deeper into the heterogeneity of micro VC characteristics and strategies. Both our interviews and data have revealed that, indeed, there is variance in these micro VC aspects. Finally, future studies could better assess the differences between micro VCs and business angels, as we have shown that the strategies analyzed in this paper do not fully explain the performance differential between startups financed by business angels and those supported by traditional and micro VCs.

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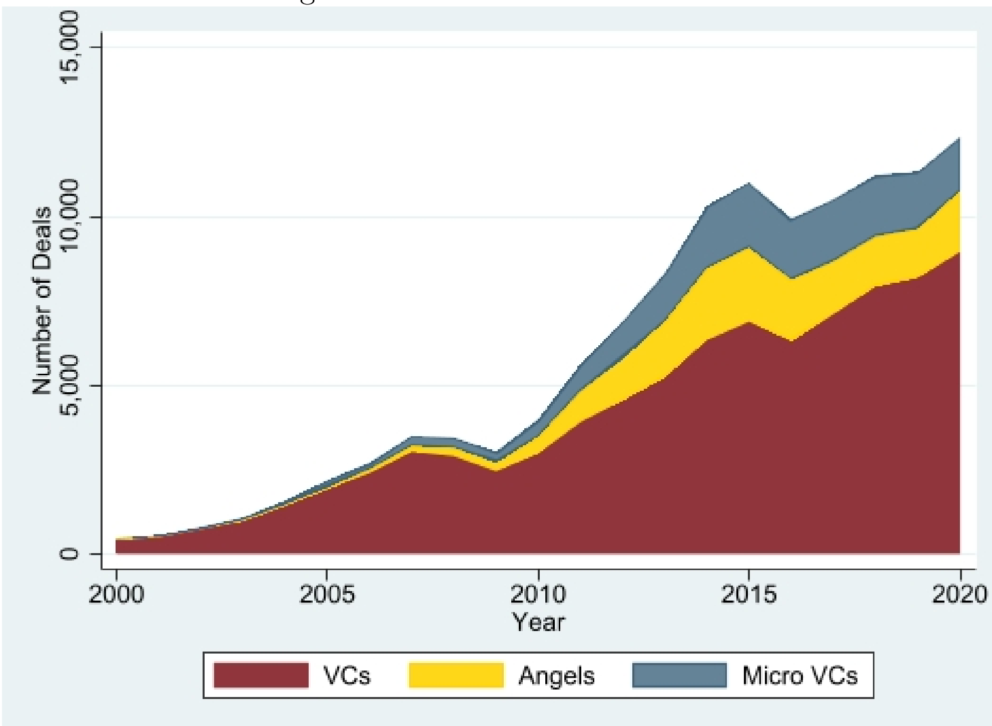
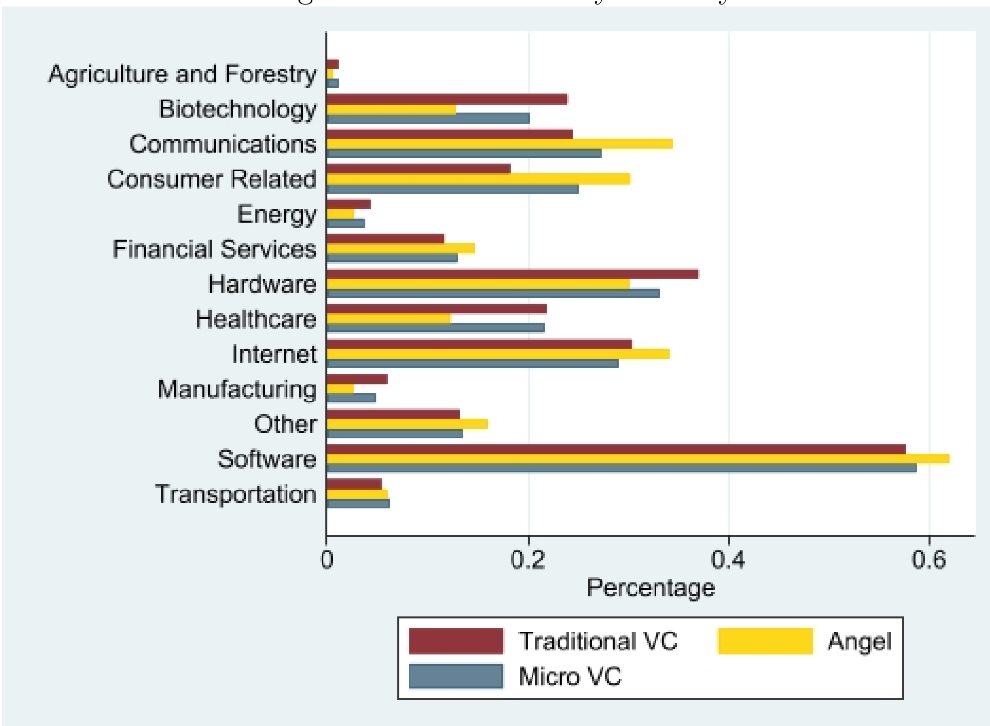
Figure 1: Investor deals over time



Notes: This figure shows the evolution of the number of US deals in which traditional VCs (red), micro VCs (blue), and business angels (yellow) participated during the 2000-2020 period.

Figure 2: Investments by industry



Notes: In this figure, we compare the propensity of micro, traditional VCs, and business angels to invest in startups operating in thirteen aggregated industry groups. Please note that a startup can be assigned to more than one industry group. The red bars represent the share of investments made by traditional VCs in each industry category reported. The blue bars represent the share of investments made by micro VCs in each industry category reported. The yellow bars represent the share of investments made by business angels in each industry category reported.

Table 1: Micro VCs: Predictions

Strategy	**Implications for screening and monitoring**	**Micro VCs vs. traditional VCs**
Investing in geographically close startups	Reduces screening and monitoring costs (Bernstein et al., 2016; Sorenson, 2018)	Because of their limited screening and monitoring capital, micro VCs should invest in closer startups than traditional VCs.
Investing in founders with successful track records	Reduces screening costs (Conti et al., 2013; Gompers et al., 2010)	If micro VCs pursued a spray and pray strategy, they might invest in startups regardless of founder experience. However, these investors may derive high returns from targeting successful founders as the latter could at least partially offset the former's limited screening and monitoring capital. If there is a positive assortative matching along the quality dimension between entrepreneurs and investors, the limited non-financial capital of micro VCs might prevent them from pairing with successful entrepreneurs.
Replacing founders with external CEOs	Important for startup professionalization (Chahine and Zhang, 2020; Conti and Graham, 2020; Ewens and Marx, 2018; Hellmann and Puri, 2002)	The limited non-financial capital of which micro VCs dispose and the fact that these investors could spread it across a large number of startups may induce them to retain the initial founders more frequently than traditional VCs.
Participate in large rounds + syndicate	Reduces screening costs, enhances monitoring, reduces risk (Brander et al., 2002; Nanda and Rhodes-Kropf, 2017)	By participating in large syndicates, micro VCs finance better projects, reduce the risks of investing in early-stage venture, capitalize on the screening and monitoring capabilities of more endowed investors. However, micro VCs' limited financial and non-financial capital may impair their ability to find suitable syndicate partners. Therefore, these investors could specialize in investments that require little syndication and are smaller in size.
Investment staging	Reduces monitoring costs (Gompers, 1995; Tian, 2011)	By conditioning their investment decisions on the information that startups gradually reveal regarding the status of their technology and management team, micro VCs could make more efficient monitoring.
Co-investing with later-stage investors	Relative specialization in screening (Sørensen, 2007)	Micro VCs may concentrate their limited non-financial capital on screening early-stage startups for later-stage traditional VCs.

Table 2: Descriptive statistics

	Mean	S.D.	Min	Max	Obs.
PANEL A: Startup level					
Age (months) as of 12.2020	105.675	61.161	0	251	28,870
California	0.434	0.496	0	1	28,870
Massachusetts	0.080	0.271	0	1	28,870
NY	0.137	0.344	0	1	28,870
With VC funding	0.799	0.400	0	1	28,870
With micro VC funding	0.340	0.474	0	1	28,870
With angel funding	0.287	0.452	0	1	28,870
Acquired	0.246	0.431	0	1	28,870
IPO	0.036	0.185	0	1	28,870
At least one serial founder	0.326	0.469	0	1	24,562
At least one successful serial founder	0.127	0.333	0	1	24,562
Founder is CEO (as of July 2022)	0.651	0.477	0	1	17,499
PANEL B: Investor-round level					
Round is seed	0.330	0.470	0	1	120,802
Round is series A	0.228	0.420	0	1	120,802
Round size ($ mill.)	17.858	55.648	0.001	7,700	105,762
Round is syndicated	0.869	0.337	0	1	120,802
Syndicated with VC	0.620	0.469	0	1	120,802
VC investor	0.705	0.456	0	1	120,802
Micro VC investor	0.147	0.355	0	1	120,802
Angel investor	0.148	0.355	0	1	120,802
PANEL C: Investor-startup level					
N. rounds invested in startup	1.518	0.940	1	12	83,735
Distance (Km.)	1,233	1,638	0	8,011	83,735
PANEL D: Investor level					
VC investor	0.319	0.466	0	1	12,973
Micro VC investor	0.045	0.207	0	1	12,973
Angel investor	0.636	0.481	0	1	12,973
California	0.385	0.487	0	1	12,973
Massachusetts	0.055	0.227	0	1	12,973
NY	0.177	0.382	0	1	12,973
N. US deals as of 12.2020	9.311	41.287	1	1,329	12,973
LP's AUM ($ mill.)	35,314	45,527	140	279,700	977
LP is corporate pension fund	0.137	0.237	0	1	1,019
LP is public pension fund	0.139	0.237	0	1	1,019
LP is foundation	0.183	0.302	0	1	1,019
LP is person/family office	0.055	0.193	0	1	1,019
LP is fund of funds	0.101	0.197	0	1	1,019
LP is insurance company	0.076	0.193	0	1	1,019
PANEL E: Investor-fund level					
N. deals/fund size ($ mill.)	1.679	18.218	0.0002	1,000	5,527
PANEL F: Investor-employee level					
TM founded a startup	0.312	0.463	0	1	15,122
TM founded a successful startup	0.236	0.376	0	1	4,658
TM worked for a VC	0.334	0.472	0	1	15,122

Table 3: Descriptive statistics: Traditional VCs vs. micro VCs

	VC		Micro VC		
	(1)		(2)		(3)
	Mean	S.D.	Mean	S.D.	Diff.
PANEL A: Investor-round level					
Round is seed	0.232	0.423	0.476	0.499	-0.244***
Round is series A	0.246	0.431	0.212	0.409	0.034***
Startup age (months) at round	44.255	32.824	34.249	28.362	10.006***
Round is syndicated	0.876	0.330	0.818	0.386	0.058***
Syndicated with VC	0.719	0.450	0.594	0.491	0.125***
Round size ($ mill.)	21.719	62.531	8.389	23.446	13.330***
PANEL B: Investor-startup level					
N. rounds invested in startup	1.672	1.047	1.400	0.774	0.272***
Distance (Km.)	1,270	1,654	1,232	1,632	38.000**
Serial founder	0.385	0.487	0.362	0.481	0.023***
Serial successful founder	0.171	0.377	0.136	0.342	0.035***
Founder is CEO (as of July 2022)	0.631	0.483	0.693	0.461	-0.062***
Acquired	0.292	0.454	0.265	0.441	0.026***
IPO	0.075	0.263	0.030	0.170	0.045***
PANEL C: Investor level					
California	0.342	0.474	0.374	0.484	0.033
Massachusetts	0.069	0.254	0.069	0.254	0.000
NY	0.178	0.383	0.155	0.362	0.023
LP's AUM ($ mill.)	36,640	44,128	28,386	51,833	8,254**
LP is corporate pension fund	0.150	0.240	0.076	0.213	0.073***
LP is public pension fund	0.148	0.240	0.091	0.222	0.057***
LP is foundation	0.173	0.290	0.236	0.351	-0.063**
LP is person/family office	0.045	0.173	0.106	0.268	-0.061***
LP is fund of funds	0.104	0.193	0.085	0.211	0.020
LP is insurance company	0.079	0.193	0.061	0.190	0.018
PANEL D: Investor-fund level					
N. deals/fund size ($ mill.)	1.256	0.177	4.100	1.295	-2.844***
PANEL E: Investor-employee level					
TM with entrepreneurial exp.	0.303	0.459	0.373	0.484	-0.070***
TM founded a successful startup	0.241	0.379	0.211	0.357	0.030*
TM with VC exp.	0.359	0.480	0.168	0.374	0.191***

Notes: The last column in each panel reports the differences of the means for micro and traditional VCs. Significance noted as: *p<0.10; **p<0.05; ***p<0.01.

Table 4: Descriptive statistics: Angel investors vs. micro VCs

	Angels		Micro VC		
	(1)		(2)		(3)
	Mean	S.D.	Mean	S.D.	Diff.
PANEL A: Investor-round level					
Round is seed	0.655	0.475	0.476	0.499	0.179***
Round is series A	0.161	0.368	0.212	0.409	-0.051***
Startup age (months) at round	26.166	24.623	34.249	28.362	-8.083***
Round is syndicated	0.887	0.317	0.818	0.386	0.068***
Syndicated with VC	0.529	0.499	0.594	0.491	-0.064***
Round size ($ mill.)	7.600	34.550	8.389	23.446	-0.789**
PANEL B: Investor-startup level					
N. rounds invested in startup	1.096	0.356	1.400	0.774	-0.305***
Distance (Km.)	1,111	1,580	1,232	1,632	-121**
Serial founder	0.404	0.491	0.362	0.481	0.043***
Serial successful founder	0.152	0.003	0.136	0.342	0.016***
Founder is CEO (as of July 2022)	0.741	0.438	0.693	0.461	0.048***
Acquired	0.242	0.429	0.265	0.441	0.023***
IPO	0.022	0.145	0.030	0.170	0.08***
PANEL C: Investor level					
California	0.408	0.492	0.374	0.484	0.034
Massachusetts	0.046	0.210	0.069	0.254	0.023**
NY	0.178	0.383	0.155	0.362	0.023

Notes: The last column in each panel reports the differences of the means for micro VCs and business angels. Significance noted as: *p<0.10; **p<0.05; ***p<0.01.

Table 5: Investor strategies

	Investor Strategies:		
	Invest in geographically close startups	Invest in startups with successful serial founders	Retain founder as CEO
	(1)	(2)	(3)
Micro VC	0.041**	-0.025**	0.017***
	(0.020)	(0.011)	(0.006)
Angel	0.095***	-0.001	0.041***
	(0.010)	(0.006)	(0.005)
Test Diff. Coefs. (p-values)	0.0028	0.0023	0.0008
Fst.-Round-type FE	Yes	Yes	Yes
Fst.-Round-Yr. × Investor State FE	Yes	Yes	Yes
Fst.-Round-Yr. × Industry Group FE	Yes	Yes	Yes
Mean DV	0.254	0.162	0.662
N	83,634	75,163	54,473
R-squared	0.085	0.036	0.162

Notes: In this table, we assess whether there is any difference between micro VCs, angels, and traditional VCs (reference outcome) relative to the following strategies: 1) invest in geographically close (column (1)); 2) invest in startups with serial successful founders, that, is founders that had experienced an IPO or an acquisition prior to starting a company (column (3)); retain one of the initial founders as the CEO (column (2)). The unit of the analysis is the investor-startup. Observations differ from one column to another as information on founders and founder-CEOs is only available for a limited sample. To account for the possibility that the effects we report for angels and micro VCs are specifically driven by their experience rather than by their organization characteristics, we control for the number of investments investors made in the five years prior to investing in a startup for the first time. *Fst.-Round-Year* refers to the year of the first startup-round in which an investor invests. Standard errors are clustered at the investor level. Significance noted as: *p<0.10; **p<0.05; ***p<0.01.

Table 6: Investor strategies: Continued

	Investor Strategies:			
	Round amt. (log) (1)	Round is syndicated (2)	Invest with VC (3)	Invest more than one round (4)
Micro VC	-0.392***	-0.038***	-0.062*	-0.104***
	(0.115)	(0.0160)	(0.036)	(0.026)
Angel	-0.287***	0.0505**	-0.081***	-0.262***
	(0.051)	(0.009)	(0.016)	(0.013)
Test Diff. Coefs. (p-values)	0.1323	0.0000	0.4516	0.0000
Round-type FE	Yes	Yes	Yes	
Round-Year × Investor State FE	Yes	Yes	Yes	
Round-Year × Industry Group FE	Yes	Yes	Yes	
Fst.-Round-type FE				Yes
Fst.-Round-Year × Investor State FE				Yes
Fst.-Round-Year × Industry Group FE				Yes
Mean DV	2.100	0.869	0.672	0.319
N	105,460	120,451	120,451	83,634
R-squared	0.518	0.052	0.102	0.135

Notes: In this table, we assess whether there is any difference between micro VCs, angels, and traditional VCs (reference outcome) relative to the following strategies: 1) round size (column (1)); 2) whether a round is syndicated (column (2)); 3) whether an investor invests with another VC in a given round (column (3)); 4) whether an investor invests more than one round in a startup (column (4)). In columns (1)-(3), the unit of observation is the investor-round; in column (4), the unit of observation is the investor-startup. To account for the possibility that the effects we report for angels and micro VCs are specifically driven by their experience rather than by their organization characteristics, we control for the number of investments investors made in the five years prior to a startup's current round (columns (1)-(3)) and a startup's first round (column (4)). Regarding round-type fixed effects, we distinguish between seed, series A, and other rounds. The year to which the fixed effects in columns (1)-(3) refer is the year in which an investor raises a given round. Conversely, the year to which the fixed effects in column (4) refer is the year in which an investor invests for the first time in a startup. Standard errors are clustered at the investor level. Significance noted as: *p<0.10; **p<0.05; ***p<0.01.

Table 7: Startup performance: Cross section

	Acquisition/IPO		
	(1)	(2)	(3)
Micro VC	-0.029***	-0.036***	-0.003
	(0.010)	(0.010)	(0.007)
Angel	-0.052***	-0.060***	-0.033***
	(0.006)	(0.006)	(0.005)
Geographically close			0.006
			(0.005)
Serial succ. founder			0.019***
			(0.006)
CEO is founder			-0.070***
			(0.005)
Amount (first round invested)			0.082***
			(0.003)
First round invested is syndicated			-0.009
			(0.008)
First round invested is syndicated with VC			0.022***
			(0.005)
Test Diff. Coefs. (p-values)	0.0065	0.0052	0.0000
Fst.-Round-type FE	Yes	Yes	Yes
Fst.-Round-Year × Investor State FE	Yes	Yes	Yes
Fst.-Round-Year × Industry Group FE	Yes	Yes	Yes
Mean DV	0.335	0.252	0.252
N	83,634	42,899	42,899
R-squared	0.197	0.204	0.237

Notes: In this table, we assess whether there is any difference between micro VCs, angels, and traditional VCs (reference outcome) relative to the performance outcomes (IPO/acquisition) of their investee startups. The unit of the analysis is the investor-startup. In column (2), we reproduce the same model as in column (1), having restricted the sample to those units for which the investor strategy measures are available. To account for the possibility that the effects we report for angels and micro VCs are specifically driven by their experience rather than by their organization characteristics, we control for the number of investments investors made in the five years prior to investing in a startup for the first time. *Fst.-Round-Year* refers to the year of the first startup-round in which an investor invests. Standard errors are clustered at the startup level. Significance noted as: *p<0.10; **p<0.05; ***p<0.01.

Table 8: Startup performance: Panel Analysis

	Acquisition/IPO (cum. prob.)	
	(1)	(2)
Cum. Micro VC	0.00457***	0.00163
	(0.00106)	(0.00171)
Cum. VC	0.01940***	0.00417***
	(0.00095)	(0.00146)
Cum. Angel	0.00133	-0.00263
	(0.00109)	(0.00180)
Startup FE		Yes
Cum. Round FE	Yes	Yes
Year × Investor State FE	Yes	Yes
Year × Industry Group FE	Yes	Yes
Mean DV	0.028	0.028
N	212,839	212,813
R-squared	0.0237	0.209

Notes: In this table, we assess whether there is any difference between micro VCs, angels, and traditional VCs (reference outcome) relative to the performance outcomes (IPO/acquisition) of their investee startups in a panel setting. The dependent variable is the cumulative probability that a startup exits via an IPO or an acquisition. We truncate the sample the year after a startup experiences an exit event. *Cum. Micro VC* is a 0/1 indicator that takes value one from the moment a startup receives micro VC funds. *Cum. VC* is a 0/1 indicator that takes value one from the moment a startup receives traditional VC funds. Similarly, *Cum. Angel* is a 0/1 indicator that takes value one from the moment a startup receives business angel funds. The unit of the analysis is the startup. In column (1), we omit startup fixed effects, which we include in column (2). Standard errors are clustered at the startup level. Significance noted as: *p<0.10; **p<0.05; ***p<0.01.

Table A1: Micro VC descriptions

ID	Description
1	We know firsthand the hard work and challenges of building successful companies. Our extensive network of strategic contacts and their presence makes a difference in how rapidly our companies achieve critical milestones. Our geographic focus is principally Silicon Valley as well as Hawaii, Texas, and Oklahoma, where the firm has extensive relationships.
2	We focus on the sectors where our experience and relationships allow us to help companies grow exponentially. Additionally, X2 has established trusted networks with deep roots across the government, military, and intelligence communities.
3	By drawing on our operating experience, navigating networks, and implementing investment intelligence, our team guides startups to scale and exits.
4	X4 is an experienced and trusted partner that supports technology entrepreneurs through capital, expertise and extensive networking, helping them scale their businesses
5	X5 seeks to establish close partnership with passionate, committed entrepreneurs and like-minded co-investors. The principals bring a broad national network of target sector contacts to bear in helping portfolio companies source customers, find strategic partners, and recruit key personnel.
6	Our skill sets in finance, media and entrepreneurship, along with our expansive network, allow us to provide the most value-add per invested dollar for early-stage companies.
7	X7 brings unmatched value to growth stage companies through our deep industry networks and world-class management experience.
8	X8 leverages its unique domain expertise, corporate partners, and industry relationships to create a self-reinforcing cycle of value within our network.
9	We are a community of fellow founder-operators with hard-fought experience + personal networks spanning every aspect of building, scaling and exiting a high-growth technology business.
10	We are entrepreneurs and founders. We have ridden the ups and downs of the startup world and found success. When we partner with an entrepreneur, we bring that understanding, along with our networks, our experience, and our capital.
11	X11 achieves this by leveraging healthcare experience and a network of industry relationships to help provide management partners with the necessary resources and support to create and implement impressive growth plans.
12	X12 is an experienced, early-stage venture capital firm focused on investing in, supporting, and building relationships with founders who are creating the future.
13	We are transparent, approachable, and entrepreneur friendly investors. Our core team is supported by a deep bench of active world-class partners, advisors, and technical experts that meet on a quarterly basis.
14	Our core assets include operational and strategic expertise, mentorship, global networking contacts, and access to seed capital and beyond.
15	We tap into our worldwide network of Wisconsin associated connections for additional knowhow, business development opportunities, and capital to further boost our efforts.
16	We strive to be worthy partners by connecting promising entrepreneurs to our network of other successful entrepreneurs and partners to help them build innovative companies of purpose, value, and integrity. We assist our entrepreneurs with helpful introductions to new customers, partners, and team members.

Notes: We anonymized micro VC names. The descriptions are obtained from Crunchbase. If missing, we used the LinkedIn descriptions.

Table A1: Micro VC descriptions: Continued

ID	Description
17	We have over 50 years of combined entrepreneurial experience in building profitable, global enterprises from the ground up and over 25 years of combined investing experience in successful information technology and life science companies. We are seed and early-stage investors with access to an extensive network of resources. Over the years, we have assembled a world-class network of serial entrepreneurs, strategic investors, and industry leaders who actively assist their portfolio as Entrepreneur Partners and Advisors. We partner with entrepreneurs and leverage the resources of their strong network to build successful companies.
18	We leverage our network of angel investors, early-stage funds and venture capital firms in order to meet the funding needs of our portfolio companies.
19	Our management team is comprised of experienced healthcare entrepreneurs with operating expertise in growing start-ups. We leverage the domain experience and contacts of their network of healthcare providers, payers, and strategic partners to validate, mentor, and grow their portfolio companies. This focused approach accelerates the adoption and revenues of a portfolio company's products and associated services.
20	Our team members have deep operational experience, access to global networks, and have led businesses spanning from startup to global Fortune 50.
21	We leverage their considerable knowledge and deep networks to accelerate commercial success of a company.
22	We always expect to provide more than just capital to our portfolio companies. We strive to use both our internal expertise and the broader network to help our managers find and recruit talent, evolve operational processes, grow revenues and build their brands.
23	We combine a strong brand, vast network, and deep experience with startup hustle to invest in exceptional early-stage software startups.
24	Our global network of partners, advisors and friends puts us in a position where very few other investment funds have been before, providing our companies with the right financing, contacts and advice to help them reach whatever incredible goal the have set for themselves. X24 was founded by proven and successful serial entrepreneurs and is supplemented by an experienced support team.
25	We invest with insane conviction, moving quickly and backing teams when others think it's too early. VC is a customer service business. Whether it's testing product, pushing pixels, leveraging our network, or forcing people to download your app, we're here to help.

Notes: We anonymized micro VC names. The descriptions are obtained from Cruchbase. If missing, we used the LinkedIn descriptions.

Table A2: Correlation table: Part 1

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
(1) Startup age	1.000											
(2) California	-0.016	1.000										
(3) Massachusetts	0.051	-0.258	1.000									
(4) NY	-0.097	-0.349	-0.117	1.000								
(5) VC funding	0.130	0.068	0.032	0.004	1.000							
(6) Micro VC funding	-0.104	-0.001	-0.019	0.030	-0.206	1.000						
(7) Angel funding	-0.157	0.060	-0.066	0.058	-0.279	0.030	1.000					
(8) Acquired	0.322	0.039	0.017	-0.014	0.115	0.010	-0.026	1.000				
(9) IPO	0.123	0.005	0.078	-0.033	0.077	-0.025	-0.044	-0.110	1.000			
(10) Serial founder	0.025	0.045	0.008	-0.019	0.030	-0.019	0.001	0.001	0.027	1.000		
(11) Success. serial founder	0.144	-0.001	0.032	-0.044	0.027	-0.065	-0.064	0.012	0.034	0.683	1.000	
(12) Founder is CEO	-0.313	0.054	-0.057	0.092	-0.045	0.053	0.097	-0.114	-0.129	-0.156	-0.308	1.000

Notes: These correlations are produced for the variables reported in Panel A of Table 2 and measured at the startup level.

Table A2: Correlation table: Part 2

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
(1) Seed	1.000							
(2) Series A	-0.382	1.000						
(3) Round size ($ mill.)	-0.183	-0.068	1.000					
(4) Round is syndicated	-0.076	0.052	0.069	1.000				
(5) Syndicated with VC	-0.215	0.083	0.103	0.556	1.000			
(6) VC investor	-0.324	0.064	0.111	0.032	0.153	1.000		
(7) Micro VC investor	0.129	-0.016	-0.068	-0.063	-0.070	-0.643	1.000	
(8) Angel investor	0.287	-0.066	-0.076	0.022	-0.127	-0.643	-0.173	1.000

Notes: These correlations are produced for the variables reported in Panel B of Table 2 and measured at the investor-round level.

Table A2: Correlation table: Part 3

Variables	(1)	(2)	(3)	(4)	(5)
(1) VC investor	1.000				
(2) Micro VC investor	-0.591	1.000			
(3) Angel investor	-0.664	-0.211	1.000		
(4) N. rounds invested in startup	0.223	-0.055	-0.219	1.000	
(5) Distance (Km.)	0.030	-0.000	-0.036	-0.019	1.000

Notes: These correlations are produced for the variables reported in Panel C of Table 2 and measured at the investor-startup level.

Table A2: Correlation table: Part 4

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)
(1) VC investor	1.000						
(2) Micro VC investor	-0.148	1.000					
(3) Angel investor	-0.905	-0.286	1.000				
(4) California	-0.062	-0.005	0.062	1.000			
(5) Massachusetts	0.044	0.014	-0.049	-0.190	1.000		
(6) NY	0.002	-0.012	0.004	-0.367	-0.111	1.000	
(7) N. US deals as of 12.2020	0.187	0.112	-0.229	0.070	0.032	-0.020	1.000

Notes: These correlations are produced for the variables reported in Panel D of Table 2 and measured at the investor level.

Table A2: Correlation table: Part 5

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
(1) VC investor	1.000								
(2) Micro VC investor	-0.148	1.000							
(3) AUM	0.067	-0.067	1.000						
(4) LP is corporate pension fund	0.115	-0.115	-0.071	1.000					
(5) LP is public pension fund	0.089	-0.089	0.293	-0.068	1.000				
(6) LP is foundation	-0.077	0.077	-0.272	-0.186	-0.214	1.000			
(7) LP is person/family office	-0.116	0.116	-0.120	-0.143	-0.129	-0.117	1.000		
(8) LP is fund of funds	0.037	-0.037	0.027	-0.088	-0.087	-0.163	-0.108	1.000	
(9) LP is insurance company	0.034	-0.034	0.072	-0.060	-0.087	-0.164	-0.091	-0.071	1.000

Notes: These correlations are produced for the variables reported in Panel D of Table 2 and measured at the investor level. We restrict the sample to micro and traditional VC investors.

Table A2: Correlation table: Part 6

Variables	(1)	(2)	(3)	(4)	(5)
(1) TM works for VC investor	1.000				
(2) TM works for Micro VC investor	-1.000	1.000			
(3) TM founded a startup	-0.051	0.051	1.000		
(4) TM founded a succ. startup	0.028	-0.028	0.061	1.000	
(5) TM founded worked for a VC	0.137	-0.137	-0.012	0.042	1.000

Notes: These correlations are produced for the variables reported in Panel E of Table 2 and measured at the investor-employee level.

Table A3: Investor strategies

	Investor Strategies:		
	Invest in geographically close startups	Invest in startups with successful serial founders	Retain founder as CEO
	(1)	(2)	(3)
Micro VC	0.040*	-0.026**	0.017***
	(0.022)	(0.011)	(0.006)
Angel	0.095***	-0.001	0.041***
	(0.011)	(0.006)	(0.005)
Test Diff. Coefs. (p-values)	0.0041	0.0019	0.0002
Fst.-Round-type FE	Yes	Yes	Yes
Fst.-Round-Year × Investor State FE	Yes	Yes	Yes
Fst.-Round-Year × Industry Group FE	Yes	Yes	Yes
Mean DV	0.250	0.160	0.677
N	77,395	71,120	52,620
R-squared	0.076	0.035	0.137

Notes: In this table, we replicate Table 5 in the main text. However, we exclude those deals that occurred before 2006 and the corresponding startups that raised those deals. Standard errors are clustered at the investor level. Significance noted as: *p<0.10; **p<0.05; ***p<0.01.

Table A4: Investor strategies: Continued

	Investor Strategies:			
	Round amt. (log)	Round is syndicated	Invest with VC	Invest more than one round
	(1)	(2)	(3)	(4)
Micro VC	-0.410***	-0.037**	-0.064*	-0.107***
	(0.120)	(0.021)	(0.038)	(0.026)
Angel	-0.291***	0.052***	-0.079***	-0.262***
	(0.053)	(0.010)	(0.016)	(0.013)
Test Diff. Coefs. (p-values)	0.0998	0.0000	0.5661	0.0000
Round-type FE	Yes	Yes	Yes	
Round-Year × Investor State FE	Yes	Yes	Yes	
Round-Year × Industry Group FE	Yes	Yes	Yes	
Fst.-Round-type FE				Yes
Fst.-Round-Year × Investor State FE				Yes
Fst.-Round-Year × Industry Group FE				Yes
Mean DV	2.043	0.863	0.655	0.303
N	93,597	108,046	108,046	77,395
R-squared	0.525	0.054	0.097	0.118

Notes: In this table, we replicate Table 6. However, we exclude those deals that occurred before 2006 and the corresponding startups that raised those deals. Standard errors are clustered at the investor level. Significance noted as: *p<0.10; **p<0.05; ***p<0.01.

Table A5: Startup performance: Cross section

	Acquisition/IPO		
	(1)	(2)	(3)
Micro VC	-0.028***	-0.036***	-0.003
	(0.010)	(0.010)	(0.007)
Angel	-0.051***	-0.059***	-0.033***
	(0.006)	(0.006)	(0.005)
Geographically close			0.007
			(0.005)
Serial succ. founder			0.017***
			(0.006)
CEO is founder			-0.069***
			(0.005)
Amount (first round invested)			0.081***
			(0.003)
First round invested is syndicated			-0.011
			(0.008)
First round invested is syndicated with VC			0.023***
			(0.005)
Test Diff. Coefs. (p-values)	0.0097	0.0072	0.0000
Fst.-Round-type FE	Yes	Yes	Yes
Fst.-Round-Year × Investor State FE	Yes	Yes	Yes
Fst.-Round-Year × Industry Group FE	Yes	Yes	Yes
Mean DV	0.309	0.236	0.236
N	77,395	41,441	41,441
R-squared	0.174	0.172	0.205

Notes: In this table, we replicate Table 7. However, we exclude those deals that occurred before 2006 and the corresponding startups that raised those deals. Standard errors are clustered at the investor level. Significance noted as: *p<0.10; **p<0.05; ***p<0.01.

Table A6: Startup performance: Panel Analysis

	Acquisition/IPO (cum. prob.)	
	(1)	(2)
Cum. Micro VC	0.00546***	0.00185
	(0.00109)	(0.00173)
Cum. VC	0.01915***	0.00443***
	(0.00097)	(0.00147)
Cum. Angel	0.00191*	-0.00229
	(0.00110)	(0.00181)
Startup FE		Yes
Cum. Round FE	Yes	Yes
Year × Investor State FE	Yes	Yes
Year × Industry Group FE	Yes	Yes
Mean DV	0.027	0.028
N	194,292	194,292
R-squared	0.023	0.211

Notes: In this table, we replicate Table 8. However, we exclude those deals that occurred before 2006 and the corresponding startups that raised those deals. Standard errors are clustered at the investor level. Significance noted as: *p<0.10; **p<0.05; ***p<0.01.

Table A7: Investor strategies

	Investor Strategies:		
	Invest in geographically close startups	Invest in startups with successful serial founders	Retain founder as CEO
	(1)	(2)	(3)
Micro VC	0.040*	-0.024**	0.017***
	(0.021)	(0.012)	(0.006)
Angel	0.093***	-0.001	0.040***
	(0.011)	(0.006)	(0.005)
Test Diff. Coefs. (p-values)	0.0042	0.0048	0.0019
Fst.-Round-type FE	Yes	Yes	Yes
Fst.-Round-Year × Investor State FE	Yes	Yes	Yes
Fst.-Round-Year × Industry Group FE	Yes	Yes	Yes
Mean DV	0.258	0.165	0.672
N	79,412	71,643	51,586
R-squared	0.084	0.040	0.162

Notes: In this table, we replicate Table 5. However, we exclude from the sample investor deals made in startups that were older than five years at the time of the first financing round. Standard errors are clustered at the investor level. Significance noted as: *p<0.10; **p<0.05; ***p<0.01.

Table A8: Investor strategies: Continued

	Investor Strategies:			
	Round amt. (log)	Round is syndicated	Invest with VC	Invest more than one round
	(1)	(2)	(3)	(4)
Micro VC	-0.386***	-0.038**	-0.063*	-0.108***
	(0.117)	(0.016)	(0.037)	(0.026)
Angel	-0.287***	0.047***	-0.082***	-0.266***
	(0.052)	(0.009)	(0.016)	(0.013)
Test Diff. Coefs. (p-values)	0.1634	0.0000	0.4672	0.0000
Round-type FE	Yes	Yes	Yes	
Round-Year × Investor State FE	Yes	Yes	Yes	
Round-Year × Industry Group FE	Yes	Yes	Yes	
Fst.-Round-type FE				Yes
Fst.-Round-Year × Investor State FE				Yes
Fst.-Round-Year × Industry Group FE				Yes
Mean DV	2.086	0.874	0.679	0.321
N	100,505	114,695	114,695	79,412
R-squared	0.526	0.052	0.105	0.138

Notes: In this table, we replicate Table 6. However, we exclude from the sample investor deals made in startups that were older than five years at the time of the first financing round. Standard errors are clustered at the investor level. Significance noted as: *p<0.10; **p<0.05; ***p<0.01.

Table A9: Startup performance: Cross section

	Acquisition/IPO		
	(1)	(2)	(3)
Micro VC	-0.028***	-0.034***	-0.001
	(0.010)	(0.010)	(0.007)
Angel	-0.052***	-0.061***	-0.033***
	(0.006)	(0.006)	(0.005)
Geographically close			0.008*
			(0.005)
Serial succ. founder			0.021***
			(0.006)
CEO is founder			-0.075***
			(0.005)
Amount (first round invested)			0.083***
			(0.003)
First round invested is syndicated			-0.009
			(0.008)
First round invested is syndicated with VC			0.020***
			(0.005)
Test Diff. Coefs. (p-values)	0.0044	0.0032	0.0000
Fst.-Round-type FE	Yes	Yes	Yes
Fst.-Round-Year $\times$ Investor State FE	Yes	Yes	Yes
Fst.-Round-Year $\times$ Industry Group FE	Yes	Yes	Yes
Mean DV	0.334	0.250	0.250
N	79,412	40,800	40,800
R-squared	0.200	0.210	0.245

In this table, we replicate Table 7. However, we exclude from the sample investor deals made in startups that were older than five years at the time of the first financing round. Standard errors are clustered at the investor level. Significance noted as: *p<0.10; **p<0.05; ***p<0.01.

Table A10: Startup performance: Panel Analysis

	Acquisition/IPO (cum. prob.)	
	(1)	(2)
Cum. Micro VC	0.00296**	0.00195
	(0.00117)	(0.00195)
Cum. VC	0.01891***	0.00281***
	(0.00100)	(0.00157)
Cum. Angel	0.00106	-0.00234
	(0.00112)	(0.00189)
Startup FE		Yes
Cum. Round FE	Yes	Yes
Year × Investor State FE	Yes	Yes
Year × Industry Group FE	Yes	Yes
Mean DV	0.03060	0.028
N	190,736	190,736
R-squared	0.023	0.209

Notes: In this table, we replicate Table 8. However, we exclude from the sample investor deals made in startups that were older than five years at the time of the first financing round. Standard errors are clustered at the investor level. Significance noted as: *p<0.10; **p<0.05; ***p<0.01.

Table A11: Startup performance: Cross section

	Acquisition/IPO		
	(1)	(2)	(3)
Micro VC	-0.024**	-0.040***	-0.011
	(0.012)	(0.015)	(0.014)
Angel	-0.060***	-0.097***	-0.064***
	(0.011)	(0.015)	(0.015)
Geographically close			0.016
			(0.011)
Serial succ. founder			0.055***
			(0.013)
CEO is founder			-0.086***
			(0.010)
Amount (first round invested)			0.114***
			(0.006)
First round invested is syndicated			-0.011
			(0.017)
First round invested is syndicated with VC			0.051***
			(0.013)
Test Diff. Coefs. (p-values)	0.0111	0.0012	0.0021
Fst.-Round-type FE	Yes	Yes	Yes
Fst.-Round-Year $\times$ Investor State FE	Yes	Yes	Yes
Fst.-Round-Year $\times$ Industry Group FE	Yes	Yes	Yes
Mean DV	0.540	0.481	0.481
N	29,366	10,043	10,043
R-squared	0.095	0.172	0.215

Notes: In this table, we replicate Table 7. However, we excluded investor-startups that received an investment from their investors after 2013: *p<0.10; **p<0.05; ***p<0.01.

Table A12: Investor strategies

	Investor Strategies:		
	Invest in geographically close startups	Invest in startups with successful serial founders	Retain founder as CEO
	(1)	(2)	(3)
Micro VC	0.021	-0.038***	0.018***
	(0.015)	(0.013)	(0.007)
Angel	0.089***	-0.002	0.041***
	(0.009)	(0.006)	(0.006)
Test Diff. Coefs. (p-values)	0.0000	0.0001	0.0002
Fst.-Round-type FE	Yes	Yes	Yes
Fst.-Round-Year × Investor State FE	Yes	Yes	Yes
Fst.-Round-Year × Industry Group FE	Yes	Yes	Yes
Mean DV	0.251	0.161	0.660
N	79,945	71,768	52,064
R-squared	0.089	0.039	0.163

Notes: In this table, we replicate Table 5. However, we exclude those micro VCs that had raised at least one fund larger than $50 million. Standard errors are clustered at the investor level. Significance noted as: *p<0.10; **p<0.05; ***p<0.01.

Table A13: Investor strategies: Continued

	Investor Strategies:			
	Round amt. (log)	Round is syndicated	Invest with VC	Invest more than one round
	(1)	(2)	(3)	(4)
Micro VC	-0.487***	-0.055***	-0.097**	-0.114***
	(0.158)	(0.021)	(0.036)	(0.035)
Angel	-0.287***	0.051***	-0.083***	-0.256***
	(0.054)	(0.010)	(0.017)	(0.015)
Test Diff. Coefs. (p-values)	0.0634	0.0000	0.6803	0.0000
Round-type FE	Yes	Yes	Yes	
Round-Year × Investor State FE	Yes	Yes	Yes	
Round-Year × Industry Group FE	Yes	Yes	Yes	
Fst.-Round-type FE				Yes
Fst.-Round-Year × Investor State FE				Yes
Fst.-Round-Year × Industry Group FE				Yes
Mean DV	2.112	0.869	0.671	0.318
N	101,160	115,285	115,285	79,945
R-squared	0.521	0.055	0.106	0.142

Notes: In this table, we replicate Table 6. However, we exclude those micro VCs that had raised at least one fund larger than $50 million. Standard errors are clustered at the investor level. Significance noted as: *p<0.10; **p<0.05; ***p<0.01.

Table A14: Startup performance: Cross section

	Acquisition/IPO		
	(1)	(2)	(3)
Micro VC	-0.040***	-0.043***	-0.001
	(0.012)	(0.011)	(0.009)
Angel	-0.051***	-0.060***	-0.033***
	(0.006)	(0.006)	(0.005)
Geographically close			0.006
			(0.005)
Serial succ. founder			0.019***
			(0.006)
CEO is founder			-0.069***
			(0.005)
Amount (first round invested)			0.082***
			(0.003)
First round invested is syndicated			-0.010
			(0.008)
First round invested is syndicated with VC			0.023***
			(0.005)
Test Diff. Coefs. (p-values)	0.2553	0.1110	0.0002
Fst.-Round-type FE	Yes	Yes	Yes
Fst.-Round-Year × Investor State FE	Yes	Yes	Yes
Fst.-Round-Year × Industry Group FE	Yes	Yes	Yes
Mean DV	0.335	0.253	0.253
N	79,945	41,136	41,136
R-squared	0.198	0.205	0.239

Notes: In this table, we replicate Table 7. However, we exclude those micro VCs that had raised at least one fund larger than $50 million. Standard errors are clustered at the investor level. Significance noted as: *p<0.10; **p<0.05; ***p<0.01.

Table A15: Startup performance: Panel Analysis

	Acquisition/IPO (cum. prob.)	
	(1)	(2)
Cum. Micro VC	0.00301***	0.00118
	(0.00115)	(0.00184)
Cum. VC	0.01916***	0.00405***
	(0.00096)	(0.00148)
Cum. Angel	0.00130	-0.00263
	(0.00110)	(0.00181)
Startup FE		Yes
Cum. Round FE	Yes	Yes
Year × Investor State FE	Yes	Yes
Year × Industry Group FE	Yes	Yes
Mean DV	0.028	0.028
N	211,708	211,708
R-squared	0.0237	0.209

Notes: In this table, we replicate Table 8. However, we exclude those micro VCs that had raised at least one fund larger than $50 million. Standard errors are clustered at the investor level. Significance noted as: *p<0.10; **p<0.05; ***p<0.01.

Table A16: Investor strategies

	Investor Strategies:		
	Invest in geographically close startups	Invest in startups with successful serial founders	Retain founder as CEO
	(1)	(2)	(3)
Micro VC	0.042**	-0.025**	0.019***
	(0.021)	(0.011)	(0.006)
Angel	0.094***	0.002	0.043***
	(0.010)	(0.006)	(0.005)
Test Diff. Coefs. (p-values)	0.0038	0.0007	0.0008
Fst.-Round-type FE	Yes	Yes	Yes
Fst.-Round-Year FE	Yes	Yes	Yes
Investor State FE	Yes	Yes	Yes
Industry Group FE	Yes	Yes	Yes
Mean DV	0.254	0.162	0.662
N	83,735	75,266	54,590
R-squared	0.070	0.019	0.140

Notes: In this table, we replicate Table 5. However, we include state, technology, and year fixed effects separately. Significance noted as: *p<0.10; **p<0.05; ***p<0.01.

Table A17: Investor strategies: Continued

	Investor Strategies:			
	Round amt. (log)	Round is syndicated	Invest with VC	Invest more than one round
	(1)	(2)	(3)	(4)
Micro VC	-0.395***	-0.038**	-0.063*	-0.105***
	(0.113)	(0.016)	(0.036)	(0.026)
Angel	-0.287***	0.052***	-0.083***	-0.262***
	(0.051)	(0.009)	(0.016)	(0.012)
Test Diff. Coefs. (p-values)	0.1126	0.0000	0.4366	0.0000
Round-type FE	Yes	Yes	Yes	
Round-Year FE	Yes	Yes	Yes	
Investor State FE	Yes	Yes	Yes	
Industry Group FE	Yes	Yes	Yes	
Fst.-Round-type FE				Yes
Fst.-Round-Year FE				Yes
Mean DV	2.100	0.869	0.672	0.319
N	105,567	120,552	120,552	83,735
R-squared	0.504	0.034	0.083	0.116

Notes: In this table, we replicate Table 6. However, we include state, technology, and year fixed effects separately. Significance noted as: *p<0.10; **p<0.05; ***p<0.01.

Table A18: Startup performance: Cross section

	Acquisition/IPO		
	(1)	(2)	(3)
Micro VC	-0.029***	-0.037***	-0.003
	(0.010)	(0.010)	(0.007)
Angel	-0.053***	-0.061***	-0.034***
	(0.006)	(0.006)	(0.005)
Geographically close			0.006
			(0.004)
Serial succ. founder			0.020***
			(0.006)
CEO is founder			-0.068***
			(0.005)
Amount (first round invested)			0.082***
			(0.003)
First round invested is syndicated			-0.008
			(0.008)
First round invested is syndicated with VC			0.021***
			(0.005)
Test Diff. Coefs. (p-values)	0.0069	0.0069	0.0000
Fst.-Round-type FE	Yes	Yes	Yes
Fst.-Round-Year FE	Yes	Yes	Yes
Investor State FE	Yes	Yes	Yes
Industry Group FE	Yes	Yes	Yes
Mean DV	0.335	0.252	0.252
N	83,735	43,025	43,025
R-squared	0.176	0.171	0.205

Notes: In this table, we replicate Table 7. However, we include state, technology, and year fixed effects separately. Significance noted as: *p<0.10; **p<0.05; ***p<0.01.

Table A19: Investor strategies

	Investor Strategies:		
	Invest in geographically close startups	Invest in startups with successful serial founders	Retain founder as CEO
	(1)	(2)	(3)
Micro VC	0.035*	-0.025**	0.023***
	(0.020)	(0.011)	(0.007)
Angel	0.098***	-0.001	0.044***
	(0.011)	(0.006)	(0.005)
Test Diff. Coefs. (p-values)	0.0005	0.0057	0.0028
Fst.-Round-type FE	Yes	Yes	Yes
Fst.-Round-Yr. × Investor State FE	Yes	Yes	Yes
Fst.-Round-Yr. × Industry Group FE	Yes	Yes	Yes
Mean DV	0.250	0.157	0.710
N	50,723	50,723	50,723
R-squared	0.077	0.050	0.181

Notes: In this table, we replicate Table 5. However, we utilize a common sample across the specifications in columns (1), (2), and (3). Significance noted as: *p<0.10; **p<0.05; ***p<0.01.

Table A20: Investor strategies: Continued

	Investor Strategies:			
	Round amt. (log)	Round is syndicated	Invest with VC	Invest more than one round
	(1)	(2)	(3)	(4)
Micro VC	-0.392***	-0.014	-0.041	-0.117***
	(0.115)	(0.017)	(0.036)	(0.042)
Angel	-0.287***	0.018**	-0.109***	-0.292***
	(0.051)	(0.007)	(0.016)	(0.014)
Test Diff. Coefs. (p-values)	0.1323	0.0060	0.0243	0.0000
Round-type FE	Yes	Yes	Yes	
Round-Year × Investor State FE	Yes	Yes	Yes	
Round-Year × Industry Group FE	Yes	Yes	Yes	
Fst.-Round-type FE				Yes
Fst.-Round-Year × Investor State FE				Yes
Fst.-Round-Year × Industry Group FE				Yes
Mean DV	2.100	0.914	0.727	0.346
N	105,460	105,460	105,460	50,723
R-squared	0.518	0.046	0.099	0.148

Notes: In this table, we replicate Table 6. However, we utilize a common sample across the specifications in columns (1), (2), and (3). In column (4), the sample is the same as that in Table A19. Significance noted as: *p<0.10; **p<0.05; ***p<0.01.

Table A21: Focus on follow-on investors

	Future round with: Traditional VC	Micro VC
	(1)	(2)
Round with Micro VC	0.055***	0.032***
	(0.006)	(0.005)
Round with Traditional VC	0.124***	-0.012**
	(0.007)	(0.006)
Round with Angel	0.075***	0.022***
	(0.006)	(0.005)
Year × Startup State FE	Yes	Yes
Year × Industry Group FE	Yes	Yes
Mean DV	0.621	0.162
N	41,607	41,607
R-squared	0.092	0.078

Notes: In this table, we test whether micro VCs specialize in screening early-stage startups for later-stage traditional VCs. We restrict the sample to startups that raised more than one round with a micro VC, business angel, or traditional VC. We then estimate a model at the startup-round level for the likelihood that a startup raises a future round with a new traditional VC (column 1) or with a new micro VC (column 2). We exclude a startup's last round as startups cannot raise a next round after the last. We control for round stage, investment-year by state and investment-year by technology fixed effects and impose robust standard errors. *Round with Micro VC* is a dummy that takes value 1 if at least one micro VC invested in the focal round; and zero elsewhere. *Round with Traditional VC* is a dummythat takes value 1 if at least one traditional VC invested in the focal round; and zero elsewhere. *Round with Angel* is a dummy that takes value 1 if at least one business angel invested in the focal round; and zero elsewhere.: *p<0.10; **p<0.05; ***p<0.01.

Time Tells: Unraveling the Temporal and Risk Dynamics of Venture Capitalists

Abstract

Access to funds is critical for new ventures, yet many struggle to secure financing. Why are some investors more likely than others to finance new ventures? We address this question by studying the influence of time and risk preferences on venture capital's investment decisions. Using data from a large-scale incentivized survey of venture capitalists in Europe, our findings reveal that patient venture capitalists favor early-stage firms, whereas risk-averse venture capitalists invest in more mature ones. Moreover, we show that risk and time preferences provide different pathways to success: risk-averse investors are more likely to exit through a trade sale, whereas patient investors exit more often through an initial public offering (IPO). The most favorable path to an IPO occurs when investors demonstrate both patience and a willingness to take risks.

Keywords: risk aversion; individual preferences; decision-making; venture capital; investment; patience; exit

1. Introduction

While new ventures are the engine of innovation, job creation, and economic growth (Dencker et al. 2009, Van Praag and Versloot 2007), they often face difficulties in raising capital because of traditional problems of asymmetric information and moral hazard (Hall and Lerner 2010), as well as emotional factors during the fundraising phase (Jiang et al. 2019). Venture capital (VC) firms have emerged as specialized investors dedicated to financing new ventures by employing screening and monitoring tools that alleviate some of these problems (MacMillan et al. 1985, Gompers and Lerner 2001, Drover et al. 2017). Thereby, VC firms can play a crucial role in fostering startups and stimulating aggregate income (Samila and Sorenson 2011). Yet, not all VC firms are equally likely to invest in early-stage firms; for example, Gompers et al. (2020) report that only 36% of VC firms focus on seed or early-stage firms.

Given that early-stage startups are particularly vulnerable to underfunding, understanding the factors that influence venture capitalists' decisions to invest in these ventures is essential. Existing literature on the drivers of early-stage investments is predominantly focused on VC firms' organizational factors (Amore et al. 2023, Chemmanur et al. 2014, Patzelt et al. 2009, Petty et al. 2023), market conditions (Cumming et al. 2005), or institutional and contextual factors (Bottazzi et al. 2016, Dushnitsky and Sarkar 2022). In contrast, the impact of venture capitalists' traits remains largely unexplored, despite a large literature devoted to the individual characteristics of key decision-makers such as CEOs and top executives (Andrei et al. 2023, Benischke et al. 2019, Galasso and Simcoe 2011, Herrmann and Nadkarni 2014, Kaplan et al. 2022, Koh et al. 2018, Malmendier et al. 2023).

This paper aims to fill this gap by investigating the role of venture capitalists' *time* and *risk* preferences on investment decisions, alongside other strategic governance decisions. Several reasons underscore the importance of focusing on both of these preferences. First, a large body of research emphasizes the pivotal role of time and risk preferences as fundamental drivers of economic decision-making (Falk et al. 2018, Gneezy et al. 2020, Tanaka, Camerer, and Nguyen 2010). These preferences are particularly relevant in the context of VC decision-making given that any entrepreneurial venture inherently entails substantial risk and often requires a prolonged period before financial gains materialize (Åstebro et al. 2014, Lévesque and Stephan 2020, Wood et al. 2021). Second, while risk and time preferences are distinct decision-making drivers, they may be intertwined in practice, as "the present is known while the future is inherently risky" (Andreoni and Sprenger 2012, p. 3357) and hence to study them together. While the literature on decision-making in entrepreneurship has predominantly focused on the separate role of either risk (Koudstaal et al. 2016) or time preferences (Gutierrez et al. 2023), evidence suggests a nuanced interplay between the two (Anderson and Stafford 2009). By analyzing how venture capitalists' time and risk preferences impact their investment decisions, this study answers the recent call for research into how these dimensions affect managerial decisions and outcomes (Park and Tzabbar 2016).

The literature has characterized venture capitalists as an homogeneous group of investors which have a high appetite for risk and some degree of patience. We will reveal that there is a high heterogenity in risk aversion and patience across venture capitalists. Yet, whether venture capitalists' time and risk preferences should matter for their investment behavior is unclear. Venture capitalists tend to be highly sophisticated investors with substantial industry expertise (Alvarez-Garrido and Guler 2018), and they typically employ standardized metrics to select and monitor startups (Gompers and Lerner 2001). They also invest considerable resources to improve deal sourcing and selection (Gompers et al. 2020), and face pressure from limited partners to generate financial returns (Petty et al. 2023, De Clercq et al. 2006). All these factors suggest that venture capitalists' idiosyncrasies should play a minimal role in investment decisions. This study challenges that assumption by providing evidence that time and risk preferences have a significant influence on how venture capitalists select new ventures and their exit strategy.

While practitioners often consider time horizon as "the most important factor to take into account" (Chladek 2021) in alternative investments,[1] such as those undertaken by VC firms, research has predominantly focused on its role at the fund level from a contractual perspective, such as the proximity to the exit period (Barrot 2017, Yao, and O'Neill 2022). Risk also plays a central role in the VC industry, but the variation in risk preferences among VC firms is not well understood. Previous studies have used coarse proxies at the firm level based on asset-pricing measures (Cochrane 2005) or return volatility (Buchner et al. 2017). We shift the focus to an antecedent of VC firms' time horizon

[1] Alternative investments refer to financial assets that are less liquid than stocks or bonds.

and risk-taking, i.e., the subjective preferences of individuals leading the VC firm, and explore how these personal preferences influence the development stage of the firms they invest in and the mode of exit. At an exploratory level, we further investigate the role of these preferences on the time taken to close a deal, the number of deals made, the required return, as well as on the use of control mechanisms (i.e. board seats, voting rights) and the syndication with other investors.

Conceptually, we draw on a rich literature in economics showing that time and risk preferences correlate with a plethora of outcomes, including educational attainments, savings behavior, borrowing patterns, and labor supply (Falk et al. 2018, Golsteyn et al. 2014, Meier and Sprenger 2010). These preferences have also been shown to be consequential in organizational settings, influencing outcomes from executive behavior to corporate strategy (Sampson and Shi 2023, Graffin et al. 2020, Graham et al. 2013, Guan et al. 2018).[2] Drawing on the idea that patience lengthens the time horizon in decision-making and reduces the urgency for short-term returns, we hypothesize that venture capitalists with greater patience will be more likely to invest in early-stage firms. In contrast, we expect risk aversion to lead investors to shy away from hazardous deals, such as those involving young ventures, which are typically riskier, and target more established ventures instead. Furthermore, we posit that patience increases the likelihood of investors successfully exiting from their investment via an initial public offering (IPO), whereas risk aversion increases the likelihood of exit through a trade sale.

To test these hypotheses, we conducted a large-scale incentivized survey of individuals who hold top positions in European VC firms. Our data contain incentivized measures of time and risk preferences (constructed as in Andersen et al. 2014 and Dohmen et al. 2011), as well as several other behavioral and demographic characteristics. By matching such survey data with information on VC deals from Pitchbook, we construct a comprehensive dataset that offers a unique opportunity to understand how venture capitalists' risk and time preferences relate to their investment decisions. The empirical analysis, covering more than 9,000 deals, provides large support for our hypotheses. It reveals that more patient venture capitalists invest in ventures at an earlier stage of development and are more likely to exit via IPO. By contrast, more risk-averse venture capitalists invest in more mature firms and

[2] These insights relate to a wider literature suggesting that individual preferences matter for professional decisions (Cronqvist et al. 2012, Malmendier et al. 2011, Pool et al. 2019).

favor exit strategies involving trade sales; perhaps surprisingly, the results on risk are generally weaker than those on time preferences. Finally, the positive effect of venture capitalists' patience on the likelihood of an IPO diminishes with increasing risk aversion, highlighting a complex interplay between risk and time preferences.

To isolate the effect of venture capitalists' preferences on their professional behavior, we verify the robustness of our findings by controlling for an extensive set of individual and firm characteristics. Moreover, to get closer to causality, we exploit VC firms with multiple funds to estimate a difference-in-differences model, thus accounting for constant VC firm-level heterogeneity. Importantly, we also show that our results become insignificant when focusing on professionals who did *not* hold top positions in their VC firms and were thus unlikely to directly influence investment decisions. Additionally, we demonstrate that our results are attributable to individual preferences rather than being a by-product of the fund's time horizon (i.e., time preferences do not affect investment behaviors just because more patient investors are more common in VC funds that are far away from the exit period). Finally, our exploratory analysis indicates that more patient investors take longer to close a deal, possibly due to more extensive due diligence, are less control-oriented, as evidenced by a lower likelihood of holding voting rights or sitting on the boards of their portfolio firms, and syndicate less frequently with other investors.

This research advances our understanding of the psychological dimensions of venture capital (Lien et al. 2022, Zacharakis and Shepherd 2001, Zacharakis and Meyer 1998) complementing a large literature on the role of venture capitalists' characteristics, including their skills, education, and experience (Aggarwal et al. 2015, Bottazzi et al. 2008, Dimov and Shepherd 2005, Ewens and Rhodes-Kropf 2015, Zarutskie 2010). It also confirms that time, despite being "largely neglected in entrepreneurship research" (Lévesque and Stephan 2020, p. 164), plays a critical role in VC investment decisions. More broadly, our findings contribute to the growing literature on the role of top decision-makers' traits on strategic decisions and outcomes (Andrei et al. 2023, Benischke et al. 2019, Galasso and Simcoe 2011, Herrmann and Nadkarni 2014, Kaplan et al. 2022, Koh et al. 2018, Malmendier et al. 2023). Furthermore, this study contributes to recent works on the reasons why investors evaluate startups differently (Brooks et al. 2014, Franke et al. 2008, Ewens and Townsend 2020, Zunino et al.

2022) and to an ongoing research stream that uses surveys and experimental methods to map the preferences of top executives (Graham et al. 2013), investors (Bodnaruk and Simonov 2016), and entrepreneurs (Koudstaal et al. 2016). Finally, our research contributes to a small literature exploring the intricate interplay between risk and time preferences (e.g., Anderson and Stafford 2009) shedding light on how these two dimensions may jointly influence VC investment decisions.

2. Literature Background and Hypotheses

2.1 Venture Capitalists' Decision-Making

The literature on entrepreneurship has extensively examined the factors that may influence the investment decisions of VC firms. One stream of research focuses on aspects related to the entrepreneurial venture and its management team, including market position factors such as entry timing and competitive rivalry (Shepherd 1999), technology (Baum and Silverman 2004), and sales and revenue potential (Block et al. 2019, Eckhardt et al. 2006). VC firms also pay close attention to the entrepreneurial venture's management team, considering education (Ko and McKelvie 2018), gender (Kanze et al. 2018), functional or industry experience (Beckman and Burton 2008, Shepherd 1999), national identity (Bottazzi et al. 2016), social capital (Batjargal and Liu 2004), local networks (Balachandran and Hernandez 2021), and prior entrepreneurial success (Gompers et al. 2010). Motivational cues such as a passion for the product (Warnick et al. 2018) and preparedness (Chen et al. 2009) can also affect VC firms' investment decisions.

A second line of research examines the characteristics of VC firms themselves. Factors such as firm reputation (Nahata 2008, Petkova et al. 2014), experience (Aggarwal et al. 2018: Franke et al. 2008), past successes (Liu and Maula 2016, Nanda et al. 2020), network relationships (Milanov and Shepherd 2013), and VC partners' human capital (Dimov and Shepherd 2005) all play a role in investment decisions. The level of experience of venture capitalists has been shown to be positively related to their success rate (Sorensen 2007). Similarities between venture capitalists and entrepreneurs, such as background, experience (Franke et al. 2006), values (Matusik et al. 2008), geographic origins (Devigne et al. 2016), ethnicity (Bengtsson and Hsu 2015) and social attributes (Claes and Vissa 2020) have also been shown to matter for VC decision-making.

One might argue that due to their extensive knowledge and expertise, together with the intermediary nature of their role aimed at generating financial returns for the limited partners, venture capitalists' decision-making will be based on objective criteria such that biases are limited and personal preferences do not matter. Yet, some works suggest that this is not the case. Guler (2007) found that the sequential investment decisions of venture capitalists were biased, potentially due to emotional attachment and escalation of commitment. Shepherd et al. (2003) write that "experienced decision-makers appear to rely on various heuristics and other forms of mental shortcuts to the same extent as those lacking experience and this can lead them into equally serious errors". Moreover, venture capitalists have also been shown to be susceptible to gender stereotyping (Malmström et al. 2017) and to overreact to weak signals (Singh et al. 2015). Other works in the existing literature have hinted at the fact that individual characteristics and systematic biases may influence VC decision-making. For instance, Gompers and colleagues wrote that "the paucity of historical operating information and the uncertainty of future cash flows makes VCs' investment decisions difficult" and less likely to rely on "cash flow or net present value (NPV) techniques to evaluate their investments" (Gompers et al. 2020, pp. 170–171). As a result, venture capitalists' decisions can be highly subjective and influenced by personal preferences. We study how risk and time preferences influence venture capitalists' investment decisions.

Several works have recognized the importance of studying the role of time and risk in entrepreneurial ventures (Åstebro et al. 2014, Das and Teng 1998, Lévesque and Stephan 2020, Wood et al. 2021). Time and risk preferences are among the most fundamental factors shaping any investment decision, as evidenced by extensive surveys linking them to economic decisions across diverse contexts (Falk et al. 2018, Sutter et al. 2013, Tanaka et al. 2010). Consequently, understanding how these preferences influence venture capitalists' decisions can provide new insights into the dynamics of early-stage investments within the venture capital industry.

2.2 Time and Risk Preferences in Decision-Making

Time preferences are a key element of decision-making (Frederick et al. 2002) that have been related to educational outcomes (Duckworth and Seligman 2005), employment decisions (Della Vigna and

Paserman 2005, Doepke and Zilibotti 2008), personal finances (Ashraf et al. 2006, Meier and Sprenger 2013), lifetime income (Golsteyn et al. 2014), and environmental sustainability decisions (Newell and Siikamäki 2015). Some studies have even suggested that an individual's degree of impatience is a better predictor of field behaviors than usual demographic variables such as gender, age, or wealth (Chabris et al. 2008). There is also evidence that time preferences and related constructs affect managerial and entrepreneurial decisions and outcomes (Gutierrez et al. 2023). Scholars in this field have suggested that corporate short-termism—the tendency to undervalue the long run (Laverty 1996)—is a "disease" (Rappaport 2005, p. 65) that leads to undesirable outcomes such as excessive risk-taking (Rahmandad et al. 2018) and misconduct (Birhanu et al. 2016). By contrast, adopting a long-term orientation—a preference to value the future over the short-term (Shipp and Jansen 2021)—has been related to investment in long-term strategies (Flammer and Bansal 2017), competitiveness (Zhang and Gimeno 2016), and, overall, to higher long-term returns (Souder et al. 2016, Flammer and Bansal 2017).

Risk preferences, too, play a crucial role in decision-making. For instance, risk tolerance has been found to be a significant predictor of various individual behaviors, including smoking, underinsurance, and investment in the stock market (Barsky et al. 1997, Cutler et al. 2008, Dohmen et al. 2011). Moreover, risk preferences can affect career choices, as individuals with a lower tolerance for risk may choose occupations with lower earning risks (Bonin et al. 2007). Conversely, less risk-averse individuals are more likely to choose self-employment over wage work (Dohmen et al. 2011, Falk et al. 2018) or to migrate to find better opportunities (Jaeger et al. 2010). The literature further suggests that differences in risk preferences also play a crucial role in managerial decision-making (MacCrimmon and Wehrung 1990). To overcome the challenges in measuring the risk aversion of managers, scholars have used various indirect measures based on observed individual behaviors, exposure to traumatic events, and demographic characteristics. For instance, Wang and Yan (2022) used personal insurance premium rates to measure CEOs' risk aversion and found a substantial association with strategic decisions such as investment in corporate social responsibility. Using the birth order of CEOs, Campbell et al. (2019) reported that earlier-born CEOs, who are assumed to be more risk-averse, take fewer strategic risks, such as investments in R&D. There is also evidence that CEOs who engage in risky activities such as owning a private pilot's license, lead firms with a higher level of debt and more volatile stocks (Cain and McKeon 2016). Likewise, CEOs who experienced traumatic experiences in their youth, and are thus expected to be more risk-tolerant, manage firms with a higher stock price-crash risk (Chen et al. 2021). Studies using self-reported measures have also shown a relationship between the risk attitudes of executives and various aspects of corporate decision-making, such as mergers and acquisitions and corporate hedging (Bodnar et al. 2019, Graham et al. 2013). Opper et al. (2017) used incentivized decision tasks (similar to those used in our project) with a sample of Chinese CEOs and found that the degree of risk aversion was positively associated with a reliance on personal networks.

Collectively, these findings suggest that the time and risk preferences of firms' leaders help explaining various aspects of corporate decision-making. Risk and time preferences are close constructs, given that the future is inherently risky (Fisher 1930). Hence, studying each of them in isolation may generate biased results. Fortunately, there are enough differences between time and risk preferences (Andreoni and Sprenger 2012) which have allowed scholars to measure them separately and study their specific effects on decision-making (e.g., Falk et al. 2018, Sutter et al. 2013, Tanaka et al. 2010). Following this approach, we develop separate hypotheses for the influence of time and risk preferences on venture capitalists' decision-making. In particular, we focus on the choice of investing in early-stage vs. more mature ventures. As mentioned in the introduction, this is justified by the evidence in Gompers et al. (2020) showing that the venture's stage of development is the primary choice in VC's decision-making: 62% of US VC firms specialize in a particular stage.

2.3 Development of Hypotheses

VC firms set specific funds, which often have a limited lifetime of around ten years, and they commit to returning payouts to the limited partners (LPs) as the fund reaches its end.[3] A consequence of this feature is that as the fund gets older, the (remaining) time horizon to invest and exit from the investment becomes shorter. The time horizon of a VC fund can affect investment decisions as "patience wanes as the fund ages and approaches the termination date" (Yao and O'Neill 2022, p. 2831). Consistent with this view, there is evidence showing that older funds are more likely to terminate investments (Guler

[3] An exception to this norm is given by the so-called rolling funds, which have gained some popularity recently.

2007, Kandel et al. 2011). Time-horizon considerations can also affect the nature of the investments selected. As argued by Barrot (2017), there is a large degree of information asymmetry between initial investors and potential buyers. However, this information asymmetry decreases when the investment matures as outcomes become more observable. Funds are therefore incentivized to wait until investments have matured before exiting. Consequently, VC funds with longer investment horizons have a higher propensity to invest in firms at an earlier stage of development (Barrot 2017).

While the investment horizon of a fund affects the maturity of the ventures selected, the way venture capitalists assess the investment horizon and evaluate possible investments is largely *subjective*, and thus, individual characteristics may affect investment decisions. As noted, existing works have shown that differences in the age, education, or experience of venture capitalists have a substantial effect on investment decisions and outcomes (Dimov and Shepherd 2005). Research has also shown that time preferences matter in the context of household finance (Bianchi 2018). A growing body of literature in finance further suggests that the risk preferences of (professional) investors affect investment decisions and outcomes (Koijen 2014, Polkovnichenko et al. 2019, Riedl and Smeets 2017). Young ventures tend to be not only riskier than more mature entrepreneurial firms (Bruderl and Schussler 1990), but they also require more time before the realization of outcomes (Manso 2011, Tian and Wang 2014). Risk-averse or impatient venture capitalists are thus expected to choose to invest in more mature ventures that will generate a less uncertain financial return in the short term. By contrast, less risk-averse or more patient venture capitalists are expected to be more willing to invest in earlier-stage ventures and be involved with their portfolio firms for a longer period to reap the benefits of younger, more innovative ventures.

Hypothesis 1a: *Venture capitalists' patience is positively associated with investments in younger and less established ventures.*

Hypothesis 1b: *Venture capitalists' risk aversion is negatively associated with investments in younger and less established ventures.*

After making an investment and following an holding period, venture capital firms have to exit from such investments to realize financial returns for LPs. To this end, they can undertake different types of exit, most notably an IPO or a trade sale. This is a crucial decision for any VC, and there is substantial research on the determinants of exit (e.g., Ozmel et al. 2013, Yao and O'Neill 2022). As this literature shows, the two exit options differ in the level of uncertainty and the ability of an investor to time the exit. Exit via IPO has historically been a highly profitable option for VC firms. As documented by Lerner (1994) and Gompers (1995), startups yield the highest return for venture investors when they go public. Hence, a trade sale has been seen as the second-best form of exit, with the IPO being the most preferred in terms of upside potential (Cumming and Johan 2008). Even if comparing the profitability of different exit paths is difficult (e.g. due to the paucity of valuation information), it is clear that IPOs represent a valuable way for venture capitalists to generate financial returns. Yet, this exit path is typically rare and might apply to only a small subset of firms in the VC's portfolio. In fact, an IPO exit is usually considered riskier and more complicated to orchestrate because it requires favorable market conditions (Lerner 1994). Because these favorable market conditions are difficult to predict at the investment stage and may or may not occur within a given time horizon, VC firms may keep the new venture in their portfolio for *potentially* longer periods. As a result, the ability of a VC firm to undertake an exit via IPO is likely to depend on investors' patience, which in turn shapes the willingness to be involved with portfolio firms over time. Importantly, VC firms often maintain their investments in the firm even after its IPO, either due to lock-up clauses or because it is optimal for them to do so. In some cases, they may even increase their holdings in the firm post-IPO (Iliev and Lowry 2020). Hence, from a temporal perspective, the IPO represents only a partial exit route.[4] Moreover, exit decisions are influenced by the industrial specificities of the country (Kräussl and Krause 2014) and, specifically, institutional elements that affect the level of risk, such as an efficient legal system (Cumming et al. 2006), which in turn increase the likelihood of an IPO exit. By contrast, exit through a trade sale is favored when venture capital firms face increased temporal pressures to exit, and it represents a more flexible way of exiting the company (Yao and O'Neill 2022).

These arguments suggest that the risk and time preferences of venture capitalists may matter for the exit strategy. Risk-averse or impatient venture capitalists are expected to choose to exit through a trade sale because this route is less sensitive than an IPO to the occurrence of favorable market

[4] In the European context, exit via IPO has been shown to take more time than trade sales and acquisitions (Félix et al. 2014).

conditions and is generally less risky. By contrast, less risk-averse or more patient venture capitalists are expected to choose to exit through an IPO.

Hypothesis 2a: *Venture capitalists' patience is positively (negatively) associated with exit via IPO (trade sale).*

Hypothesis 2b: *Venture capitalists' risk aversion is positively (negatively) associated with exit via trade sale (IPO).*

3. Data and Methods

3.1 Survey Design

Surveys are a commonly used method for gaining insight into how investors make decisions, and have been widely employed in studies of professional investors (Bodnaruk and Simonov 2016, Da Rin and Phalippou 2017, Gompers et al. 2016, 2020, Strebulaev and Wang 2022). Building on similar approaches, we developed a survey aimed at measuring the economic preferences of venture capitalists in Europe (see the next section for details on the variables).

After developing a draft survey, we circulated it among academics and professionals in the VC industry for comments. This step enabled us to develop a better version by improving the style and language, including new questions and shortening others. The final version of the survey contained 15 questions and was designed in *Qualtrics*. We solicited all survey respondents via email, using a mailing list compiled from Pitchbook. In cases where Pitchbook did not provide an email address, two research assistants manually searched for the missing information. We identified all individuals on Pitchbook who had at least one professional experience in an entity identified as an independent venture capital, corporate venture capital, government venture capital, or angel investor in Europe. The time frame covers deals made from 1997 to 2022. From that list, we removed individuals who held junior positions (as identified by their full titles reported by Pitchbook), and thus, were not directly responsible for the investment strategies of their funds. In particular, we dropped individuals who had titles such as "Analyst," "Associate," or "Assistant".

We administered the survey between April 2022 and September 2022, using the Qualtrics website. In total, we sent 14,727 invitations (net of bounced emails). We sent a reminder to participants who did not reply after approximately one month. To encourage completion, we offered investors who completed the survey an early look at the aggregate results (after the survey was closed but before the results were released to the public) as well as an invitation to an academic workshop. Furthermore, participants were informed that those who completed the survey would be eligible to participate in a lottery with a monetary prize (a gift card of up to approximately €2,400) depending on their answers to the questionnaire. The survey was confidential, and all the reported results are based on the aggregation of many responses to prevent anyone from inferring the answers of any specific respondent. However, the survey was not anonymous, and we were able to match the responses with the information on Pitchbook to analyze how the economic preferences of respondents correlated with their investment strategies and outcomes.

The survey took participants approximately 15 minutes to complete, with a median completion time of 12 minutes.[5] As reported in Table 1, we received responses from 735 investors (amounting to a response rate of 5%), of which 358 made it to the end of the survey. Figure A1 of the Appendix shows the response rate by country. Focusing on their last position, 77.9% of respondents worked at an independent venture capital firm, 9.3% at a corporate venture capital unit, 1.2% at a government venture capital, and 8.5% as angel investors. Among respondents, 3.1% held positions in more than one class of investing entity (e.g., independent and corporate) at the same time.

3.2 Survey Measures

Our survey contained questions related to the individual economic and social preferences of venture capitalists as well as questions related to their demographic characteristics and the investment activities of their VC firms. Here, we describe the questions used in this empirical analysis.

In the first section, we asked two questions to better define the investment behavior of venture capitalists. The aim was to integrate the information provided by Pitchbook with additional details gathered through the survey. Specifically, following Gompers et al. (2020), we asked venture capitalists to provide information on the number of deals their firm considers in a typical year, the required internal

[5] The 25^{th} and 75^{th} percentiles were 8 and 19 minutes, respectively.

rate of return (IRR) from an investment, and how long they usually take to close a deal (i.e., number of days).

Next, we elicited the time preferences of the respondents by using a modified version of the method in Andersen et al. (2008). Time preferences are usually measured by asking participants to choose between a smaller but sooner payment versus a larger but later payment. This allowed us to measure to what extent the *present* and *future* are traded off (Sutter et al. 2019). In our survey, we used a payoff table with 14 questions (listed in Appendix Table A1). For example, Option A offered a payment of €400[6] in 1 month, while Option B offered an amount X ranging from €410 to €552 in 7 months (from question 1 to question 14). Participants were asked to choose between Option A and Option B for each of the 14 questions. The row in which participants switched from the payment in 1 month (Option A) to the payment in 7 months (Option B) represents the index used to assess the time preferences. The lower the switching point, the greater the individual's patience. The final payment that corresponded to this question was determined on a random selection of one of the 14 questions.

We elicited risk preferences using an incentivized multiple-price list lottery similar to the one developed by Koudstaal et al. (2016), which was based on the approach described by Dohmen et al. (2011). The participants faced 11 pairs of questions and were asked to choose between two lottery options (reported in Appendix Table A1). Option A was a risky choice, a lottery with a 50% chance of winning €330 and a 50% chance of winning nothing. Option B was a safe choice, a sure amount that increased in steps of €30 from one decision to the next (from €20 in row 1 to €310 in row 11). The *switching point* was calculated as the row in which participants switched between the lottery (Option A) and the sure amount (Option B). The sooner the participant switches from Option A to Option B, the greater the individual's risk aversion. The participant chose A or B in each row, and one row was later selected at random for the payout of the selected participant's amount.[7]

[6] To define the payoffs, we followed Andersen et al. (2008). We feel confident this is an acceptable amount to fairly pay the participants for the time spent answering the survey.

[7] Given that participants may make inconsistent decisions either by having more than one switching point or making backward choices—starting with Option B and switching to A (Charness et al. 2013)—we programmed both the risk and time preference questions in such a way as to enforce monotonicity. As soon as the participants switched from Option A to Option B, Option B was automatically selected for all the remaining rows.

We also included in the survey several questions taken from the World Value Survey (WVS). We used a question aimed at capturing the importance of luck, which is relevant as a control variable given the role of beliefs around luck in investment and risk-taking (Fisman et al. 2022). Participants were asked to rate the extent to which they agreed that the roles of luck and connections are important for individual success on a scale from 1 to 10, with higher values indicating that luck is more important than hard work. Moreover, we used a question that measured the extent to which participants believed that people could be trusted (on a scale from 0 to 4, where higher values indicate more trust). Accounting for this dimension is important in light of the evidence from Bottazzi et al. (2016), who reported that trust influences VC decisions.

Concerning the demographic details, we only requested survey respondents to state their year of birth because we had access to the other basic demographic information through Pitchbook. The survey also contained further behavioral traits (i.e., loss and ambiguity aversion) (as in Koudstaal et al. 2016). These variables were used to check the robustness of our results. Finally, the survey also contained an incentivized modified dictator game that used a charity association as a counterpart and three WVS questions related to interpersonal relationships and gender preferences. These variables were not used for the analysis given that they were not central to the research question of this paper.

3.3 Measures From Other Sources

We constructed a set of individual-level variables, which we used as controls in the analysis. First, we employed a discrete variable that identified the highest level of education attained by the investor. The variable was equal to 0 if the investor did not attain any degrees, 1 if the investor attained a BSc degree, 2 if the investor attained an MSc degree, 3 if the investor attained an MBA, and 4 if the investor attained a PhD. One of the questions in the survey asked respondents to provide their year of birth, which we used to calculate their age. For those who did not respond to this question, education and age were retrieved by manual searches on LinkedIn and investors' websites, or inferred by looking at the years elapsed since the year when they obtained their bachelor's degree. In such cases, age was calculated as the number of years that elapsed since the degree plus 22. Using Pitchbook, we were also able to identify the gender of the respondents, their prior entrepreneurial experience (i.e., whether they appeared as a founder in any of the firms), and VC experience (computed as the number of deals made as lead partner by the respondent).

Then, we matched respondents to the investor firms they worked for. To ensure that the respondents played an active role in such firms, we only considered investments completed by the respondents' firms during their job tenure. Given that information on the start and end date is often missing in Pitchbook, we retrieved it manually from LinkedIn or investors' websites. Moreover, for the main analysis, we focused on investments completed by the firms in which the respondents held top management positions (as identified by their full titles reported in Pitchbook). The reason for this is that the risk and time preferences of the respondents should be relevant for the VC investments only when the respondents held top management positions (so they could actively influence the investment decisions of their firms). To identify such top management positions, we considered titles such as "Partner", "GP", "Head", "President", "VP", "Founder", "Founding", "Principal", "Managing Director", "Investment Director", "Executive", "Chief", "Chairman", "Chairwoman", and "CEO". If one of these words appeared in the title of the respondent, or if the respondent was an angel investor, then we considered the respondent as having a top management role, and thus, we retained the deals completed by the investor. In the rare case in which two or more respondents worked for the same firm at the same time and held top management positions, we retained the survey responses of the individual with the longest tenure at the VC firm (we thus dropped the deals completed by 17 respondents).

To ensure that the risk and time preferences of investors affected their firms' investments, in a robustness analysis, we also retained investments completed by firms in which the respondents did not hold the above-mentioned roles, and we conducted a separate analysis for respondents holding titles such as "Venture Analyst," "Manager," and "Consultant." In the following section, we show that the results were largely insignificant when using these respondents.

Information on deals was obtained from Pitchbook, which is one of the most comprehensive databases in entrepreneurial finance and is regularly used by researchers in venture capital as well as by professional investors (e.g., Yu 2020, Yao and O'Neill 2022). The information provided by Pitchbook is mainly based on disclosed information from LPs and GPs, filings of national regulators, and other publicly available information. From Pitchbook, we obtained information on the date and the amount (in USD) invested by VC firms in startups, the founding year of the startup, and whether and how the investor exited, among others. Details on the key variables are reported in the next section.

3.4 Samples and Summary Statistics

Table 1 reports information on the number of people who took part in our survey. As previously mentioned, out of the 14,727 invitations, we received a response from 735 people (amounting to a response rate of 5%), of which 358 (49%) completed the survey in full. Of these, we have full information on all relevant variables (including those retrieved from Pitchbook) for 347 respondents. At the time of responding to the survey, the respondents held positions at 758 unique investment firms or as business angels.[8] 2% of the respondents did not permit us to use their responses, whereas 1% of them delegated the fulfillment of the survey to someone else.[9]

INSERT TABLE 1 HERE

Table 2 presents the main variables used in the regression analyses, while Appendix Table A2 provides a description. As shown in Panel A, 78% of the respondents held at least one top management position in their firm. Their average age was 45, and 12% of respondents were females. About one-third of them had at least one experience as a founder and, on average, a VC experience of 4 deals as lead partner.[10] Regarding the main explanatory variables, the mean value for patience was 8.6 (on a 0–14 scale), whereas the mean for risk aversion was 5.2 (on a 0–11 scale). Importantly, these variables display a fairly high standard deviation. That is, venture capitalists are quite heterogeneous in terms of time and

[8] The number of unique investment firms may differ from that of unique investors for two reasons: (1) multiple respondents can work at the same investment firms; (2) respondents can hold positions at more than one investment firm.

[9] Figure A2 of the Appendix reports the geographic origin of the investors who responded to our survey (indicated by the red bars). The most represented countries are the UK (20%), Germany (12%), the Netherlands (10%), and Sweden (8%). The figure also shows (indicated by the grey bars) the representation of each country in the universe of investors drawn from Pitchbook, applying the same restrictions for identifying the survey sample, i.e., VC investors in top positions. As shown, the proportions of each country within the respondents sample largely mirrors the relative size of their VC markets in Europe.

[10] Appendix Table A3 offers a comparison of the demographic characteristics between the survey respondents and the population of VC investors in Pitchbook. As shown, respondents are largely similar to the population with two exceptions: respondents are, on average, one year older and are more likely to hold a Ph.D.

risk preferences. This counters existing portraits of venture capitalists as somewhat patient investors with a high appetite for risk. The correlation between patience and risk aversion was equal to 0.236.

In the survey, as mentioned before, we further asked the respondents the average time it took them to close a deal, the required IRR from an investment, and the number of deals considered in the last year. As shown in Panel B, the average number of days to close a deal was approximately 98 (median of 90), which is fairly close to the value reported in Gompers et al. (2020) (83 days). The average required IRR was 46 (median of 25), which is above the value found in Gompers et al. (2020) (31) but the median value in our sample was close to that in that study. Finally, the average number of deals considered by the responders in our sample was 222 (median of 50).

Panel C reports information at the deal level. We had 9,787 deals completed between 2000 and 2020 (after excluding deals with missing values concerning key variables) while the respondents held a top management position in an investment firm or as an angel investor. These deals involved 6,317 unique ventures. On average, ventures receiving funding from our sample of investors were 4 years old, with 31% classified as late-stage by Pitchbook. The average amount raised by the startup up to the focal deal was equal to approximately $27.4 million (median of $4.4 million), and the average deal size was $14.6 million (median of $3 million). Approximately 24% of the deals included terms that granted investors voting rights. Syndication was prevalent, occurring in 81% of the deals, with an average syndicate comprising 3.5 partners.

As reported in Panel D, roughly 25% of the investors had a director sitting on the board of the startups they invested in (the level of analysis here is the deal-investor, and this explains the number of observations). Finally, focusing on exit strategies, we find that 6.2% of the investors exited through an IPO, and 25.3% exited through a trade sale, translating to absolute figures of 230 and 894 exits, respectively.[11]

[11] We restrict the sample to the first investment completed by the investor in the venture so that each investor-venture pair was unique, even if the investor had invested multiple times in the same venture. Furthermore, we restrict the sample to deals completed by December 2017. As we tracked ventures until mid-2022, this procedure allowed for a minimum of 4.5 years to exit from an investment (Nahata 2008). These restrictions explain why the exit variables in Panel D cover 3,726 observations rather than the 9,787 observations in Panel C.

INSERT TABLE 2 HERE

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4. Results

4.1 Venture Selection

In Hypothesis 1a, we argued that venture capitalists' *patience* is positively associated with investments in younger and less established ventures, whereas in Hypothesis 1b, we argued that venture capitalists' *risk aversion* is negatively associated with investments in younger and less established ventures. To test these hypotheses, we used OLS regressions where the dependent variables were the natural logarithm of 1 plus the age of the venture (in years) at the time of the deal (Columns 1 and 2 of Table 3). As alternative measures, we used a dummy that had a value of 1 if the investment was in a late-stage venture and a value of 0 elsewhere (Columns 3 and 4 of Table 3), or the natural logarithm of 1 plus the amount raised by the venture up to the time of the focal deal (Columns 5 and 6 of Table 3). These can be considered different measures of the stage of development of the ventures that received funding from the investors in our study.

The main explanatory variables were investors' *patience* and *risk aversion*. Both variables were standardized to have zero mean and variance equal to 1. To isolate the specific effect of time and risk preferences, we include both variables in the regression analyses; however, our results hold if we include them separately. In all models, we control for the effects of time, geography, industry, and investor type on the outcomes of interest. In particular, we included a set of dummies for the year of the investment, the countries where the startup and the investor were based, the industry where the startup operated, and the classification of investors provided by Pitchbook (e.g., venture capital, corporate venture capital, etc.). In Columns 2, 4, and 6 of Table 3, we further included the individual characteristics described in the previous section to control for the effects of demographic traits, experience, and beliefs on the outcomes of interest. Specifically, we control for VC experience, individual age, founding experience, gender, and the highest educational degree attained. Moreover, we control for the respondents' trust and luck beliefs from the WVS questions (both standardized). Standard errors were clustered at the investor level.

A one-standard-deviation increase in investors' patience led to a 6 percent decrease in the age of the startups they invested in (Columns 1–2), and a 4 percentage-point decrease in their probability to invest in late-stage startups (Columns 3–4). Furthermore, more patient venture capitalists invested in less established startups, i.e., ventures that had raised 23% less money up to the focal deal (Columns 5–6). Table 3 also shows the statistically significant effect of the risk aversion of respondents on most of the outcomes considered: risk-averse respondents were more likely to invest in older and later-stage startups (Columns 1–4) but the effect is insignificant if we focus on the amount previously raised by the ventures. Among the control variables, the strongest effect originated from the variable corresponding to founder experience: investors who were previous entrepreneurs were significantly more likely to invest in younger and less developed firms. In Appendix A6, we further show the results obtained using the logarithm of deal size as dependent variable: patient investors make significantly smaller deals (which is in line with the previous evidence on their tendency to invest in younger and less established firms).

INSERT TABLE 3 HERE

While the results so far are consistent with our hypotheses, ascertaining causality is difficult. To provide a causal interpretation, we re-estimated the model in Table 3 separately for respondents who worked at VC firms that were the lead investors in the given deal. The intuition is that risk and time preferences should have a more pronounced impact on startup selection for lead investors, as they actively shape the direction of the investment compared to non-lead investors, who typically follow the lead of other VC firms. Figure 1 illustrates the point estimates of time and risk preferences obtained by estimating the models in Table 3 separately for lead and non-lead investors. As shown, the economic magnitudes are almost always larger for lead investors, though we also observe some statistical significance for non-lead investors. As an alternative test, we re-estimated the models by retaining only the deals completed by investors in which respondents did *not* hold top management positions. In such cases, the economic preferences of the respondents should not substantially influence investment behavior. Consistent with this notion, we found that the coefficients of patience and risk aversion were insignificant (Appendix Table A4).

INSERT FIGURE 1 HERE

Furthermore, we estimated a difference-in-differences model that took advantage of the fact that certain VC firms have multiple (sequential) funds (Table 4). We linked the respondents to the funds they worked for (and where they held top management positions, as previously defined) while using the fund(s) raised by the same VC firms before the respondents joined them as counterfactuals.[12] Leveraging this longitudinal variation allowed us to control for constant heterogeneity at the VC firm level. To ensure the consistency of the VC firm behind the VC fund, we excluded those funds that were raised jointly by two or more firms. We constructed a dummy variable (*Post Entry*), which was equal to 1 for the period following the entry of the respondents into a fund of a VC firm, and 0 for the same firm in the period prior to the entry of the respondent into a firm's fund. We then interacted this dummy with the level of patience and risk aversion of the respondents. As a result, the coefficient of patience remained statistically significant, validating our prior findings. However, the coefficient of risk aversion is insignificant.

Another challenge for the interpretation of our results is that venture capitalists with certain economic preferences (e.g., more patient) self-select into VC funds with longer time horizons. If so, our results will not capture the effects of individual characteristics on investment decisions but, instead, those of the funds' time horizon. To alleviate this concern, we estimated a regression in which the dependent variable is the funds' vintage year, and the right-hand side of the model includes the variables that we used so far (Appendix Table A5). This analysis was performed at the fund level and included the observations for which the vintage year was available in Pitchbook. We found no significant

[12] For a few large funds, we had more than one respondent; thus, we retained the answers provided by the individual with the most senior position or with the longest experience in VC if they had the same title. We discerned the funds that VC firms raised prior to the ones in which the respondents participated by using Pitchbook, which provides information on the chronological order of the funds raised by VC firms.

association between the risk and time preferences of individuals and the vintage year of the VC fund where they work, which suggests that our results are not driven by the selection of more patient (or less risk averse) venture capitalists into VC funds with longer horizons.

INSERT TABLE 4 HERE

4.2 Exit Strategies

Hypothesis 2a proposes that venture capitalists' patience is positively (negatively) associated with exit via IPO (trade sale), whereas Hypothesis 2b proposes that venture capitalists' risk aversion is negatively (positively) associated with exit via IPO (trade sale). To test these hypotheses, in Column 1 of Table 5, we use as a dependent variable a dummy that had a value of 1 if the investor exited through an IPO from its investment in the startups, and 0 otherwise. In Column 2, we use as a dependent variable a dummy that had a value of 1 if the investor exited through a trade sale from its investment in the startup, and 0 otherwise. In this analysis, each investor-portfolio company pair was unique, even though the investor may have participated in multiple rounds of financing. When this happened, we retained only the first investment in the startup (Nahata 2008). As noted earlier, we restricted the sample to deals completed by December 2017; tracking startups until mid-2022, this procedure allowed for a minimum of 4 years for an investor to exit from an investment. In unreported analyses, we checked the robustness of the findings by considering only deals completed by December 2016 to give investors an additional year to experience a successful exit.

We used linear probability regressions with the same set of controls as in Table 3. Furthermore, since we previously found that investors' patience and risk aversion influence the type of ventures funded, we further included variables that accounted for differences in startup characteristics, such as the age and stage of development of the startup at the time of the deal, the cumulative amount raised by the startup up to the focal deal, and the size of the focal deal (i.e., the three dependent variables used in Table 3). Adding these controls is useful to ensure that the effects of patience and risk aversion on the exit strategies are not merely driven by the differences in the selection of startups. Standard errors are again clustered at the investor level.

The results presented in Table 5 corroborate our hypotheses, albeit only at the 10% level for some analyses. A one-standard-deviation increase in patience improves the chances of exit via IPO by roughly 1 percentage point (Column 1) but decreases the likelihood of a trade sale by roughly 3.1 percentage points (Column 2). Similarly, a one-standard deviation increase in risk aversion decreased the likelihood of exit via IPO by 1 percentage point (Column 1) but increased the likelihood of a trade sale by roughly 1.9 percentage points (Column 2).

As shown earlier, a large portion of the deals in our sample are syndicated. This may raise the question of how the time and risk preferences of an individual venture capitalist might impact the exit outcomes. In Columns (3) and (4) of Table 5, we show that the effects of time and risk preferences on the exit type are economically and statistically stronger when focusing on deals in which the venture capitalist included in our sample was the lead investor, potentially exerting a more influential voice in determining the venture's exit strategy.[13]

INSERT TABLE 5 HERE

In supplementary analyses, we explored the interaction effect between investors' patience and risk aversion in shaping the two exit strategies. Specifically, we re-estimated the regression in Table 5 by also including the interaction between patience and risk aversion. Figure 2 shows the plot of the coefficient of the effect of patience on IPO and trade sales (and relative 95% confidence intervals) along the different values of risk aversion. As shown in the left panel of Figure 2, patience has a significant positive effect on IPO exit for low to moderate levels of risk aversion; such a positive effect declines with risk aversion and becomes insignificant when risk aversion is high. In other words, patience can increase the likelihood of an IPO when the investor is also prone to take risks. The right panel of Figure

[13] Going beyond the result for lead investors, we speculate that venture capitalists' time and risk preferences may matter for exit because, for example, investors with similar preferences tend to sort into the same syndicate. Our data are not adequate to capture this effect because we have multiple respondents in the same syndicate in a very limited number of cases.

2 indicates that the negative effect of patience on exit through a trade sale does not substantially change as a function of risk aversion.

INSERT FIGURE 2 HERE

4.3 Post-hoc Analysis

This section includes a set of additional analyses that provide further insights into the role of time and risk preferences in VC decision-making, but for which the existing theory does not allow the development of clear hypotheses. First, we used the survey questions regarding the average number of days it takes for respondents to close a deal, the number of deals considered in the previous year, and the required IRR from an investment, as dependent variables in Columns 1–3 of Table 6. Given the unit of observation was a single response, our controls were limited to individual-level factors without considering specific startup characteristics. As shown in Column 1, more patient investors spent substantially more time to close a deal (potentially owing to a longer due-diligence phase), with a one-standard-deviation increase in patience lengthening the time to close a deal by 12.2%. This thoroughness in selection may contribute to the higher likelihood of exiting through an IPO observed among patient venture capitalists. Conversely, respondents' patience does not bear any substantial effect on the number of deals considered in a year (Column 2) nor on the required IRR (Column 3). Similarly, respondents' risk aversion does not appear to have any significant effect on these variables.

Next, we evaluate the characteristics of the deals in our sample. Several studies have explored how the involvement of VC firms in the startups they have invested in affects the success rates of those startups. The extent to which VC firms can influence the key decisions undertaken by startups is defined in the contracts, which establish how the relationship between the startup and the investors will unfold in the short and long term (Ewens et al. 2022). Broadly, these contracts allocate cash flow and control rights (Kaplan and Strömberg 2003), which might include, among others, the possibility for the investors to sit on the board of the startups in their portfolio or have voting/veto rights. The extent of control rights over the startup may provide an additional explanation for the exit strategies of VC firms, which we documented in the previous section. Existing works show that the exit strategy of VC firms depends on the distribution of control between investors and the entrepreneur (Cumming 2008). As entrepreneurs exhibit a strong preference for exit via IPO because it increases private benefits while allowing them to stay involved in the firm (Cumming and Johan 2008, Schwienbacher 2008), lower control of the VC firm over the startup increases the chances of exiting through an IPO. Because more patient (less risk-averse) investors prefer exiting through an IPO rather than an acquisition, they might opt for a more hands-off approach.

Venture capitalists can exert control over the startups in their portfolio in two ways: by sitting on their board and by acquiring voting rights. In the remainder of Table 6, we used as a dependent variable a dummy that had a value of 1 if someone who represented the investor sat on the board of the startup (Column 4), and a dummy that had a value of 1 if the terms of the deals granted voting rights to the investors (Column 5). The first analysis was conducted at the investor-deal level, whereas the second was at the investor-startup level (and this explains the larger sample size in Column 5). We applied a linear probability model and adopted the same set of control variables as in the previous regressions. Standard errors were clustered at the investor level. The results showed that more patient individuals were less likely to sit on the board of the startups in their portfolio and to hold voting rights. Conversely, risk aversion did not influence the investors' propensity to sit on the board of their portfolio startups, but increased their propensity to participate in deals allocating voting rights to them.

The choice of syndicate partners is also crucial for the outcomes of an investment. VC partners not only share the risk associated with the investment but also share managerial and financial resources (Brander et al. 2002, Manigart et al. 2005). Once the VC has chosen its investment partner(s), they become mutually dependent on each other (Meuleman et al. 2010). By diffusing information within a network (Sorenson and Stuart 2001), syndication has the potential to increase the quantity and quality of resources available for screening and monitoring activities, counteracting information asymmetries (Tian 2012), thus reducing the riskiness of the investments and facilitating the fast growth of the startup after the investment. We tested whether patience and risk preferences influenced the propensity to syndicate. Again, we estimated OLS regressions at the investor-deal level and computed standard errors clustered at the investor level. The analyses reveal that patience decreased both the propensity to syndicate (Column 6) and the size of the syndicate partnership (Column 7). A possible interpretation is that less patient investors that seek quicker exit may resort to other investors' opinions, networks and resources to grasp the exit potential of their investments. Risk aversion, surprisingly, showed no significant relationship with syndication, despite its potential to reduce investment risk through collaborative efforts. This could be because syndicated investments, while distributing risk among investors, tend to be inherently riskier (Brander et al. 2002), countering the expected risk reduction.

INSERT TABLE 6 HERE

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5. Conclusion

Several recent works have emphasized the problems of short-termism for firm strategies (Sampson and Shi 2023, Qian et al. 2023). At the same time, scholars have debated how to incentivize executives to tolerate the failure intrinsic to certain value-creating actions like innovation (Manso 2011). Combining insights from behavioral economics and entrepreneurship research, this study contributes to the literature by theorizing and empirically showing that venture capitalists' patience is positively associated with the length of time horizons in decision-making and thus reduces the pressure to realize gains in the short term. By contrast, venture capitalists' risk aversion is positively associated, albeit less precisely, with investments into larger and more established firms, which are closer to exit. Time and risk preferences also matter for the exit strategies of VC firms: patience spurs the ability to exit via IPO, whereas risk aversion increases the probability of exiting through a trade sale. Our conclusions are based on comparative primary data collection through a large-scale survey including incentivized decision tasks, which captured information regarding the time preferences, risk aversion, and demographic characteristics of individuals holding top management positions in European VC firms.

Our study makes a step towards a better understanding of the behavioral mechanisms underlying the decision-making of venture capital. In particular, we assessed how individual-level time and risk preferences shape the investment decisions of venture capitalists. In so doing, we delve into a rather unexplored but highly relevant research topic that concerns the role of economic preferences in shaping the evaluations of entrepreneurial projects by venture capitalists. Given the difficulty in getting first-hand individual data, our study is unique in its ability to measure the individual preferences of venture capitalists and connect them to behaviors and outcomes.

However, our study faced limitations that should be taken into account. First, one of the challenges with primary data collection in the form of a survey is that participants self-report their answers. Although we aimed to increase the reliability of the survey by incentivizing the questions on economic preferences, some answers remained purely self-reported. Second, there are potential unobserved heterogeneity problems. That is, unobserved characteristics of venture capitalists may explain their investment decisions in ways that can alter our results. Third, we measured time and risk preferences at a given point in time and used them to explain the decisions of venture capitalists for all years in the sample; in so doing, we implicitly assumed that time and risk preferences are temporally stable.[14] Future research could address these limitations by investigating the decision-making of venture capitalists in experimental settings, allowing for more direct observation and isolation of the behavioral mechanisms, as well as manipulation of time and risk preferences. It would also be useful to replicate our findings in larger samples drawn from different institutional contexts. Finally, future studies can transcend our focus on time and risk preferences and study the role of social preferences or other behavioral traits.

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[14] Some works have suggested that time preferences tend to be stable (Meier and Sprenger 2015). Risk aversion has also shown certain stability (Beauchamp et al. 2017), even though scholars have pointed to time variations following adverse events (Guiso et al. 2018).

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Figures and Tables

Figure 1. Results for Lead and Non-Lead Investors

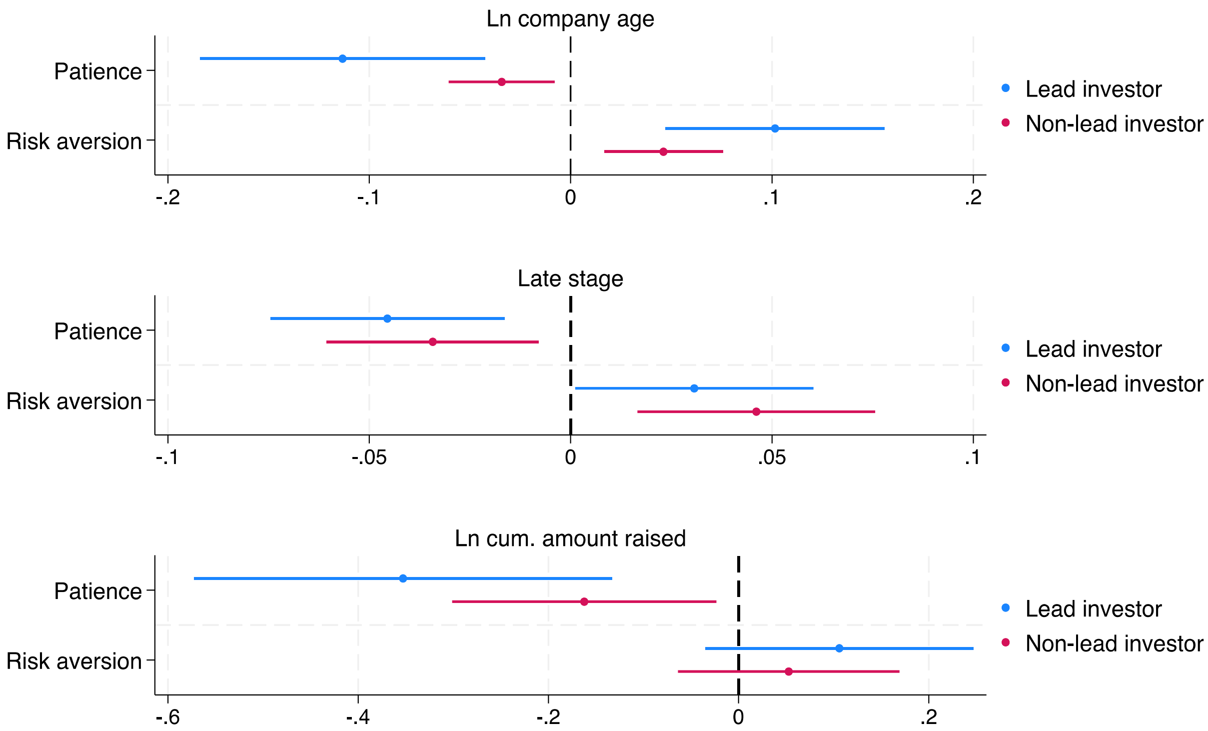
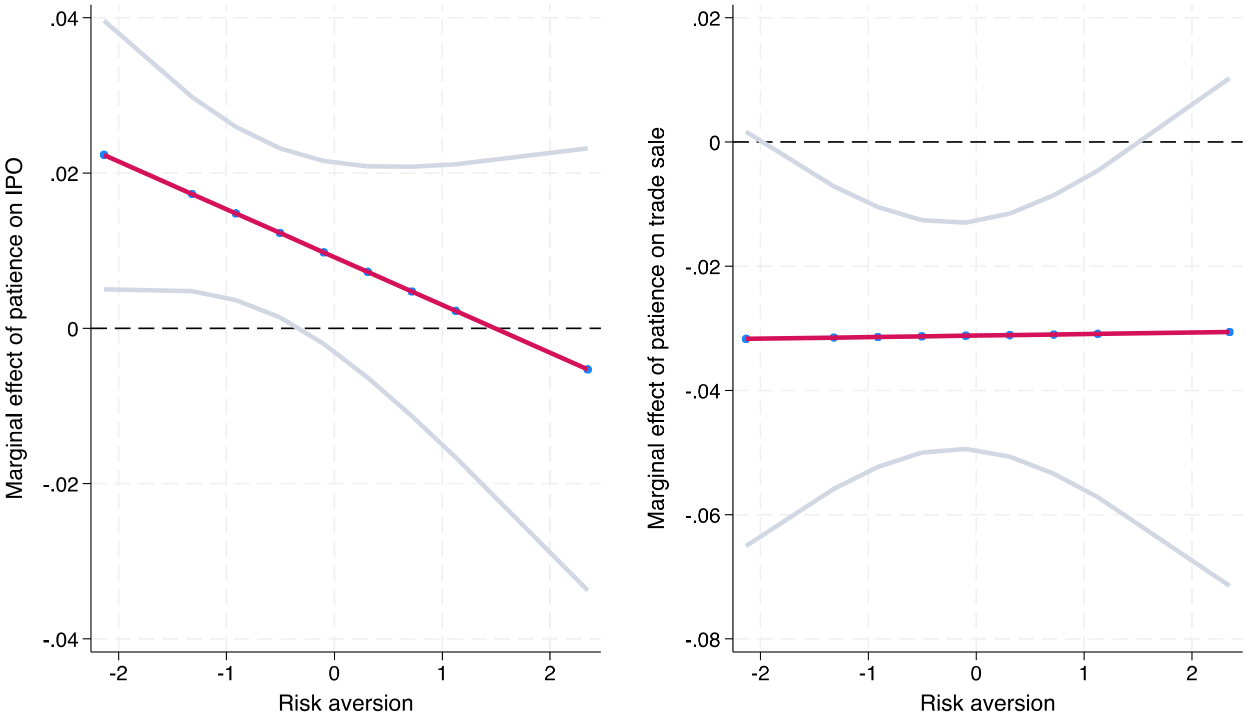


Figure 2. Effect of patience on exit modes by different levels of risk aversion



These figures show the results obtained by estimating the regression in Table 6 by also including the interaction between patience and risk aversion. The figures plot the marginal effects of patience on IPO (left panel) and trade sale (right panel) and relative 95% confidence intervals along the different values of risk aversion.

Table 1. Survey Completeness

	Number	%
Unique respondents	735	
Survey completed	358	48.7%
No consent given	17	2.3%
Completed for someone else	9	1.2%

This table reports information on the number of people that have taken part in our survey. *Unique respondents* provide information on the number of people that replied to our survey. *Survey completed* reports information on the number (and the relative percentage) of respondents that completed the survey. *No consent given* reports information on the number (and the relative percentage) of respondents who did not give consent to use their responses. *Completed for someone else* reports information on the number (and the relative percentage) of respondents that delegated the fulfillment of the survey to someone else.

Table 2. Summary Statistics

	Obs.	Mean	s.d.	Median
Panel A. Individual characteristics				
Top management role	347	0.781	0.414	1
Age	347	45.487	11.598	47
Female	347	0.121	0.326	0
Founder experience	347	0.314	0.464	0
VC experience	347	4.121	8.001	1
Patience	347	8.786	4.497	10
Risk aversion	347	5.328	2.286	6
Luck	347	3.605	1.926	3
Trust	347	2.478	0.881	3
Panel B. Investment characteristics				
Days to close a deal	347	97.983	54.609	90
Number of deals considered	347	222.660	424.41	50
Required IRR	347	46.531	109.571	25
Panel C. Deal-level characteristics				
Company age	9,787	4.135	3.573	3
Late-stage round	9,787	0.307	0.461	0
Cum. amount raised	9,787	27.434	108.958	4.482
Voting rights	9,787	0.239	0.427	0
Syndication	9,787	0.807	0.395	1
Syndicate partners	9,787	3.521	3.969	3
Panel D. Investor-venture level characteristics				
IPO	3,726	0.062	0.241	0
M&A	3,726	0.253	0.403	0
Board seat	7,108	0.246	0.431	0

This table reports summary statistics concerning the main variables used in the regression analyses. The variables are described in detail in Appendix Table A2.

Table 3. Patience, Risk aversion, and Startup Selection

Dependent variable:	Ln company age		Late-stage round		Ln cum. amount raised	
	(1)	(2)	(3)	(4)	(5)	(6)
Patience	-0.0487**	-0.0578**	-0.0335***	-0.0391***	-0.2374***	-0.2333***
	(0.025)	(0.026)	(0.013)	(0.013)	(0.085)	(0.088)
Risk aversion	0.0688**	0.0842***	0.0396**	0.0429***	0.0828	0.0655
	(0.031)	(0.023)	(0.017)	(0.013)	(0.068)	(0.057)
Ln age		0.1982***		0.1109**		0.1745
		(0.072)		(0.051)		(0.267)
Female		0.1004		0.0686*		0.3238
		(0.063)		(0.041)		(0.215)
Founder experience		-0.2038***		-0.1194***		-0.4103***
		(0.041)		(0.025)		(0.130)
VC experience		0.0197		0.0143		0.1228***
		(0.017)		(0.010)		(0.047)
Luck		0.0068		-0.0061		-0.0709
		(0.017)		(0.010)		(0.054)
Trust		0.0165		0.0240**		0.0267
		(0.020)		(0.012)		(0.066)
Deal year	Yes	Yes	Yes	Yes	Yes	Yes
Investor country	Yes	Yes	Yes	Yes	Yes	Yes
Company country	Yes	Yes	Yes	Yes	Yes	Yes
Company industry	Yes	Yes	Yes	Yes	Yes	Yes
Investor type	Yes	Yes	Yes	Yes	Yes	Yes
Education dummies	No	Yes	No	Yes	No	Yes
Observations	9,787	9,787	9,787	9,787	9,787	9,787

This table presents the results of OLS regressions. The unit of observation is the respondent-deal. All deals completed by the firms for which the respondent was working during his/her tenure were retained. The variables are described in detail in Appendix A2. Standard errors clustered by investor are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 4. Patience, Risk aversion, and Startup Selection: Difference-in-differences

Dependent variable:	Ln company age	Late-stage round	Ln cum. amount raised
	(1)	(2)	(3)
Patience×Post-entry	-0.0389**	-0.0285**	-0.2479***
	(0.019)	(0.014)	(0.036)
Risk aversion×Post-entry	-0.0211	-0.0183	0.0476
	(0.025)	(0.019)	(0.044)
Investor FE	Yes	Yes	Yes
Observations	5,507	5,507	5,507

This table presents the results of difference-in-differences regressions. The unit of observation is the respondent-deal. All deals completed by the funds for which the respondent was working were retained. The deals completed by the funds raised before the funds for which the respondents worked are used as counterfactuals. *Post-entry* is a dummy having value 1 for the deals completed by funds for which the respondents were working for; 0 for the deals completed by funds belonging to the same firm but raised before the fund joined by the respondent. Deals completed by funds raised by multiple investors were dropped. When we had more than one respondent per fund the most senior respondent was considered. The other variables are described in detail in Appendix A2. Standard errors clustered by investor are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 5. Patience, Risk aversion, and Exit Strategy

Dependent variable:	IPO	Trade sale	IPO	Trade sale
	(1)	(2)	(3)	(4)
Patience	0.0096*	-0.0312***	0.0257***	-0.0348**
	(0.0057)	(0.0093)	(0.0082)	(0.0160)
Risk aversion	-0.0096*	0.0194**	-0.0130**	0.0409***
	(0.0053)	(0.0082)	(0.0063)	(0.0125)
Ln age	-0.0008	-0.0190	-0.0096	0.0447
	(0.0274)	(0.0394)	(0.0395)	(0.0777)
Female	0.0681**	-0.0285	0.1269***	-0.0173
	(0.0282)	(0.0369)	(0.0447)	(0.0634)
Founder experience	0.0127	-0.0204	-0.0184	0.0569*
	(0.0135)	(0.0195)	(0.0180)	(0.0320)
VC experience	0.0031	0.0071	0.0022	0.0032
	(0.0040)	(0.0078)	(0.0080)	(0.0152)
Luck	-0.0036	0.0125	-0.0133	-0.0007
	(0.0066)	(0.0079)	(0.0081)	(0.0130)
Trust	-0.0025	0.0147	-0.0114	0.0002
	(0.0048)	(0.0102)	(0.0080)	(0.0169)
Ln company age	-0.0054	0.0186	-0.0059	0.0315*
	(0.0057)	(0.0127)	(0.0077)	(0.0160)
Late-stage round	0.0375**	-0.0568***	0.0338	-0.0802**
	(0.0165)	(0.0203)	(0.0237)	(0.0346)
Ln cum. amount raised	0.0423***	0.0277	0.0184	0.0550
	(0.0060)	(0.0195)	(0.0255)	(0.0377)
Deal year	Yes	Yes	Yes	Yes
Investor country	Yes	Yes	Yes	Yes
Company country	Yes	Yes	Yes	Yes
Company industry	Yes	Yes	Yes	Yes
Investor type	Yes	Yes	Yes	Yes
Education dummies	Yes	Yes	Yes	Yes
Observations	3,726	3,726	1,423	1,423

This table presents the results of OLS regressions. All deals completed by the firms for which the respondent was working during his/her tenure were retained, and in the case of multiple deals in the same venture, we retained the first one. We also restricted the sample to deals completed by December 2017 so as to allow sufficient time to realize the exit. Columns (3) and (4) re-estimate the models in Columns (1) and (2) by restricting the analysis to deals in which the investor in our survey was the lead investor. The variables are described in detail in Appendix A2. Standard errors clustered by investor are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 6. Patience, Risk aversion, Investment and Management Style

Dependent variable:	Ln days to close a deal	Ln number of deals	Required IRR	Board seat	Voting rights	Syndic-ation	Ln syndicate partners
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Patience	0.1218***	-0.0984	-4.3202	-0.0426**	-0.0256**	-0.0502**	-0.0950**
	(0.0352)	(0.1153)	(8.3916)	(0.017)	(0.011)	(0.021)	(0.039)
Risk aversion	-0.0125	0.074	-10.5721	0.0092	0.0212**	-0.0061	-0.0354
	(0.0375)	(0.1047)	(8.0087)	(0.018)	(0.009)	(0.010)	(0.027)
Ln age	0.5044***	-1.5555***	-2.8306	0.0403	-0.0190	0.0019	-0.0622
	(0.1587)	(0.3911)	(17.1082)	(0.074)	(0.030)	(0.041)	(0.095)
Female	0.0437	0.2211	-11.6501	0.0810*	0.0087	0.0551	0.1049
	(0.1149)	(0.3128)	(8.6442)	(0.045)	(0.029)	(0.034)	(0.085)
VC experience	-0.2848***	-0.2323	-4.0065	-0.1342***	-0.0271	-0.0180	-0.0288
	(0.0841)	(0.2313)	(17.9614)	(0.035)	(0.018)	(0.018)	(0.043)
Founder experience	0.0329	0.4914***	-4.1611	0.0540***	0.0057	0.0102	0.0319
	(0.035)	(0.1107)	(3.1802)	(0.016)	(0.008)	(0.008)	(0.019)
Luck	0.0893**	-0.1468	-8.6902*	-0.0057	-0.0029	-0.0024	-0.0014
	(0.0354)	(0.101)	(5.1738)	(0.018)	(0.008)	(0.011)	(0.023)
Trust	0.0091	0.1652	12.0676	0.0152	-0.0078	-0.0025	-0.0013
	(0.0388)	(0.1072)	(12.9186)	(0.016)	(0.009)	(0.011)	(0.022)
Investor country	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Education dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Deal year				Yes	Yes	Yes	Yes
Company country				Yes	Yes	Yes	Yes
Company industry				Yes	Yes	Yes	Yes
Investor type				Yes	Yes	Yes	Yes
Observations	329	329	329	7,108	9,787	9,787	9,787

This table presents the results of OLS regressions. In Columns (1)-(3), the unit of analysis is the individual response to our survey, whereas in Columns (4)-(7), the unit of observation is the respondent-startup. In the latter, only the first investment completed by the firms for which the respondent was working during his/her tenure was retained. The variables are described in detail in Appendix A2. Robust standard errors in Columns (1)-(3), and clustered by investor in Columns (4)-(7) are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Appendix

Figure A1. Response rate by country

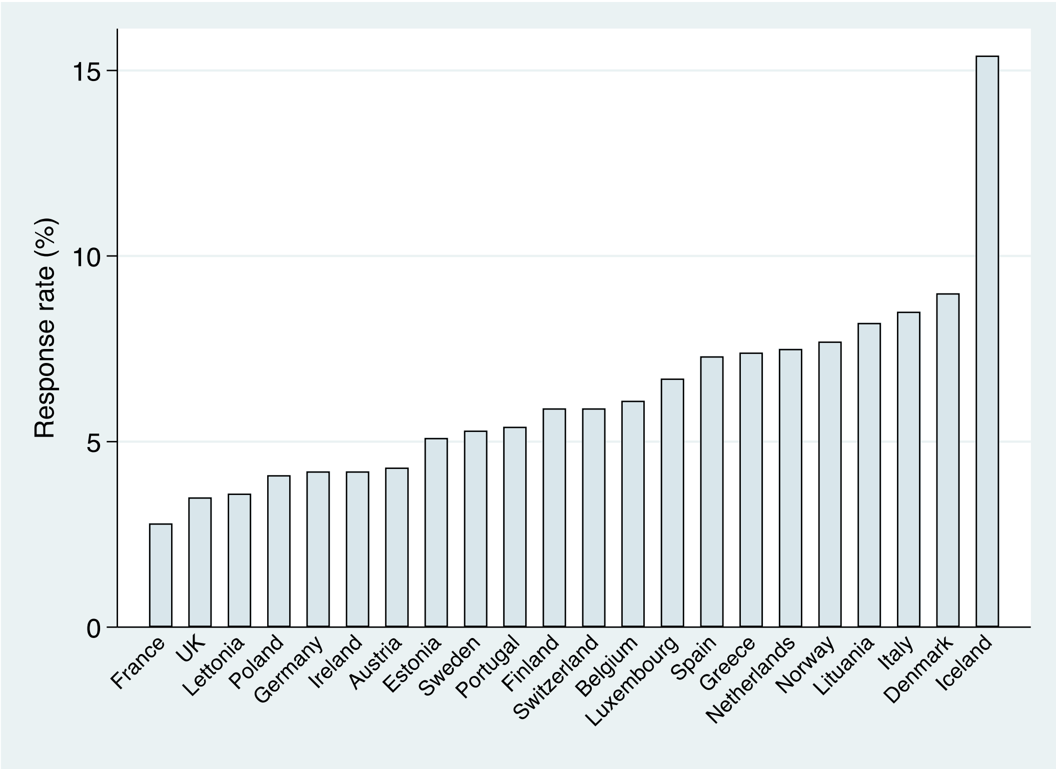


Figure A2. Geographic Origin of Respondents

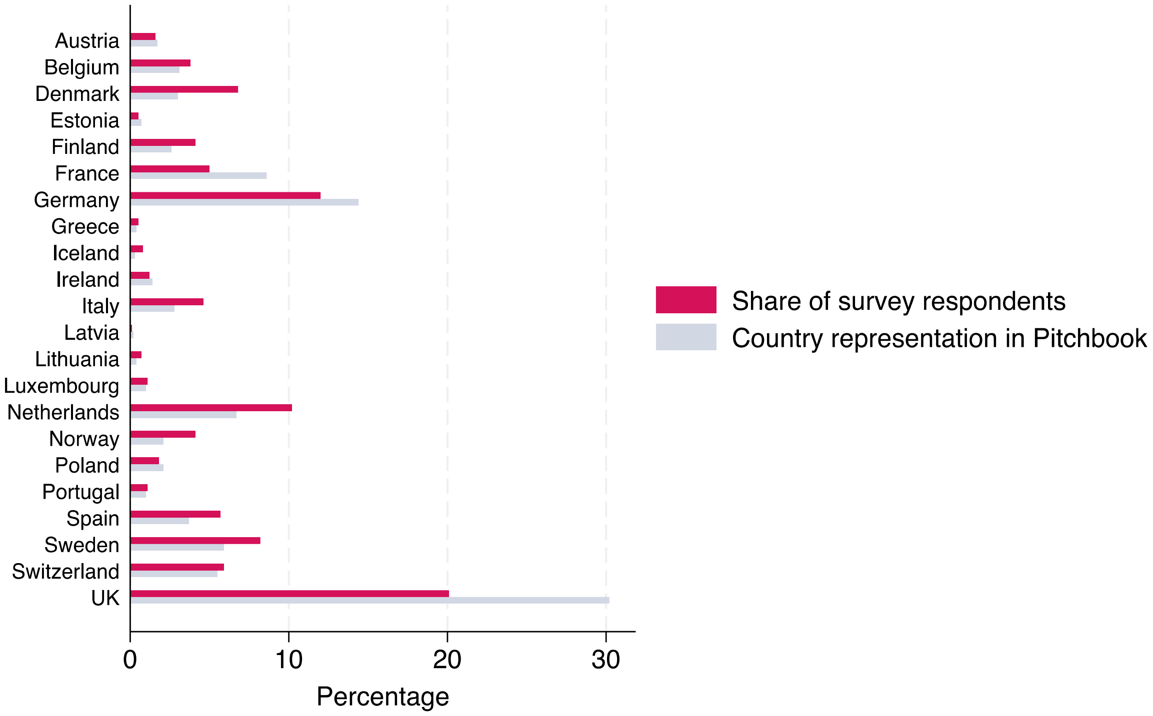


Table A1. Measures of Time and Risk Preferences

Time preferences		
The answer to this question will contribute to determining the monetary award for the winning participant (if you did not opt out of the lottery). You will answer a series of questions comparing two options: Option A offers 400 € paid in one month; Option B offers a different amount in each question paid in seven months. If you are selected as the prize winner (and did not opt out of the lottery), we will randomly choose one of the fourteen questions below to determine part of your monetary reward. For each monetary amount X (on the left side), please choose carefully between Option A or Option B for each row.		
	Option A Receive 400 € in 1 month	**Option B** Receive X € in 7 months
X: 410 €	○	○
X: 420 €	○	○
X: 430 €	○	○
X: 441 €	○	○
X: 451 €	○	○
X: 462 €	○	○
X: 473 €	○	○
X: 484 €	○	○
X: 495 €	○	○
X: 506 €	○	○
X: 517 €	○	○
X: 529 €	○	○
X: 540 €	○	○
X: 552 €	○	○

Risk preferences

You will answer a series of questions comparing two options: Option A offers a 50% chance of receiving 330 €; Option B offers a sure amount, different in each question. If you are selected as the prize winner (and did not opt out of the lottery), we will randomly choose one of the eleven questions below. Your answer to this question will determine part of your monetary reward. In case you chose Option A, the computer will randomly determine the amount. For each monetary amount X (on the left side), please choose carefully between Option A or Option B for each row.

	Option A Receive 330 € with probability of 50%	**Option B** Receive X € for sure
X: 20 €	○	○
X: 50 €	○	○
X: 80 €	○	○
X: 110 €	○	○
X: 140 €	○	○
X: 170 €	○	○
X: 200 €	○	○
X: 230 €	○	○
X: 250 €	○	○
X: 280 €	○	○
X: 310 €	○	○

Table A2. Variable Description

Variable name	Description
Unique respondents	Number of people who replied to our survey.
Survey is completed	Number (and the relative percentage) of respondents who completed the survey (i.e., who replied to all the questions).
No consent given	Number (and the relative percentage) of respondents who did not consent for us to use their responses.
Completed for someone	Number (and the relative percentage) of respondents that delegated the fulfillment of the survey to someone else.
Age	Age of the respondent as of today. This was one of the questions the respondents had to reply to in our survey. For those that stopped responding to the survey before this question, the age of the individuals has been retrieved by manual search on the internet or by inferring it by looking at the years elapsed since the year in which they obtained their bachelor's degree. In such cases, *Age* was computed as the number of years that elapsed since the degree plus 22. Such piece of information has been retrieved by looking at respondents' Linkedin profiles and from Pitchbook.
VC experience	Number of VC financing rounds made as lead partner by the respondent (as reported in Pitchbook).
Founder experience	Dummy having a value of one if the respondent has an experience as a founder reported in Pitchbook; zero otherwise.
Female	Dummy having a value of one if the respondent is a female; zero otherwise.
Top management role	Dummy having a value of one if the respondent had a top management role. To identify people holding a top management position we use keywords in their titles such as "Partner", "GP", "Head", "President", "VP", "V.P", "Founder", "Founding", "Principal", "Managing director", "Investment director", "Executive", "Chief", "Chairman", "Chairwoman", "CEO", and "C.E.O.". If in the title of the respondent appeared one of these words or if the respondent was an angel investor, then we considered the respondent as having a top management role.
Education	Discrete variable identifying the highest level of education attained by the respondent. It has a value of 0 if the respondent did not attain any degrees; 1 if the respondent attained a B.Sc. degree; 2 if the respondent attained an M.Sc. degree; 3 if the respondent attained an MBA; 4 if the respondent attained a PhD. To retrieve this information we relied upon information from other sources (i.e., LinkedIn profiles and investors' websites).
Patience	This variable captures the respondent's future orientation/patience. It takes values from 0 to 14. Higher values correspond to a greater future orientation/patience. See Appendix Table A1 for the list of questions used.

Risk aversion	This variable captures the respondent's risk aversion. It takes values from 0 to 11.The sooner the participant switches from Option A to Option B, the greater the individual's risk aversion. See Appendix Table A1 for the list of questions used.
Luck	This variable reports the extent to which the individual agrees with the statement "Hard work doesn't generally bring success - it ́s more a matter of luck and connections" vs "In the long run, hard work usually brings a better life". The answers range between 1 (hard work importance) and 10 (luck importance).
Trust	This variable reports the extent to which the individual agrees with the following statement "Would you say that most people can be trusted". The answers range from 0 (strongly disagree) to 4 (strongly agree).
Days to close a deal	Average number of days to close a VC deal in the last year.
Number of deals considered	Number of VC deals considered in the last year.
Required IRR	Required internal rate of return from an investment.
Company age	Age of the startup at the time of the deal (in years).
Late-stage round	Dummy having a value of 1 if the investment is considered by Pitchbook as an investment in a late-stage startup; 0 elsewhere.
Cum. amount raised	Amount raised by the startup up to the time of the focal deal (in million $).
Deal size	Amount raised by the startup in the focal deal (in million $).
Investor type	Classification of the investor provided by Pitchbook. This is a discrete value that can assume different values. The most common ones are venture capital, corporate venture capital, and angel investor.
IPO	Dummy having a value of 1 if the investor exited through an IPO from its investment in the startup; 0 elsewhere.
M&A	Dummy having a value of 1 if the investor exited through a trade sale from its investment in the startup; 0 elsewhere.
Board seat	Dummy having a value of 1 if someone representing the investor is seated on the board of the startup; 0 elsewhere.
Voting rights	Dummy having a value of 1 if the terms of the deal granted the investors voting rights; 0 elsewhere.

Table A3. Sample comparison

	Respondents	Full sample	Difference
Age	48.534	47.195	1.338**
			(0.584)
Female	0.164	0.179	-0.015
			(0.014)
Founder experience	0.301	0.302	-0.002
			(0.017)
MBA	0.255	0.232	0.023
			(0.019)
PhD	0.168	0.125	0.043***
			(0.015)

Standard errors are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table A4. Economic Preferences and Company Selection: Evidence from Non-Key People

Dependent variable:	Ln company age	Late-stage round	Ln cum. amount raised
	(1)	(2)	(3)
Patience	0.0466	0.0295	-0.0052
	(0.043)	(0.030)	(0.105)
Risk aversion	0.0010	0.0257	0.1120
	(0.030)	(0.021)	(0.097)
Controls	Yes	Yes	Yes
Deal year	Yes	Yes	Yes
Investor country	Yes	Yes	Yes
Company country	Yes	Yes	Yes
Company industry	Yes	Yes	Yes
Investor type	Yes	Yes	Yes
Observations	6,414	6,414	6,414

This table replicates the specifications in Columns (2), (4), (6) and (8) of Table 4 using deals made by VC firms in which the respondent to our survey does not hold top management positions (as described in Appendix A2). Standard errors clustered at the investor level are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table A5. Relationship Between Fund Time-Horizon and VC Preferences

Dependent variable: Vintage year				
	(1)	(2)	(3)	(4)
Patience	-0.2730	-0.3788	-0.1489	0.0559
	(0.663)	(0.657)	(0.613)	(0.747)
Risk aversion	0.6852	0.6882	0.6356	0.6525
	(0.850)	(0.877)	(0.782)	(0.830)
Female		-0.2017	-2.3256	-1.6217
		(1.706)	(2.058)	(1.796)
Founder experience		-0.0117	-0.6515	-0.4349
		(0.934)	(0.862)	(0.930)
Luck		-0.6885	-0.8317*	-0.9474*
		(0.466)	(0.438)	(0.499)
Trust		-0.0755	-0.2256	-0.3219
		(0.424)	(0.422)	(0.519)
Ln age			-6.4403***	-5.3566**
			(2.166)	(2.150)
Observations	186	186	186	186
Fund Country	No	No	No	Yes

Standard errors clustered at the investor level are reported in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table A6. Patience, Risk aversion, and Deal Size

Dependent variable: Ln deal size		
	(1)	(2)
Patience	-0.2263***	-0.2254***
	(0.0786)	(0.0774)
Risk aversion	0.0554	0.0386
	(0.0575)	(0.0499)
Ln age		0.1065
		(0.2339)
Female		0.3023*
		(0.1824)
Founder experience		-0.3136***
		(0.1132)
VC experience		0.1050**
		(0.0420)
Luck		-0.0646
		(0.0456)
Trust		0.0359
		(0.0580)
Deal year	Yes	Yes
Investor country	Yes	Yes
Company country	Yes	Yes
Company industry	Yes	Yes
Investor type	Yes	Yes
Education dummies	Yes	Yes
Observations	9,787	9,787

This table presents the results of OLS regressions. The unit of observation is the respondent-deal. All deals completed by the firms for which the respondent was working during his/her tenure were retained. The variables are described in detail in Appendix A2. Standard errors clustered by investor are reported in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.