Strategic Investment in Competitors: Theory and Evidence from Technology Startups*

Mario Leccese†

July 22, 2025

Abstract: I examine how venture capitalists' (VCs) investments in competing startups affect portfolio firm outcomes. Prior investments in a business area shape VCs' evaluation of subsequent opportunities, often resulting in the selection of higher-quality startups over time. Common VCs internalize intra-portfolio competition and allocate support strategically. I find that startups funded after a prior investment in the same business area raise more capital and are more likely to secure follow-on funding than those not sharing a VC with a competitor. Initially funded startups benefit when competing investments occur in the same year but are otherwise disadvantaged, especially as portfolio competition intensifies.

JEL classification: G24, G32, L22, O31
Keywords: Common Ownership, Venture Capital, Competition, Technology

---

*I thank Ginger Zhe Jin, Andrew Sweeting, and Liad Wagman for their guidance and support throughout this project. I am also indebted to Cecilia Bustamante for several helpful discussions. I thank Rajshree Agarwal, Florian Ederer, Michael Ewens, Agata Farina, Guillaume Fréchette, Tong Liu, Rich Mathews, Bruno Pellegrino, Merih Sevilir, Timothy Simcoe, Pablo Slutzky, Dan Vincent, Chenyu Yang, and Rosemarie Ziedonis for helpful comments, as well as conference and seminar participants at the University of Maryland, Boston University, University of Toronto, ESADE, Universitat Pompeu Fabra, Universidad Carlos III de Madrid, Georgia Institute of Technology, WEFI Student Workshop, BSE Summer Forum, DRUID, EARIE, and the Harvard-Oxford Conference on Common Ownership. I am also grateful to Crunchbase and S&P for providing access to the data and to the Washington Center for Equitable Growth for financial support.
†Boston University, Questrom School of Business, 595 Commonwealth Avenue, Boston, MA 02215. Email: leccese@bu.edu.

1. Introduction

Technology startups play a critical role in driving economic value by creating job opportunities and accelerating the development and dissemination of innovations (Haltiwanger, Hathaway and Miranda 2014). Although only a small fraction of them access venture capital financing, they emerge as the foremost contributors to the realized value, highlighting the importance of venture capitalists (VCs) in shaping the development and market success of new technologies (Kortum and Lerner 2000; Chemmanur, Krishnan and Nandy 2011; Samila and Sorenson 2011; Puri and Zarutskie 2012).[1] While it is widely acknowledged that VCs build portfolios by investing in a variety of startups, a more recent trend involves the inclusion of competing startups within these portfolios (Eldar and Grennan 2021). Given that the role of VCs extends beyond screening and financing to include a wide range of activities—such as mentoring founders, providing access to their network of experts and firms, or providing strategic and operational guidance—that can significantly influence startup growth (Hellmann and Puri 2002; Bernstein, Giroud and Townsend 2016), a fundamental question arises: How does sharing a VC with a competitor affect startup performance through these VC-driven interventions?

The presence of competing startups in the portfolio can influence a VC's involvement in the management and support of portfolio companies. On the one hand, internalizing product market competition can lead a common VC to channel more resources towards one specific startup, possibly at the expense of another. This could entail the selective redirection of information resources.[2] In theory, there could even be cases where such competition-driven dynamics lead to the discontinuation of a startup (Fulghieri and

[1] Lerner and Nanda (2020) report that in the US fewer than 0.5% of startups are backed by VCs, but 88.6% of the R&D expenditure of public companies originates from VC-backed firms.

[2] An example of this is Alarm.com suing ABS Capital Partners for "misuse of confidential information" after the latter added a direct competitor (Resolution) to their portfolio. See https://casetext.com/case/alarmcom-holdings-inc-v-abs-capital-partners-inc for additional details on this case. According to Cox Pahnke et al. (2015), an entrepreneur who found themselves in a similar situation stated: "[I have become] part of a hedging game where [intellectual property] may be leaked in one direction or the other."

Sevilir 2009). On the other hand, there is also a potential for mutual gain when a VC is shared by competing startups. The adverse effects that such startups exert on each other due to competition might be outweighed by the synergies a shared investor can realize. This could involve enhancing the value of competing startups by facilitating the exchange of innovative resources within the portfolio (González-Uribe 2020) or creating strategic alliances (Lindsey 2008). Additionally, information exchanges may even enhance the ability of startups to coordinate in the product market and relax competition (Azar, Schmalz and Tecu 2018).

Nonetheless, it is important to consider that VCs strategically assess how a startup interacts with the rest of their portfolio in the product market when making investment decisions.[3] This screening process not only impacts the types of startups that will share a VC with a competitor in equilibrium but also shapes the activities that a VC undertakes to maximize the overall value of the portfolio.

In this paper, I develop a novel framework to interpret the motives and consequences of VCs' strategic investments in competing startups, while also examining the interplay between VCs' screening and post-investment involvement in shaping the outcomes of portfolio firms. In particular, I identify two effects: the influence effect and the selection effect. The influence effect arises from the internalization of competition among portfolio startups, which affects the VC's post-investment involvement and, in turn, startup performance. The selection effect captures how investing in a particular business area shapes the VC's evaluation of future opportunities within that niche. For example, after backing an initial startup, a VC may gain experience and improve its screening ability, update its beliefs based on new information about the market or the initially funded firm, or strengthen its reputation, thereby attracting higher-quality startups. As a result, VCs tend to fund higher-quality startups in a given business area following an initial

[3] Hellmann (2002) shows that the support a VC provides to a startup depends on whether the startup is a complement or a substitute to another asset in the VC's portfolio. This strategic consideration influences the ex-ante likelihood of investment.

investment. This selection dynamic shapes the VC's portfolio management strategy and may give rise to incentives for the VC to prioritize the performance of startups that are subsequently financed within a business area, potentially at the expense of initial investments. When competition between startups is intense or the quality gap between them is sufficiently large, it may even be optimal for the VC to discontinue the initial startup. By contrast, when the selection effect is weak or absent, or when competition is low, common VC ownership is more likely to benefit portfolio startups.

I test these predictions using venture investment data from Crunchbase (2008-2021), in combination with data from S&P 451 Research, a database that classifies startups that have been acquired according to a unique hierarchical taxonomy of the technology space. This taxonomy is widely used in financial analysis and it is more systematic, more reliable, and more detailed than alternative taxonomies that have been used to study the technology space (Cheng et al. 2023; Jin, Leccese and Wagman 2023, 2024). Each firm in the S&P database is assigned to one of about two hundred categories, representing the firm's core business. I refer to these categories as "business niches." While business niches do not necessarily align with antitrust market definitions, observing investments in startups in the same business niche is still informative about potential competition that may happen in antitrust markets in or related to that business niche. Using the k-nearest neighbors classifier, which is a non-parametric and instance-based machine learning method, I extrapolate the S&P taxonomy to the Crunchbase data. This enables me to define, for each startup in the sample, the set of potential competitors as those operating in the same business niche.

In the empirical analysis, addressing the selection effect requires assumptions about unobserved startup quality, which introduces potential endogeneity concerns. If the unobserved quality is time-invariant, then startup fixed effects can absorb the selection effect. However, if the unobserved quality can change over time, an instrumental variable approach becomes necessary. To address this, I instrument the indicator for whether a startup shares a VC with a competitor using a binary variable equal to one if the VC has previously invested in competing startups in other business niches. This instrument is plausibly correlated with the endogenous variable, as it reflects the VC's historical tendency to invest in competing startups. At the same time, it satisfies the exclusion restriction under the assumption that a VC's past activity in other niches is orthogonal to its expertise, reputation, or private information within the focal niche.

I find that, following their VC's investment in a competing startup, startups exhibit poorer performance compared to others that do not share any VC with a potential competitor ("solo startups"). By contrast, startups later financed by the VC in the same business niche outperform solo startups. On average, these "subsequent startups" secure a minimum of 48% more venture capital and possess a 2% to 4% higher likelihood of successfully raising a startup round each year after receiving funding from the VC, in comparison to solo startups. While these results are partly attributable to the selection effect, they also indicate that investing in competitors enables VCs to exert an additional positive influence on their portfolio startups. However, this influence is primarily directed towards subsequent startups, while startups initially financed are hurt. Moreover, I delve into various heterogeneous effects guided by the theory. Notably, I demonstrate that when two competing startups receive funds from the same VC within a short time frame, and hence the selection effect is weak, each startup benefits from sharing the VC.

This paper contributes to the emerging literature on the implications of VCs' investments in related startups for portfolio firm growth. Li, Liu and Taylor (2023) find that VCs investing in pharmaceutical ventures developing drugs for related diseases tend to withhold funding from projects that fall behind. In contrast, Eldar and Grennan (2024) show that startups operating in the same—broadly defined—industry and backed by the same VC tend to raise more capital, fail less, and exit more successfully. I develop a simple framework to help reconcile these findings by highlighting the interaction between selection and influence effects. This interaction arises from the way a prior investment in a given business niche informs the VC's subsequent investment choices within that area. When such dynamics lead to differences in startup quality, the influence a VC exerts post-investment will depend on the chronological order in which related startups are funded. This unique aspect of my analysis highlights the potentially adverse consequences associated with sharing a VC with a competitor for startups that are the VC's initial investment in the business niche. In addition, using a very granular classification of tech business areas, I provide empirical evidence of shifts in common VCs' influence effect in response to variations in the intensity of competition among their portfolio startups. This implies that the varying degrees of competition across the industries examined in the literature could contribute to the divergent findings. For instance, Li, Liu and Taylor (2023) focus on the pharmaceutical sector, an industry marked by intense patent competition (Levin, Klevorick and Nelson 1987; Cohen, Nelson and Walsh 2000; Schroth and Szalay 2010), whereas Eldar and Grennan (2024) study startups spanning all sectors of the economy.

Another closely related paper to mine is by González-Uribe (2020), who shows that companies joining a VC's portfolio exhibit, on average, a 60% increase in several measures of exchanges with other portfolio companies, compared to matched companies outside the portfolio. I extend this framework and complement its implications by considering the investor's incentives in driving these exchanges when startups are potential competitors, and by examining how investors evaluate these exchanges at the time of the investment.

My findings also have practical implications for entrepreneurs. While prior work emphasizes the benefits of connecting with other entrepreneurs in the same industry (Baum, Calabrese and Silverman 2000; Stuart 2000; Ozcan and Eisenhardt 2009), I show that when the connection occurs via a shared VC, it may have negative consequences for the first entrepreneur to form the tie. The challenge is that, at the time of investment, this entrepreneur cannot anticipate whether the VC will later back a competitor and asymmetrically allocate support—an outcome that is typically not contractible.[4] Since larger and more experienced VCs are more likely to invest in potentially competing startups, my framework suggests that entrepreneurs should approach such investors with caution. By contrast, entrepreneurs who join a VC portfolio that already includes a competitor are more likely to benefit from the relationship.

Finally, my work contributes to the literature on the impact on innovation of investors' common ownership of companies (He and Huang 2017; Kostovetsky and Manconi 2020; Antón et al. 2024).[5] First, I complement this line of research by studying a different institutional setting, where VCs have more significant control rights relative to institutional investors (Gompers et al. 2020), and there are formal and informal mechanisms through which VCs can influence their portfolio startups' management strategies, such as the appointment of board representatives (Amornsiripanitch, Gompers and Xuan 2019; Ewens and Malenko 2020). Second, I contribute to this literature by examining the outcomes of technology startups instead of the patenting activity of public companies. From a policy standpoint, this is particularly relevant because technology startups not only affect the pipeline of innovations but can also determine changes in market structure by entering markets and competing with established incumbents. On the one hand, VCs' investments in competitors negatively affect the initial startups invested in a particular business niche, potentially leading to reduced innovation and future market competition. On the other hand, this benefits the subsequent startups the VCs invest in that business niche. While this paper does not conclusively determine

[4]This challenge reflects both the difficulty of defining who competes with whom—particularly in the tech sector, where market boundaries are fluid (Jin, Leccese and Wagman 2025)—and the bargaining power held by VCs. For example, Hsu (2004) shows that the median VC-backed entrepreneur receives only one offer, and those with multiple offers often accept less favorable terms to partner with more reputable investors. In addition, Hellmann (2002) highlights the difficulty of contracting over VCs' post-investment actions such as the level of support.

[5]A widespread theoretical and empirical literature studied the anti-competitive effects of common ownership on entry (Newham, Seldeslachts and Banal-Estanol 2018) and prices (e.g., O'Brien and Salop (2000), Azar, Schmalz and Tecu (2018) and Antón et al. (2023)), or quantified the potential welfare losses through this channel (Backus, Conlon and Sinkinson 2021; Ederer and Pellegrino 2022).

the average net effect on welfare, the results emphasize the importance for policymakers to assess the potential consequences of VCs' investments in competing startups.

The rest of the paper is organized as follows. In Section 2, I present the conceptual framework for VC investment in competing startups. In Section 3, I provide an overview of the data and outline the procedure to construct the final sample. In Section 4, I discuss the empirical framework, along with the primary analysis concerning the overall effect on outcomes of sharing a VC with a competitor. In Section 5, I explore the heterogeneous effects around the key comparative statics of the theory. Concluding remarks are in Section 6.

2. Conceptual Framework

In this section, I introduce a simple framework to examine a VC's decision-making when considering whether to finance competing startups, and I characterize the resulting optimal strategies and their implications for startup outcomes. A full solution of the model is provided in Appendix A. I focus on two key mechanisms. The selection effect captures how prior investments in a business area shape the VC's evaluation of subsequent opportunities, leading to later investments with higher expected quality. The influence effect arises once a VC holds stakes in competing startups and internalizes the strategic interaction between them, influencing how support is allocated across the portfolio. When the difference in quality between startups is sufficiently high, or when competition between them is particularly intense, the VC may reallocate resources to the higher-quality firm. As a result—due to the selection effect—the initial startup may be disadvantaged while the subsequent one benefits. This highlights how the interaction between selection and influence can lead to asymmetric outcomes within the portfolio.

Consider the problem of a risk-neutral investor ("the VC") that has *just* invested in a startup (startup 1) operating in a certain business niche, and has to decide whether to invest in a second startup (startup 2) operating in the same business niche, and hence potentially in competition with startup 1. Startup 2 seeks to raise an amount F. The VC has expectations q_i over startup i's true probability of success $q_i^o \in [0, \bar{q}]$. If the VC invests in startup 2, they can take different actions, which I refer to as "portfolio management strategies," to influence portfolio startups' probabilities of success and consequently the overall value of the portfolio. These capture the additional influence that only a VC with competing portfolio startups can exert.

Competition between startups is modeled by assuming that for an investor the future return from a startup is lower if the competing startup also remains active.[6] In particular, I assume that if a startup fails, its investor earns zero, while a startup that succeeds when the rival startup fails generates a value of R for its investor. If, instead, both startups succeed, each generates a value of $R(1-\phi)$ for its investor, with $\phi \in \left[\frac{1}{2}, 1\right]$ parametrizing the intensity of competition between startups. Thus, startup competition diminishes the value for investors, which drops to zero when $\phi = 1$, as if the startups were producing homogeneous products and engaging in Bertrand competition.

I consider four possible portfolio management strategies and I assume that they cannot be contracted upon at the investment stage (Hellmann 2002).

First, a common VC can increase the value of both startups by enabling coordination in strategy, resource use, and development. This can be achieved, for instance, by promoting the exchange of innovation resources within the portfolio (González-Uribe 2020). I refer to this approach as *coordination*. Under this strategy, I assume that the VC increases each startup's probability of success, q_i, by a factor τ.[7] Second, a common VC may choose to *play favorites*—for example, by sharing knowledge or resources with

[6] This is what makes a VC with two competing startups in the portfolio a strategic investor in the sense of Hellmann (2002), who defines a strategic investor as one that "[...] owns some assets whose value is affected by the new startup."

[7] Dessí and Yin (2015) use a similar approach to study the drivers and consequences of entrepreneurs' choices between venture capital and alternative financing. To ensure that the resulting success probability $q_i + \tau$ remains below one, I impose the condition $0 \leq \tau \leq 1 - \bar{q}$.

only one of the two startups. In this case, the favored startup i sees its probability of success rise to $q_i+\tau$, whereas that of the other startup j remains at q_j. Third, the VC may adopt a passive approach, refraining from any intervention and leaving both startups' probabilities of success unchanged.

Li, Liu and Taylor (2023) show that a drug project is less likely to progress if it shares a common VC with a similar drug project that has just progressed. Motivated by this evidence, I also allow the VC to discontinue one of the portfolio startups. This strategy can be optimal since the possibility of divesting one of the startups, even when potentially successful, allows the VC to extract more surplus from the remaining one (Fulghieri and Sevilir 2009). An important caveat is that VCs are typically minority shareholders with only partial control, and hence may not always have the ability to shut down a startup. Nonetheless, by cashing out early or denying follow-up funding, VCs may provide a strong negative signal to the market about a startup's prospect, hurting its ability to survive. In what follows I abstract from these dynamics and assume that the VC can shut down portfolio startups at no cost.

Influence and selection effects. In this setting, when a VC holds both startups in its portfolio, for any τ, the optimal management strategy depends on the degree of competition between the startups and their expected probabilities of success. First, a passive approach is never optimal.[8] The VC always has an incentive to either coordinate the startups or favor one over the other. When competition between the startups is strong, the VC is more likely to play favorites—that is, to channel resources and support toward the more promising startup. This avoids diluting value across two directly competing firms. Conversely, when both startups have relatively low chances of success, the VC is more inclined to coordinate them. Sharing knowledge or resources between the two

[8] A passive approach may dominate coordination or playing favorites when both startups have a high likelihood of success. However, in these cases, the VC prefers to discontinue one of the startups—even for low levels of competition—due to the high risk of cannibalization.

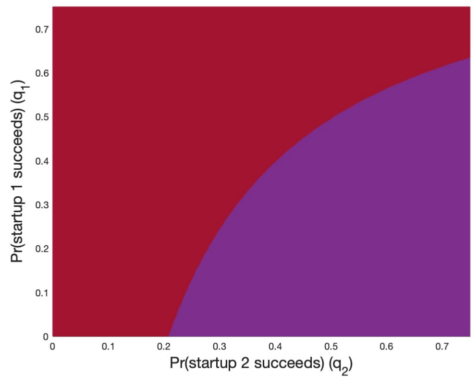
can hedge against failure and increase the odds that at least one succeeds.

I refer to the impact of portfolio management strategies on startup performance as the *influence effect* of a common VC. Identifying this requires comparing a startup's expected payoff when sharing the VC with a competitor against what would have been the expected payoff of that *same* startup if it did not share the VC with a competitor.

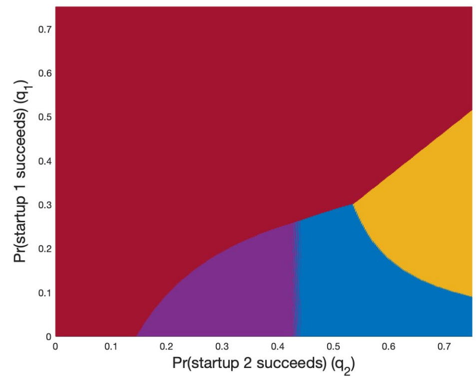
VCs do not invest in startups randomly. This implies that startups subsequently receiving venture capital from an investor that had already invested in their business area may differ systematically from that VC's initial investment or from startups not sharing an investor with a potential competitor. I refer to the existence of such differences as the selection effect.

One possible mechanism, which is explored in the analytical model presented in Appendix A, is that, by investing in a specific business niche, VCs acquire a deeper understanding of the market's dynamics, risks, and opportunities through improved screening enabled by the initial investment. Thus, selection arises from the real option value of waiting: by delaying the subsequent investment decision, the VC gains access to additional information and this learning process enhances its ability to identify promising startups within the same niche. Under this interpretation, I assume that the VC not only observes the realization of q_1 but also learns the realization of q_2 before deciding whether to invest in startup 2. I formally define the selection effect as the difference in the expected probability of success of startup 2 when financed by the VC versus when financed by a competing investor who lacks information about q_1 and q_2 and instead treats them as independent random variables. The competing investor is assumed to be just indifferent between investing and not investing.

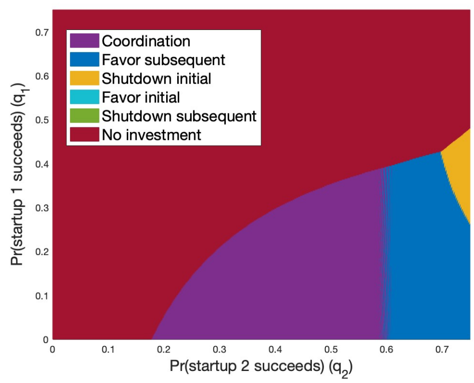
Similar empirical patterns could arise even in the absence of learning. First, in a two-sided matching process between VCs and entrepreneurs (Sørensen 2007), a VC entering a new business niche may initially struggle to attract high-quality startups, as entrepreneurs often prefer investors with relevant domain expertise. As the VC builds a



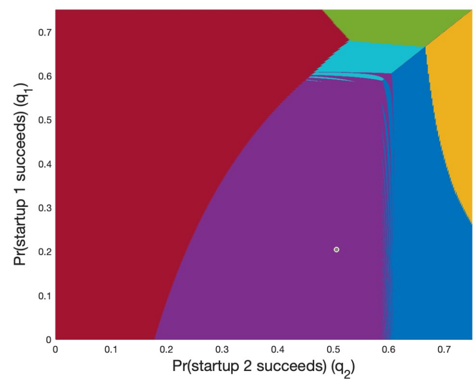
A. Weak competition ($\phi = 0.5$)



B. Intense competition ($\phi = 1$)



C. Moderate competition ($\phi = 0.75$)



D. Moderate competition with continuing startup 2

FIGURE 1. Optimal investment and portfolio management

Notes: Figures A, B, and C show the optimal investment and portfolio management strategy of the VC as a function of q_1 and q_2, for different levels of startup competition ϕ. In Figure D $\phi = 0.75$ startup 2 remains operational even if unable to raise capital from the VC. All simulations assume that q_1 and q_2 are drawn from any distribution over $\left[0, \frac{3}{4}\right]$ with mean μ at the midpoint of the interval and $\tau = 0.15 \cdot \mu = 0.5625$. R is normalized to 1, and, since a competing investor must be just indifferent between investing and not investing, $F = \mu\,(1 - \phi\mu)$.

track record, it becomes more attractive to stronger startups. This reputation-based matching can lead to a pattern where subsequent investments are of higher quality. Second, the arrival of new information about the initial startup may influence the VC's decision to invest in a subsequent one. For example, if startup 1 underperforms but the business niche remains promising, the VC may choose to invest in another startup in the same space, leading to a selection pattern unrelated to the VC's improved screening ability.[9]

In Figure 1, panels 1A, 1B and 1C illustrate the VC's optimal strategy as a function of q_1 and q_2 across different levels of startup competition. The figure assumes that q_1 and q_2 are drawn from a distribution with support on $\left[0, \frac{3}{4}\right]$, with mean μ at the midpoint of the interval. The parameter τ is calibrated such that the VC can increase the probability of success of an average startup by 15%, i.e., $\frac{\tau}{\mu} = 0.15$.

Conditional on investing in startup 2, when competition is weak ($\phi = 0.5$ in Figure 1A), the VC always prefers to engage in coordination. Conversely, as ϕ increases, the incentive to favor the subsequent startup grows, and as ϕ approaches 1 (Figure 1B), the VC becomes more likely to discontinue startup 1, provided that quality difference between the startups is large enough.

Since an uninformed competing investor would finance startup 2 for any (q_1, q_2), the maroon area, which represents the areas in which the VC decides not to invest, identifies the selection effect. The VC invests in startup 2 only when q_2 is greater than q_1, explaining why the initial startup never benefits from sharing the VC with the subsequent. While the selection effect originates from the information advantage of the VC relative to a competing investor, its magnitude depends on the intensity of startup competition and startup qualities. Having already invested in the initial startup leads to internalizing the cost that the success of both startups generates. This cost tends to rise when ϕ or q_1 grows, thus increasing the selection effect.[10]

However, when q_1 is sufficiently high, the VC has little incentive to invest in a subsequent startup, as the expected losses from intensified competition outweigh the potential gains. This dynamic may somewhat attenuate the magnitude of the selection effect, as some startups may end up not sharing a VC with a competitor precisely because of

[9] Figure A.4 and similar simulations varying τ suggest that the VC may be willing to invest in a low-quality startup 2 when startup 1's quality is even lower and τ is sufficiently high.

[10] Naturally, as $\tau \to 0$, the effects of coordination and playing favorites become indistinguishable from passive management. In this case, the VC is more likely to avoid investing in startup 2 altogether if it expects that startup to have a lower chance of success than the initial one.

their high quality.[11] This result is partly driven by the assumption that, in the absence of funding from the VC, startup 2 cannot continue operations.

Figure 1D relaxes this assumption by allowing startup 2 to remain active even if the VC does not finance it—perhaps because it secures financing from an alternative investor. Under this scenario, the VC may still find it optimal to invest in startup 2 even when q_1 is high, either to coordinate the two firms, to favor the initial startup, or to ultimately shut down the subsequent one. This investment-to-kill strategy—reminiscent of the behavior documented in majority-control acquisitions by Cunningham, Ederer and Ma (2021)—as well as favoritism toward startup 1, arises only when q_1 is very high. For instance, a high q_1 may result from a first-mover advantage or the saturation of the business niche. In the model, these cases are relatively rare compared to the more common outcome of favoring startup 2. Moreover, while alternative investors may occasionally step in, a VC's decision to pass on a startup can significantly reduce that firm's chances of raising capital elsewhere. For example, if startup 2's ability to continue is made stochastic, a failure probability as low as 35% is sufficient to eliminate the VC's incentive to invest in the subsequent startup merely to favor the initial one. For all these reasons, such cases play a less central role in my overall analysis.

3. Data

I use data from two sources: Crunchbase (CB) and Standard and Poor's (S&P) Global Market Intelligence.

CB is a leading open-source comprehensive dataset of venture capital investments that has been used extensively in VC investment research. The focus of CB is primarily on tracking funding rounds of technology startups. My sample covers funding rounds that took place globally between 2008 and 2021, and includes information on the date

[11] This force and its relevance in the context of my model are discussed in detail in Appendix A.1.

of the round, the number and identities of investors, the amount raised, the type of financing (e.g., Seed, Series A), the startup funded, as well as information on startup's exit (acquisition, IPO, shutdown). Moreover, for each startup in the database, CB displays a business description and a set of relevant product keywords (e.g., 'software', 'data analytics', 'healthcare', 'banking', etc).

The tech M&A database maintained and operated by S&P Global Market Intelligence is called 451 Research (henceforth, S&P). In the S&P database, each observation is an M&A transaction associated with a change in majority ownership. In total, it covers 41,796 M&A transactions involving 15,323 unique acquirers recorded between 2010 and 2020. All target entities are firms operating in the Information, Communication, and Energy Technology sector (ICET or simply "tech") sector but acquirers can operate in any sector. Important to my analysis, S&P classifies the acquiring and acquired companies into a hierarchical technology taxonomy that has 4 levels, with level-1 being the broadest tech category (resembling an industry, such as "Application Software" and "Internet Content and Commerce," in some cases similar to 4-digit NAICS codes such as 5112 and 5191). All level-1 "parent" categories in the S&P technology taxonomy have level-2 "children" categories, but not all level-2 categories have further children levels. I refer to level-1s as "tech categories" and to the combination of a level-1 and a level-2 category as a "business niche" (BN). In total, there are about two dozen tech categories and two hundred BNs, yielding an average of approximately nine BNs per tech category.

The reliability of the S&P taxonomy is confirmed by its wide usage for financial analysis. According to an internal statistic reported by S&P, more than 85% of tech bankers advising more than 10 deals per year rely heavily on this dataset for their trend and valuation analysis. Moreover, Jin, Leccese and Wagman (2024) show that the partition of the tech space implied by the S&P taxonomy is finer than that implied by the portion of CB Insights—another database that tracks technology M&As—used for related academic research (e.g., Prado and Bauer (2022)), and that S&P classifies firms with more similar businesses as “closer” in its taxonomy.

3.1. Sample Construction and Summary Statistics

To study the effects of VCs’ investment in potentially competing startups on startups’ outcomes, a necessary step is defining in which cases a VC is investing in competitors. Startups often raise multiple rounds and in each round, potentially new VCs may decide to invest. Additionally, even within the same round, multiple VCs may invest together as a syndicate. To that extent, I associate each startup with a unique investor, namely the lead VC at the first round of venture capital financing. Focusing on the lead VC is common in the entrepreneurial finance literature examining monitoring and post-investment involvement (e.g., Bernstein, Giroud and Townsend (2016)), as lead VCs are significantly more likely to hold board seats and play an active role in the startup’s operations (Amornsiripanitch, Gompers and Xuan 2019).

I focus on the subsample of startups raising their first round of VC financing between 2008 and 2019 to have enough time to evaluate startups’ performance afterward. Typically this round coincides with the Series A funding round, and it is often considered a key moment for the growth of the startup given that both the business plan and the pitch deck emphasizing product-market fit have usually been completed.

Most importantly, for each startup in the sample, I need to define the set of competitors. To that end, I extrapolate the S&P taxonomy to the investment data by leveraging CB’s business descriptions and keywords, and S&P’s BNs for the subset of companies that were acquired, to match each startup recorded only in CB to a unique BN. To do this, I use the k-nearest neighbors (k-NN) classifier, which is a non-parametric and instance-based machine learning method used for both classification and regression tasks. The main idea is that data points belonging to the same class tend to be close to each other in the feature space. After constructing and cleaning a string including the business description and the CB-assigned keywords for each startup, I identify the startups that were acquired, and hence for which BNs are available, by merging CB with S&P. This constitutes the "training sample." Then, I use the term frequency-inverse document frequency (TF-IDF) method to represent each startup as a vector and compute the cosine similarity between any startup in the training sample and any query startup. Specifically, given each vector representing a startup S_i, the cosine similarity between any pair of startups (i, j) is:

$$pairwise\_cosine_{ij} = \frac{\boldsymbol{S_i} \cdot \boldsymbol{S_j}}{||\boldsymbol{S_i}|| \ ||\boldsymbol{S_j}||}.$$

Finally, I assign each query startup to a BN by using a majority vote among the 'k' nearest neighbors, where k is a hyperparameter that I choose to maximize the accuracy of the prediction, i.e. $k = 10$. In Appendix B I outline the algorithm in greater detail and evaluate its performance.

In this way, I can assign a BN to every startup in the sample and define any pair of startups belonging to the same BN as potentially "in competition." I define the set of *"linked"* startups as those that, at some point in time, will share their VC with an active competing startup.[12] I will compare them with the remaining non-linked startups raising their first round of venture capital financing between 2008 and 2019 ("solo startups"). Additionally, I further distinguish linked startups into two groups: (i) "first startups," which represent the first startups financed by a VC in a BN; (ii) "subsequent startups," which are all the other linked startups. For example, in 2010 Sequoia invested in Pocket Gems, defined by CB as a "[...] creator of innovative entertainment on mobile," and in 2012 in Kiwi, a "mobile entertainment company building mobile games and tools [...]." Since both startups belong to the same BN (i.e., "Mobility / Mobile Content") and

[12] I define an active startup as one that has not yet exited. In some cases, VCs invest in their second startup in a BN after many years. To prevent startups at vastly different life-cycle stages from being tagged as linked, I reset the investment count in a BN after four years.

share the lead VC, they are tagged as linked startups. In addition, given that Pocket Gems is also Sequoia's first startup invested in the BN, this is tagged as the first startup.

Using information available in CB on rounds of financing earlier and later than the first round of VC financing, I can construct a panel dataset at the startup-year level, where each startup enters the dataset in the year in which the startup is started and exits it in case of acquisition, IPO or shutdown. Table C.1 provides summary statistics for linked startups, distinguishing first and subsequent, for solo startups, and for the full sample (linked and solo startups together).

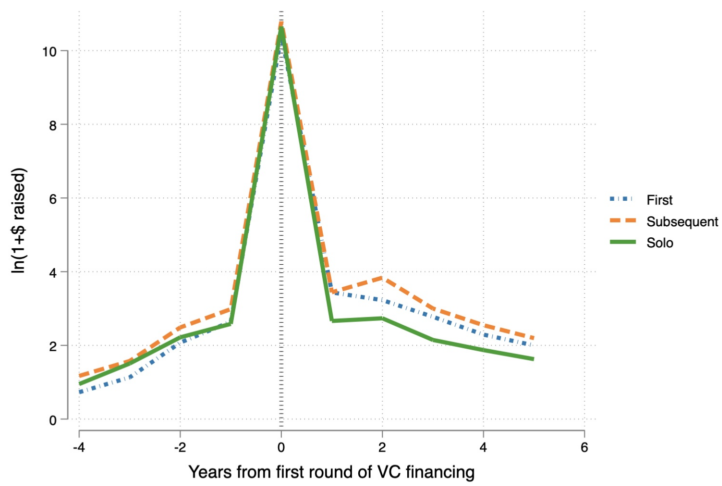


FIGURE 2. Average yearly funds raised by different groups of startups

My final sample includes a total of 33,796 startups, and the number of linked startups equals 9,738 (28.8%).[13] However, only 13% of the investors invest in competitors. These investors are larger and more experienced VCs, as measured by the total number of rounds participated up to the focal one. Hence, while it is not uncommon for competing entrepreneurs to raise venture capital from the same VC, this investment strategy appears to be pursued only by a subset of large and experienced investors.

Finally, Figure 2 illustrates the funding dynamics of the three groups of startups

[13]Of these 33,796 startups, 35% are tagged as the first startup, suggesting that there are cases where VCs make more than two investments in the same BN.

defined over time, measured as the distance (in years) from the first round of venture capital financing (year 0). The graph exhibits a notable spike at year 0, as, by construction, all startups in the sample raise a round in that year. Before this, subsequent startups secure more funding compared to the other identified groups. However, after the first round of VC financing, the gap in the capital raised each year between subsequent and solo startups widens. This trend is consistent with the existence of potential advantages of being backed by an investor who already has a competing startup in their portfolio.

4. Empirical Analysis of VCs' Investment in Competitors

The conceptual framework developed in Section 2 highlights how common VC ownership can affect startup outcomes through the interplay of selection and influence effects. First, the selection effect captures how prior investments in a business niche shape the VC's evaluation of subsequent opportunities. As a result, VCs are more likely to invest in a second, potentially competing startup only if its expected quality is sufficiently high. Second, conditional on making the investment, the VC internalizes the competition between the two startups and chooses a portfolio management strategy that maximizes overall portfolio value. This gives rise to the influence effect. Because of the selection effect, a common VC may favor higher-quality subsequent startups, potentially to the detriment of initial investments.

In what follows, I outline the empirical framework used to test these predictions and then present the main results.

4.1. Empirical Framework

The empirical analyses use panel data of startups to compare the outcomes of startups that at some point in time will share their VC with an active competing startup (linked startups) with those of all the other startups raising their first round of venture capital financing between 2008 and 2019 (solo startups). A startup is included in the sample from the origination year and is removed from the sample after a successful exit or a shutdown, if any. Given a startup i, operating in BN m in year t, the econometric specification is as follows:

$$
\begin{aligned}
Y_{imt} = {} & \alpha_1 \cdot Linked_i + \alpha_2 \cdot First_i + \beta_1 \cdot SharedVC_{it} + \beta_2 \cdot First \times SharedVC_{it} + \\
& + \beta_3 \cdot Post_{it} + \beta_4 \cdot (First_i \times Post_{it}) + \pi \cdot X_{imt} + \alpha_{mt} + \varepsilon_{imt},
\end{aligned} \tag{1}
$$

where Y_{imt} are outcome variables like the funds raised by startup i in year t or whether the startup raised a round, $Linked_i$ equals one for all linked startups, $First_i$ equals one only for the subset of linked startups that were the first startups invested in the BN, $SharedVC_{it}$ is a dummy equal to one if startup i shares a lead VC with a competitor as of year t, $Post_{it}$ is a dummy equal to one if year t is after startup i raised its first round of VC financing, X_{imt} is a vector of control variables capturing startup past growth, and α_{mt} are BN by year fixed effects. Standard errors are clustered at the startup level.[14]

The two key coefficients of interest are β_1 and β_2. The former captures the average effect of sharing a VC with a competitor for subsequent startups, while $(\beta_1 + \beta_2)$ is the impact on the initial one (startup 1 in the model of Section 2). Note that, since a startup's VC is defined as of the time of the first round of VC financing, the time in which a subsequent startup joins the portfolio of the common VC is always the first round year. Conversely, the startups for which *First* equals one may start sharing a VC with a competitor later on in their life cycle. In this sense, while β_3 controls for the effect of having raised the first round of VC financing for any startup (linked or solo), β_4 captures the effect of the VC before they invest in a competitor. Therefore, $(\beta_1 + \beta_2 + \beta_4)$ measures the total influence of the VC on the first startup invested in the BN.

[14] I cluster standard errors at the startup level, as this corresponds to the unit of assignment for the "treatment" (Abadie et al. 2023). However, the results remain robust when using alternative clustering, such as at the BN or investor level, or employing two-way clustering at the BN-year or investor-year levels.

If VCs were randomly matched to competing startups, estimating β_1 and β_2 in Equation 1 (henceforth, the "baseline model") using Ordinary Least Squares (OLS) would yield unbiased estimates of the influence effect. However, as discussed in Section 2, startups that share a VC with a competitor may differ systematically from those that do not, with subsequent startups often possessing inherently higher quality. This introduces a source of bias, stemming from the econometrician's inability to fully observe and control for all the fundamental determinants of startup quality. In the theory, these are captured by the success probabilities q_1 and q_2. If the unobserved startup quality is time-invariant, this bias can be addressed by adding startup fixed effects to the baseline model (henceforth the "FE model"). In this case, estimating β_1 and β_2 via OLS on the FE model recovers the influence effect, while the difference between estimates from the baseline and FE models identifies the selection effect.

In practice, however, startup quality may change over time due to unpredictable shocks, such as changes in management or market developments, and these may be correlated with a VC's decision to invest in a competing firm. In such cases, fixed effects alone cannot account for the selection effect, resulting in biased estimates of the influence effect.

To address these concerns, I adopt an instrumental variables (IV) approach that includes startup fixed effects (henceforth the "IV model"). A good instrument must satisfy two conditions: (i) it must be correlated with the VC's decision to invest in startups within the same business niche; and (ii) it should be unrelated to the quality of the startups, thereby satisfying the exclusion restriction. To put it differently, it must affect startup outcomes only through this investment decision.

To isolate variation in the VC's decision to invest in competing startups that is plausibly exogenous to startup quality, I construct an instrument equal to one if the VC has previously invested in competing startups in other BNs. This binary variable varies across VCs, BNs, and years, and captures persistent features of a VC's investment strategy. Due to organizational inertia in strategy, internal processes, and resource allocation, VCs tend to behave consistently over time (Weigelt and Camerer 1988), making past behavior a credible predictor of future decisions.

The exclusion restriction assumes that a VC's prior investments in competing startups outside the focal niche are uncorrelated with the unobserved, time-varying quality of startups within the focal niche. While startup fixed effects account for time-invariant heterogeneity, they do not capture variation arising from unpredictable shocks, such as changes in management or team dynamics. The instrument addresses this residual endogeneity by exploiting variation in the VC's general investment style, rather than its specific expertise, reputation, or private information within the focal niche. Importantly, this identification strategy allows for different sources of selection. While learning-by-investing is one such driver, Section 2 also considers cases where the VC revises its beliefs about the initial startup after observing early signs of underperformance, or where reputational sorting in a two-sided matching process shapes access to higher-quality startups.

As a robustness check, I also estimate a model with VC fixed effects to control for time-invariant investor characteristics—such as reputation, sectoral focus, or access to deal flow—that may jointly influence investment patterns and startup outcomes.[15] Due to collinearity, it is not feasible to include both startup and VC fixed effects in the same model. Nevertheless, the VC fixed-effects specification provides complementary evidence by examining whether observed selection patterns are driven by persistent differences across investors rather than startup-level dynamics.

While the empirical strategy addresses key sources of endogeneity, it does not fully eliminate the possibility that unobservable, match-specific factors jointly influence both a VC's decision to invest and a startup's willingness to accept funding. The instrumental variables approach helps account for the selection effect, but residual bias may persist due to endogenous matching or other unobserved startup–VC complementari-

[15]This includes the possibility that VCs attract similar types of startups across time.

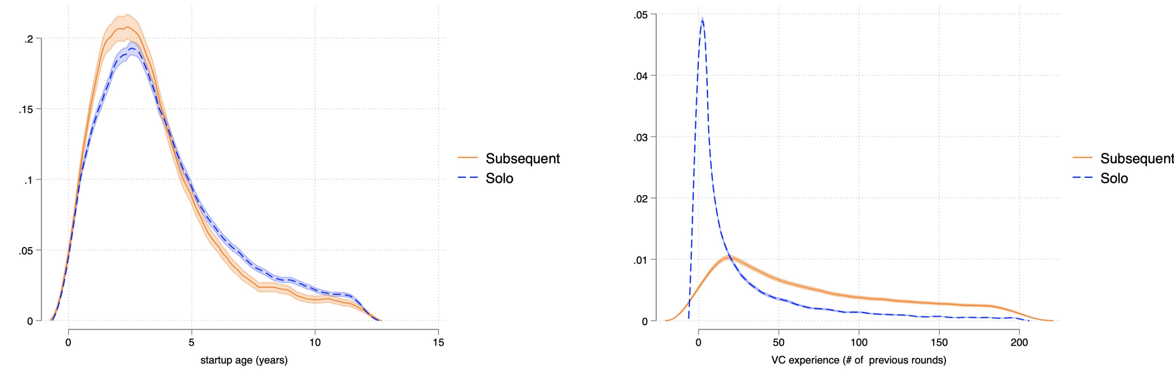
ties. Accordingly, the findings should be interpreted as strong evidence of differential outcomes associated with common VC ownership, rather than as definitive estimates of causal effects.

These challenges are shared, to varying degrees, with related empirical work. For instance, Li, Liu and Taylor (2023) instrument common VC ownership using geographic distance between startups, which may raise concerns about the exclusion restriction if location affects startup outcomes through channels other than shared ownership, such as access to the same labor market. Eldar and Grennan (2024) implement a difference-in-differences design based on the staggered introduction of liability waivers for investors with stakes in conflicting business opportunities. This identification strategy requires focusing on earlier cohorts of startups and relies on a relatively broad industry classification, which may limit the precision in capturing intra-portfolio competition. The approach adopted here leverages a theory-motivated instrument based on VCs' broader investment histories and applies it to a more granular business classification, enabling heterogeneity analyses that shed light on potential underlying mechanisms.

4.2. Results

I begin by documenting how startups that eventually share their VC with a competitor are significantly different from—and possibly ex-ante more likely to outperform—solo startups. Figure 3 indicates that subsequent startups tend to be relatively younger at the time of their first round of VC financing (left panel), and to be funded by more experienced VCs (right panel), as measured by the total number of previous rounds participated. This suggests their propensity for rapid growth and success.

In Table 1, I present the findings from a regression that examines the cross-section of startups within the sample, focusing on the year in which they secure their initial round of VC financing. The dependent variable is a binary indicator, taking the value of



A. startup age

B. VC experience

FIGURE 3. Selection in strategic investment in competitors

Notes: The figures show kernel densities estimates with 95% confidence intervals for the age of the startup as of the first round of venture capital financing (panel A), and for the experience of the lead VC at the first round of VC financing (panel B). In both cases, startups are grouped into subsequent and solo.

one for linked startups and zero for others. I regress this on a binary variable denoting whether the VC has previously invested in competing startups outside the focal BN (referred to as $\mathbb{1}\{VC\_past\_SIC\_in\_other\_BN\}$ or simply the "instrument"), the age of the startup, the VC's experience, and metrics quantifying both VC and startup competition within the BN. I approximate VC competition using the logged number of VCs "active" in the BN, where those who made an investment in the BN within the past two years are categorized as active. Moreover, defining N_{mt} as the total number of startups active in BN m at year t, I compute a proxy for startup competition as:

$$BN\_competition\_index_{mt} = \ln(1 + N_{mt}) \times \frac{N_{mt}(N_{mt} - 1)}{2} \sum_{i}^{N_{mt}} \sum_{j \neq i}^{N_{mt}} \text{pairwise\_cosine}_{ij},$$

where the first term accounts for the fact that competition is more intense in BNs with more active startups, and the second term captures how similar startups are within the BN by calculating the average pairwise cosine similarity between startups in BN m.

Table 1 shows that more experienced investors exhibit a greater inclination towards investing in competing startups, and this trend is particularly pronounced in business

TABLE 1. Selection of linked startups

VARIABLES	(1) *Linked*	(2) *Linked*	(3) *Linked*
$\mathbb{1}\{VC\_past\_SIC\_in\_other\_BN\}$	0.415***	0.412***	0.406***
	(0.0137)	(0.0143)	(0.0148)
BN_competition_index	0.375***	0.263***	0.0928**
	(0.0385)	(0.0518)	(0.0358)
BN_active_VCs	0.0253***	0.0592***	0.0297***
	(0.00177)	(0.00551)	(0.00572)
Startup_age	-0.000415	-4.09e-05	-0.000305
	(0.000609)	(0.000525)	(0.000582)
VC_experience	0.0507***	0.0544***	0.0569***
	(0.00457)	(0.00454)	(0.00444)
Observations	33,796	33,796	33,796
R-squared	0.272	0.288	0.298
Year FE		✓	✓
BN FE			✓

Notes: *** p<0.01, ** p<0.05, * p<0.1. The table reports the results of different specifications estimated via OLS in which the outcome is a binary variable which equals one if the startup is linked and zero otherwise. The sample is the cross-section of startups raising their first round of venture capital financing between 2008 and 2019. Robust standard errors are reported in parentheses.

niches characterized by heightened levels of both VC and startup competition. Moreover, the regression analysis offers compelling support for the instrument's relevance, showing that VCs with prior investments in competing startups within a specific BN have a 40% higher likelihood of replicating such behavior in a distinct BN in the future.[16]

If investing in competitors benefits subsequent startups while hurting initial ones, the estimate of β_1 in Equation 1 will be positive and statistically significant and the estimate of β_2 will be negative, statistically significant, and larger in absolute value than β_1.

Columns (1) and (4) of Table 2 present the results for the Baseline model, which I estimate using OLS. The coefficient on *SharedVC* (β_1) is both positive and statistically

[16]Including BN and year of first VC financing fixed effects affects the magnitude of the estimated coefficients but not their sign and statistical significance.

significant at the 1% level. This indicates that, after they start sharing a VC with a competitor, startups raise approximately 58% more venture capital and exhibit a 2.5% higher likelihood of conducting a funding round each year. However, this effect is heterogeneous across the timing at which startups become part of the common VC's portfolio. Notably, β_2, which is the coefficient on *First* $\times$ *SharedVC*, takes on a negative value, surpassing β_1 in absolute magnitude. This suggests that the first startup invested in the BN exhibits a decline in performance once a competing startup joins the VC's portfolio. Column (4) shows that this particular startup has a 29.2% lower probability of raising an additional funding round compared to a solo startup. Simultaneously, the coefficient associated with *First* $\times$ *Post* shows that upon receiving the initial round of VC financing from the eventual common VC, the startup experiences an increase in both its probability of having a funding round and the capital raised. Consequently, the total impact of securing the first round of VC financing from this VC is a reduction of 50% in the amount of future capital raised and by 7% in the likelihood of raising a further funding round. Lastly, together, the coefficients on *Linked* and *First* imply that subsequent startups have on average ex-ante superior outcomes relative to solo startups, whereas this does not appear to apply to first startups. This provides evidence consistent with the selection effect.[17]

Columns (2) and (5) in Table 2 present the findings yielded by the FE model estimated using OLS. If incorporating startup fixed effects addresses the selection effect, β_1 and β_2 can be interpreted as the additional influence on a startup's outcomes exerted by a VC shared with a competitor. Comparing β_1 in columns (2) and (5) with β_1 in columns (1) and (4) reveals that out of the total positive effect relative to solo startups—amounting to 57.6% (2.5%)—on future capital raised (probability of conducting a fund-

[17]The selection effect does not directly compare solo and initial startups. While the sum of α_1 and α_2 in column (4) is close to zero—suggesting similar ex-ante VC funding—in column (1) α_1 is smaller in absolute value than α_2. This is consistent with the model in Section 2, where lower-quality initial startups are more likely to attract a subsequent investment while some solos may be high-quality startups for which the VC has no incentive to fund a competitor.

ing round), 48 (2) percentage points can be attributed to the VC's influence, while the rest is due to the inherent quality of the startup, i.e., the selection effect. The estimate of β_2 reaffirms that the first startup invested in the BN exhibits worse outcomes than solo startups after its VC's investment in a competitor.

TABLE 2. Investment in competitors and startup performance

	ln(1+$ raised)			$\mathbb{1}$\{round raised\}		
	(1) (OLS)	(2) (OLS)	(3) (IV)	(4) (OLS)	(5) (OLS)	(6) (IV)
Linked	0.126**			0.013***		
	(0.048)			(0.004)		
First	-0.204***			-0.013**		
	(0.071)			(0.006)		
Post	2.572***	6.697***	6.579***	0.262***	0.569***	0.564***
	(0.044)	(0.053)	(0.059)	(0.003)	(0.003)	(0.004)
First × *Post*	2.674***	0.979***	1.225***	0.222***	0.097***	0.098***
	(0.134)	(0.153)	(0.302)	(0.009)	(0.008)	(0.020)
SharedVC	0.455***	0.392***	0.929***	0.025***	0.020***	0.042***
	(0.067)	(0.096)	(0.134)	(0.005)	(0.006)	(0.008)
First × *SharedVC*	-3.820***	-1.428***	-2.122***	-0.317***	-0.137***	-0.154***
	(0.142)	(0.152)	(0.369)	(0.009)	(0.010)	(0.026)
Observations	286,321	286,192	286,192	286,321	286,192	286,192
Adj. R-sq	0.111	0.349		0.146	0.382	
BN × Year FE	✓	✓	✓	✓	✓	✓
Startup FE		✓	✓		✓	✓

Notes: *** p<0.01, ** p<0.05, * p<0.1. In columns (1) and (4) ((2) and (5)), the table reports the results of the Baseline (FE) model estimated via OLS. In columns (3) and (6), the table reports the results of the IV model estimated via 2SLS. All regressions include controls for the cumulative funds and number of rounds raised by the startup up to $t-1$, as well as the stage reached at any year before the first round of VC financing. Standard errors are reported in parentheses and are clustered at the startup level. The first-stage coefficients on the instruments for *SharedVC* and *First* × *SharedVC* are 0.89 and 0.59, respectively, and both are statistically significant at the 1% level. Full first-stage results are reported in Appendix C.

Since startup fixed effects alone may not suffice to identify the influence effect, columns (3) and (6) of Table 2 present the results obtained from the IV model, which I estimate via two-stage least squares (2SLS). The table shows that, for both dependent variables, the estimated β_1 is now larger in magnitude than the one estimated via the

FE model. For example, column (6) shows that joining the portfolio of a VC that has already invested in a competitor increases the probability of raising a venture round by 4% relative to solo startups. This represents an economically meaningful effect given that the average probability of raising a round in any given year is 0.25.

At first glance, this result may appear in contradiction with the direction of the selection effect. However, it is common for IV estimates to be larger than their OLS counterparts (Jiang 2017). In my case, the reason might be that the IV-compliers are the startups financed by those VCs that tend to make a larger number of investments, not only spanning multiple BNs, but also making more than one investment in at least two niches. Since these VCs are typically larger and more experienced, they might be more able to internalize competition externalities within their portfolios and channel relevant information or resources toward subsequent startups. This is in line with the empirical evidence documenting how more experienced VCs outperform those with less experience (Gompers, Kovner and Lerner 2009). Hence, the instrument has a meaningful impact on whether a startup is linked only for this subgroup of VCs that is likely to exhibit larger local average treatment effects (LATEs).[18]

In terms of the heterogeneous effects for the first startups invested in the BN, the IV model aligns with the previous findings. Specifically, I find that a shared VC reduces the probability of raising a round for the first startup by 0.26 of one standard deviation.[19] The economic significance of these estimates is high, although the size of the effect is lower than that estimated by Li, Liu and Taylor (2023). They find that a shared VC reduces the probability of progressing to the next stage of development for a project lagging behind by 0.53 of one standard deviation. This difference is consistent with my

[18]The first-stage coefficients reported in Table C.2 support the relevance of the instruments. In addition, Figure C.2 presents 95% confidence sets for β_1 and β_2 that are robust to weak identification and align with the point estimates in Table 2. Consistent with this, the Kleibergen-Paap Wald rk F-statistic—which accounts for potential heteroskedasticity and clustered standard errors—exceeds the conventional threshold of 10.

[19]The FE model yields an estimate of 0.27 of one standard deviation.

hypothesis concerning the role played by the intensity of competition, which tends to be higher in the pharmaceutical industry.

In the model of Section 2 I also discuss how in certain circumstances the VC might have an incentive to discontinue the first startup invested in the BN. Table 3 provides supporting evidence for this conjecture. Column (1) presents the results of the Baseline model, while columns (2) and (3) show the results of the FE and IV models. The dependent variable is equal to one if the startup is shut down in a given year and zero otherwise. The estimates of β_1 and β_2 suggest that the first startup invested in the BN is significantly more likely to be discontinued relative to solo startups, while the same does not hold for subsequent startups. However, the magnitude of the effect is relatively small (less than 1%).[20]

TABLE 3. Effect of investing in competitors on startup shutdown

	(1) (OLS)	(2) (OLS)	(3) (IV)
First × *Post*	-0.005***	-0.002***	-0.008***
	(0.000)	(0.001)	(0.002)
SharedVC	-0.001**	-0.001	0.000
	(0.000)	(0.000)	(0.001)
First × *SharedVC*	0.006***	0.003**	0.009***
	(0.001)	(0.001)	(0.003)
Observations	286,192	286,192	286,192
Adj. R-sq	0.003	0.121	
BN × Year FE	✓	✓	✓
Startup FE		✓	✓

Notes: *** p<0.01, ** p<0.05, * p<0.1. In column (1) ((2)), the table reports the results of the Baseline (FE) model. In column (3), the table reports the results of the IV model estimated via 2SLS. All regressions include controls for the cumulative funds and number of rounds raised by the startup up to $t-1$, as well as the stage reached at any year before the first round of VC financing. Standard errors are reported in parentheses and are clustered at the startup level.

[20] Table C.3 shows that, as compared to solo startups, subsequent (first) investments are more (less) likely to receive follow-up funds from their VC after they begin to share the VC with a competitor.

Robustness checks. I run several robustness checks. First, to isolate the role played by VCs, I consider a different specification in which I add investor fixed effects to Equation 1 instead of startup fixed effects. The estimated coefficient for *SharedVC*—reported in Table C.6—is smaller but still positive and significant. Overall, the results are robust to this alternative specification.[21] Additionally, since not all startups raise seed rounds, I also consider an alternative specification in which each startup enters the sample after the first round of VC financing. Table C.8 shows that results are robust, even when I include VC fixed effects.

Second, I exclude first startups and, following Chemmanur, Krishnan and Nandy (2011), I adopt a two-step cross-sectional Heckman-type estimation structure and employ a switching regression with endogenous switching methodology to distinguish selection and influence effect.[22] Using the same instrumental variable, I compute the inverse mills ratio and show in Table C.4a that in the second stage, the corresponding estimates are positive and significant only for linked startups (i.e., subsequent startups). This suggests that VCs that have already invested in the BN select their next investment based on some unobservable factors, and these factors positively affect future startup performance. This finding provides additional evidence in line with the selection effect. Moreover, this procedure enables me to run counterfactual analyses comparing the overall performance after the first round of VC financing for linked and solo startups. In particular, Table C.4b shows that a subsequent startup would raise roughly 23% less if it did not share a VC with a competitor. This is qualitatively consistent with my previous findings.

Third, I explore an alternative approach, once again excluding the first startups from the pool of linked startups. In particular, I use propensity score matching (PSM) to align

[21]In the analysis reported in Table 2 I do not control for any characteristic of the VC, such as size or experience, because these may potentially be correlated with the error term of the regression. However, Table C.7 shows that results are robust when I augment the FE and IV models with VC characteristics interacted with the *Post* dummy.

[22]See Heckman (1979) and Maddala (1983) for more details on this procedure.

the remaining linked and the solo startups based on observable startup characteristics such as the number of rounds and the amount of funding raised before the first round of venture capital financing, as well as the year of this round. Then, I compare matched linked and solo startups within 3 years before and after their first round of venture capital financing using a Difference-in-Differences (DiD) methodology, where the time variable is defined as the years from the first round of VC financing. Figure C.3 illustrates that—consistently with Table 2—subsequent startups outperform solo startups in terms of both the amount of funding raised and the likelihood of securing a funding round.

Finally, it is worth noting that in the conceptual framework outlined in Section 2, the VC's potential to invest is limited to a maximum of two startups within the same BN, while the previous analyses presented allowed for more than one subsequent startup invested in a BN. Thus, I run an additional robustness check narrowing my focus to the VC's first two startups invested in a given BN. The results of this analysis are presented in Table C.5, and are consistent with those presented in Table 2.

Evidence on operational impact. The influence effect operates as somewhat of a black box, encompassing all actions undertaken by the VC beyond the initial screening. In practice, common VCs can influence startup outcomes in several ways. For example, they may facilitate information flows within the portfolio, allocate time and resources unevenly across startups, or, in some cases, contribute to a decision to discontinue a startup. Due to data limitations, I cannot directly test these specific channels. However, regardless of the exact mechanism, the influence effect inherently requires some degree of investor activism. To explore this, I run eight additional regressions using four distinct binary variables as dependent variables, within both the FE and IV models. The first binary variable equals one when a new board member is appointed; the second equals one when a former board member leaves the board. The third variable equals one when a new executive is hired, whereas the fourth is one when an executive leaves the management team of the startup.[23]

I find that after a competing startup is integrated into a VC's portfolio, linked startups are more likely to see an executive replaced and a director stepping down from the board, compared to solo startups. These results, summarized in Table C.9 of the Appendix, emphasize the active role VCs play, even when they invest in competing startups, in influencing the operations of their portfolio companies.

5. Heterogeneous Effect and Timing of Investment in Competitors

In this section, I examine the heterogeneity of the influence effect with respect to key components of the model presented in Section 2, which predicts that the performance gap between subsequent and initial startups increases with the strength of the selection effect, the intensity of startup competition, and the VC's ability to enhance startup success. I then explore potential drivers of staggered investments, focusing on investor competition as a factor influencing the timing of subsequent investments.

5.1. Investment Timing, Knowledge Transfers and Startup Competition

The model predicts an interaction between the selection and influence effects: when the selection effect is strong and the quality gap between subsequent and initial startups is large, the VC has a greater incentive to favor the subsequent startup at the expense of the initial one. Regardless of the underlying source of selection, a longer time lag between consecutive investments in the same business niche provides the VC with more opportunity to develop expertise, improve screening ability, build reputation, and gather information about the niche or the initial startup's prospects. This, in turn, increases the likelihood of investing in a relatively higher-quality subsequent startup.

[23]Recruiting a non-founder CEO is a common action through which VCs influence the operations and strategic direction of portfolio firms (Lerner 1995; Hellmann and Puri 2002; Ewens and Marx 2018).

Therefore, I conjecture that as the temporal gap between consecutive investments within the same niche widens, the selection effect strengthens, leading to a more pronounced performance gap between initial and subsequent startups.

TABLE 4. Heterogeneous effects: Investment timing

	ln(1+$ raised)		𝟙{round raised}		𝟙{Shutdown}	
	(1) Same year	(2) Same or different years	(3) Same year	(4) Same or different years	(5) Same year	(6) Same or different years
SharedVC	0.889***	0.794***	0.048***	0.032***	0.000	-0.000
	(0.120)	(0.130)	(0.008)	(0.009)	(0.001)	(0.001)
First × *SharedVC*	0.025	-1.770***	-0.025	-0.194***	0.002	0.008
	(0.294)	(0.577)	(0.020)	(0.040)	(0.003)	(0.006)
First × *SharedVC* × *Lag*		-0.657**		-0.002		0.006*
		(0.316)		(0.022)		(0.003)
Observations	233,791	241,531	233,791	241,531	233,791	241,531
BN × year FE	✓	✓	✓	✓	✓	✓
Startup FE	✓	✓	✓	✓	✓	✓

Notes: *** p<0.01, ** p<0.05, * p<0.1. Odd columns show the results of the IV model restricting attention to the subsample of linked startups that received the first round of VC financing in the same year. Even columns show the results of the IV model adding the interaction between *First* × *SharedVC* and the log of the number of days between the two investments in the same BN (*Lag*). Linked startups are those that were either the first or the second startup invested in the BN. All regressions include controls for the cumulative funds and number of rounds raised by the startup up to $t-1$, as well as the stage reached at any year before the first round of VC financing. Standard errors are reported in parentheses and are clustered at the startup level.

To study this hypothesis, I construct two different tests, the results of which are summarized in Table 4. In both tests, for linked startups, I restrict attention to the first two investments made by a VC in any BN. The first test compares solo startups to the subsample of linked startups that raised the first round of VC financing in the same year. For these linked startups, the selection effect is anticipated to be less pronounced, thus increasing the VC's incentive to engage in symmetric knowledge sharing. In effect, columns (1) and (3) show that both startups—symmetrically as *First* × *SharedVC* is not significant at 5%—register improved outcomes when sharing the VC, raising more funds and being more likely to raise a round in the following years. In the second test, I

TABLE 5. Heterogeneous effects: VC experience

	ln(1+$ raised)		𝟙{round raised}	
	(1) (OLS)	(2) (IV)	(3) (OLS)	(4) (IV)
SharedVC	0.240**	0.680***	0.014**	0.030***
	(0.102)	(0.147)	(0.006)	(0.009)
First × *SharedVC*	-1.271***	-1.743***	-0.133***	-0.155***
	(0.160)	(0.479)	(0.010)	(0.034)
First × *SharedVC*× *VC_experience*	-0.201*	-0.343*	-0.003	-0.017
	(0.109)	(0.194)	(0.007)	(0.014)
Observations	265,891	265,891	265,891	265,891
Adj. R-sq	0.351		0.382	
BN × Year FE	✓	✓	✓	✓
Startup FE	✓	✓	✓	✓
VC characteristics × *Post*	✓	✓	✓	✓

Notes: *** p<0.01, ** p<0.05, * p<0.1. The table shows the results of the FE and IV model adding the interaction between *First*×*SharedVC* and *VC_experience*. All regressions include controls for the cumulative funds and number of rounds raised by the startup up to $t-1$, as well as the stage reached at any year before the first round of VC financing and VC characteristics interacted with the *Post* dummy. VC characteristics include: age and experience of the lead VC, and the experience of the most experienced non-lead VC. Standard errors are reported in parentheses and are clustered at the startup level.

augment the IV model with the interaction between *First* × *SharedVC* and the time lag between investments in the same BN (*Lag*). The model predicts a negative coefficient for the capital raised and the probability of a successful round, along with a positive coefficient for startup shutdown. The results displayed in column (2), (4) and (6) are consistent in sign with the predictions of the model, although the estimates of the coefficient multiplying *First* × *SharedVC*× *Lag* are not significant at the 5% level for the probability of raising a round and the probability of startup shutdown.

In the conceptual framework τ, which captures the VC's ability to increase a startup's success probability when also backing a competitor, is one of the parameters shaping the influence effect. A higher τ increases the likelihood that the VC favors the subsequent startup.[24] While τ is not directly observable, it can be interpreted as reflecting a VC's

[24]This, along with the comparative statics on ϕ, is formally derived in Appendix A.

ability to generate synergies across portfolio firms or facilitate knowledge flows. A natural assumption is that more experienced VCs are more likely to identify and exploit complementarities across portfolio startups. If this is the case, the performance gap between first and subsequent startups should be larger for more experienced VCs.

I test this hypothesis by introducing the interaction between *First* × *SharedVC* and *VC_experience* in the FE and IV models. This term should negatively impact startup performance. Table 5 shows that the estimates of the coefficients multiplying the interaction term of interest are consistent in sign with the prediction of the model. However, they are not statistically significant at the 5% level.

TABLE 6. Heterogeneous effects: Startup competition

	ln(1+$ raised)		𝟙{round raised}		𝟙{Shutdown}	
	(1)	(2)	(3)	(4)	(5)	(6)
SharedVC_TC	0.263***	0.293***	0.0112*	0.0150**	-0.000531	-0.000533
	(0.0990)	(0.0989)	(0.00618)	(0.00617)	(0.000543)	(0.000552)
First_TC × *SharedVC_TC*	-1.167***	-1.189***	-0.138***	-0.141***	0.00442***	0.00429***
	(0.154)	(0.154)	(0.0100)	(0.0100)	(0.00115)	(0.00115)
SharedVC	0.198*	0.156	0.0135*	0.00832	-0.000217	-0.000142
	(0.120)	(0.121)	(0.00745)	(0.00749)	(0.000620)	(0.000632)
First × *SharedVC*	-0.871***	-0.852***	-0.0806***	-0.0768***	0.000929	0.000867
	(0.176)	(0.176)	(0.0114)	(0.0114)	(0.00108)	(0.00109)
Observations	286,259	286,192	286,259	286,192	286,259	286,192
R-squared	0.426	0.430	0.455	0.459	0.226	0.229
TC × Year FE	✓		✓		✓	
BN × Year FE		✓		✓		✓
Startup FE	✓	✓	✓	✓	✓	✓

Notes: *** p<0.01, ** p<0.05, * p<0.1. The table reports the results of the model of Equation 2, which also include controls for the cumulative funds and number of rounds raised by the startup up to $t-1$, as well as the stage reached at every year before the first round of VC financing. Standard errors are reported in parentheses and are clustered at the startup level.

Finally, I examine how the intensity of startup competition influences the magnitude of the influence effect. Since a common VC internalizes the negative externalities arising from competition between portfolio firms, the model predicts a greater likelihood of favoring the subsequent—and higher-quality—startup as competition becomes more intense.

To empirically test this prediction, I leverage the hierarchical structure of the S&P taxonomy, wherein each tech category encompasses multiple BNs. In particular, I exploit the variation stemming from startups that share a common VC with another startup operating within the same tech category but in a different BN. The underlying assumption is that startups within the same tech category (TC) yet different BNs exhibit a comparatively lower degree of competition than those operating within the same BN. This assumption is consistent with the empirical evidence in Jin, Leccese and Wagman (2024), who show that the business descriptions of firms in the same S&P business niche tend to be more similar than those of firms in the same tech category but different BN.

This test requires the introduction of two additional variables to Equation 1, namely *SharedVC_TC* and *First_TC*. These variables are conceptually identical to their BN counterparts but are based on tech categories instead. I consider the following specification, where an observation is a startup i in tech category n and BN m in year t:

$$\begin{aligned} Y_{inmt} = {} & \alpha_i + \alpha_{nt} + \beta_1 \cdot SharedVC_{it} + \beta_2 \cdot (First_i \times SharedVC_{it}) + \beta_3 \cdot Post_{it} + \\ & \beta_4 \cdot (First_i \times Post_{it}) + \gamma_1 \cdot SharedVC\_TC_{it} + \gamma_2 \cdot (First\_TC_i \times SharedVC\_TC_{it}) \\ & + \gamma_3 \cdot (First\_TC_i \times Post_{it}) + \pi \cdot X_{imt} + \varepsilon_{inmt}. \end{aligned} \tag{2}$$

If β_2 in Equation 2 is negative and statistically significant, it indicates that when startups operate not only within the same tech category but also within the same BN, the performance gap between subsequent and first startups widens. Interpreting the shift from operating within the same tech category to the same BN as a discrete increase in startup competition, this result would support my hypothesis.

Table 6 reports the results of the model of Equation 2 estimated via OLS for three different dependent variables (i.e., the log of venture capital raised, whether a round in a given year is raised, or an indicator for startup shutdown), and including either TC by year (α_{nt}) or BN by year (α_{mt}) fixed effects. As β_1 is positive for the first two dependent variables and negative for shutdown, but never statistically significant at the 5% level, the results suggest that investing in startups within the same BN enables the VC to realize only minor and statistically insignificant mutual benefits compared to when startups operate within the same tech category but in different business niches. By contrast, being the first startup invested in the BN reduces the ability to raise venture capital, but does not significantly affect the probability of being discontinued. Specifically, a startup that is the first invested in a BN raises roughly 58% (i.e., 14% of one standard deviation) less venture capital and is about 8% (i.e., 18% of one standard deviation) less likely to raise an additional round after its VC invests in a startup operating in the same BN relative to the scenario in which its VC invests in a startup operating only in the same tech category. In essence, these findings empirically support the notion that the degree of competition among startups in the portfolio of the same VC shapes the relative performance dynamics between portfolio startups.

5.2. Timing of Investment in Competitors

When competition to supply capital is intense, investors may face pressure to act quickly in order to secure attractive opportunities, potentially reducing the time available for deliberation between investments. Therefore, I study whether the time lag between the first and subsequent investment in the same business niche decreases with investor competition.[25] This has implications for the selection effect, as a shorter lag may limit the VC's ability to gather relevant information, thereby affecting the quality of the startups financed.

To approximate VC competition, I use *BN_active_VCs*, which is computed as the number of active VCs within the BN (log-transformed). This metric considers VCs that

[25]This relationship is formally derived in the analytical model in Appendix A, where VC competition (β) is the main determinant of the timing of subsequent investments.

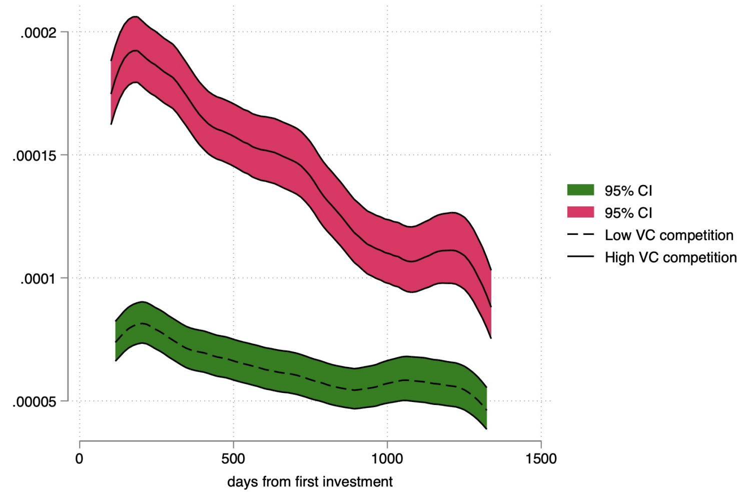


FIGURE 4. Hazard of the second investment in the same BN

Notes: The graph reports smoothed hazard estimates where the "failure" is represented by a VC making a second investment in a BN it has already invested in. Hazards are grouped into high vs. low VC competition, and groups are defined according to the medians.

have made investments within the BN over the past two years.[26] I begin by categorizing BNs based on high and low VC competition, determined by the median value of *BN_active_VCs*. In Figure 4, I illustrate the smoothed hazard estimates for each category, where the "failure" corresponds to a VC making a second investment in a BN wherein they have already invested. This plot is generated from a fully non-parametric model, with the main dataset being the cross-section of all linked and solo startups, excluding subsequent startups that are not the second startup invested within the same BN. In this dataset, I compute for each VC-BN pair the days until the next investment.[27] Consistent with my conjecture, Figure 4 shows that, immediately after having invested in the initial startup, the conditional probability of investing in a second startup is significantly higher in BNs characterized by high VC competition than in BNs with lower VC competition.

[26]This variable captures in each year changes in VCs' average interest towards investing in a given BN, thus varying both over time and across BNs, as shown in Figure C.4. While *BN_active_VCs* offers a reasonable approximation of the pool of potential investors for a startup, it is worth noting that in the analytical model, β represents competition originating from all investors, not exclusively from those who have previously invested in the BN.

[27]For pairs that do not display further investments, the variable is set to reflect what it would have been if an investment occurred at the very end of the dataset.

However, the gap narrows as the number of days from the initial investment increases.

TABLE 7. Determinants of the timing investment in competitors

	(1)	(2)	(3)	(4)
DEP. VAR.	ln(investment lag) (OLS)		$\mathbb{1}$\{second investment\} (Duration model)	
BN_active_VCs	-0.0952*	-0.134**	0.164***	0.0210
	(0.0491)	(0.0583)	(0.0233)	(0.0206)
Observations	6,327	6,327	26,151	26,151
R-squared	0.015	0.028		
Year FE	✓	✓	✓	✓
BN FE		✓		✓

Notes: *** p<0.01, ** p<0.05, * p<0.1. Columns (1) and (2) refer to a specification estimated via OLS where the sample is the cross-section of linked startups that were the first or the second startup financed by the same VC in a BN. Columns (3) and (4) report the result of a duration model where the dependent variable is a binary variable for whether VC makes a second investment in a BN. The sample also includes solo startups. The regressions also control for the degree of competition in the BN as measured by *BN_competition_index*. Robust standard errors are reported in parentheses.

Next, I develop two additional formal tests for this hypothesis, the outcomes of which are summarized in Table 7. First, Columns (3) and (4) of Table 7 display the results obtained from the semi-parametric Cox duration model. Column (3) shows that a marginal increase in VC competition yields an 18% increase in the likelihood of investing in a new startup within the same BN.[28] However, column (4) suggests that the observed results are primarily driven by persistent differences across BNs.

Columns (1) and (2) of Table 7 narrow the focus to the subset of investor-BN pairs where the investment in the subsequent startup eventually occurred. For this subsample it is possible to compute the temporal lag—measured in days (log-transformed)—until the investment in the subsequent startup. I use this variable as a dependent variable in a specification including *BN_active_VCs* as the key regressor of interest. According to my hypothesis, the coefficient associated with *BN_active_VCs* is expected to be negative,

[28] The 18% is computed as: $\left[\exp(0.164) - 1\right] \times 100$.

as increased VC competition should accelerate the decision to invest in an additional startup within the same BN, thereby reducing the time lag. The results are consistent with this expectation, even when including business niche and year of investment fixed effects in the regression.

6. Conclusion

This paper investigates how the strategic investments made by VCs in competing startups shape startup outcomes. I develop a simple theoretical framework showing that prior investments in a specific business niche influence a VC's evaluation of subsequent opportunities, resulting in subsequent startups—when funded—being of higher expected quality than initial or solo startups. The strength of this selection effect, along with the intensity of competition among portfolio startups, serve as the primary drivers of a common VC's influence effect.

In the empirical analyses, I leverage a unique taxonomy of the technology space provided by S&P, which I extrapolate to venture investment data from Crunchbase using a machine learning method. Employing both a fixed effects model and an instrumental variable approach, I find that the initial startups invested in a particular business niche, following their VC's investment in a competing startup, exhibit poorer outcomes relative to those that do not share a common VC with a potential competitor. By contrast, subsequent startups invested in the same business niche outperform solo startups. This relative performance gap widens as competition between portfolio startups intensifies. While these results can be in part attributed to the selection effect, they also indicate that investing in competitors enables VCs to yield an additional positive influence on their portfolio startups. This positive influence is channeled by common VCs towards subsequent startups, while initial investments are negatively affected. However, I also show that when two competing startups are funded in the same year—limiting the scope for selection—both tend to benefit from sharing the same VC.

These findings help to reconcile contrasting evidence in the literature (Li, Liu and Taylor 2023; Eldar and Grennan 2024) by demonstrating the importance of the selection effect and the intensity of competition among startups in shaping how common VCs manage and support their portfolio firms. Moreover, they have practical implications not only for VCs in terms of optimizing screening and portfolio management strategies for startups within the same business niche but also for entrepreneurs, who must weigh the costs and benefits of establishing ties with VCs. Ultimately, the results offer insights into the dynamics of competition within the tech space, with implications for regulations related to competition and VC investments.

To formulate effective policies, a clear understanding of the welfare implications of VCs' investments in competing startups is essential. Given the importance of technology startups in driving innovation and economic growth, and the significant role played by VCs, conducting analyses that quantify the social costs and benefits stemming from such investments is a natural direction for future research.

References

Abadie, Alberto, Susan Athey, Guido W Imbens, and Jeffrey M Wooldridge. 2023. "When should you adjust standard errors for clustering?" *The Quarterly Journal of Economics*, 138(1): 1–35.

Amornsiripanitch, Natee, Paul A Gompers, and Yuhai Xuan. 2019. "More than money: Venture capitalists on boards." *The Journal of Law, Economics, and Organization*, 35(3): 513–543.

Antón, Miguel, Florian Ederer, Mireia Giné, and Martin Schmalz. 2023. "Common ownership, competition, and top management incentives." *Journal of Political Economy*, 131(5): 1294–1355.

Antón, Miguel, Florian Ederer, Mireia Giné, and Martin Schmalz. 2024. "Innovation: The Bright Side of Common Ownership?" *Management Science*, forthcoming.

Azar, José, Martin C Schmalz, and Isabel Tecu. 2018. "Anticompetitive effects of common ownership." *The Journal of Finance*, 73(4): 1513–1565.

Backus, Matthew, Christopher Conlon, and Michael Sinkinson. 2021. "Common Ownership and Competition in the Ready-to-Eat Cereal Industry." National Bureau of Economic Research Working Paper 28350.

Baum, Joel AC, Tony Calabrese, and Brian S Silverman. 2000. "Don't go it alone: Alliance network composition and startups' performance in Canadian biotechnology." *Strategic management journal*, 21(3): 267–294.

Bernstein, Shai, Xavier Giroud, and Richard R Townsend. 2016. "The impact of venture capital monitoring." *The Journal of Finance*, 71(4): 1591–1622.

Chemmanur, Thomas J, Karthik Krishnan, and Debarshi K Nandy. 2011. "How does venture capital financing improve efficiency in private firms? A look beneath the surface." *The Review of Financial Studies*, 24(12): 4037–4090.

Cheng, Zhaoqi, Ginger Zhe Jin, Mario Leccese, Dokyun Lee, and Liad Wagman. 2023. "M&A and innovation: A new classification of patents." *American Economic Association: Papers and Proceedings*, 113: 288–293.

Cohen, Wesley M, Richard Nelson, and John P Walsh. 2000. "Protecting their intellectual assets: Appropriability conditions and why US manufacturing firms patent (or not)."

Cox Pahnke, Emily, Rory McDonald, Dan Wang, and Benjamin Hallen. 2015. "Exposed: Venture capital, competitor ties, and entrepreneurial innovation." *Academy of Management Journal*, 58(5): 1334–1360.

Cunningham, Colleen, Florian Ederer, and Song Ma. 2021. "Killer acquisitions." *Journal of Political Economy*, 129(3): 649–702.

Dessí, Roberta, and Nina Yin. 2015. "Venture capital and knowledge transfer." SSRN Working Paper 2642596.

Ederer, Florian, and Bruno Pellegrino. 2022. "A tale of two networks: Common ownership and product market rivalry." National Bureau of Economic Research.

Eldar, Ofer, and Jillian Grennan. 2021. "Common ownership and entrepreneurship." *American Economic Association: Papers and Proceedings*, 111: 582–586.

Eldar, Ofer, and Jillian Grennan. 2024. "Common Venture Capital Investors and Startup Growth." *Review of Financial Studies*, 37(2): 549–590.

Ewens, Michael, and Matt Marx. 2018. "Founder replacement and startup performance." *The*

Review of Financial Studies, 31(4): 1532–1565.

Ewens, Michael, and Nadya Malenko. 2020. "Board Dynamics over the Startup Life Cycle." National Bureau of Economic Research Working Paper 27769.

Fulghieri, Paolo, and Merih Sevilir. 2009. "Size and focus of a venture capitalist's portfolio." *The Review of Financial Studies,* 22(11): 4643–4680.

Gompers, Paul, Anna Kovner, and Josh Lerner. 2009. "Specialization and success: Evidence from venture capital." *Journal of Economics & Management Strategy,* 18(3): 817–844.

Gompers, Paul A., Will Gornall, Steven N. Kaplan, and Ilya A. Strebulaev. 2020. "How do venture capitalists make decisions?" *Journal of Financial Economics,* 135(1): 169–190.

González-Uribe, Juanita. 2020. "Exchanges of innovation resources inside venture capital portfolios." *Journal of Financial Economics,* 135(1): 144–168.

Haltiwanger, John, Ian Hathaway, and Javier Miranda. 2014. "Declining business dynamism in the US high-technology sector." *Available at SSRN 2397310*.

Heckman, James J. 1979. "Sample selection bias as a specification error." *Econometrica: Journal of the econometric society,* 153–161.

He, Jie Jack, and Jiekun Huang. 2017. "Product market competition in a world of cross-ownership: Evidence from institutional blockholdings." *The Review of Financial Studies,* 30(8): 2674–2718.

Hellmann, Thomas. 2002. "A theory of strategic venture investing." *Journal of financial economics,* 64(2): 285–314.

Hellmann, Thomas, and Manju Puri. 2002. "Venture capital and the professionalization of start-up firms: Empirical evidence." *The journal of finance,* 57(1): 169–197.

Hsu, David H. 2004. "What do entrepreneurs pay for venture capital affiliation?" *The journal of finance,* 59(4): 1805–1844.

Jiang, Wei. 2017. "Have instrumental variables brought us closer to the truth." *Review of Corporate Finance Studies,* 6(2): 127–140.

Jin, Ginger Zhe, Mario Leccese, and Liad Wagman. 2023. "How Do Top Acquirers Compare in Technology Mergers? New Evidence from an S&P Taxonomy." *International Journal of Industrial Organization,* 89: 102891.

Jin, Ginger Zhe, Mario Leccese, and Liad Wagman. 2024. "M&A and technological expansion." *Journal of Economics & Management Strategy,* 33(2): 338–359.

Jin, Ginger Zhe, Mario Leccese, and Liad Wagman. 2025. "The Role of Digital Platforms in Shaping Tech Venture Innovation." National Bureau of Economic Research Working Paper 33370.

Kortum, Samuel, and Josh Lerner. 2000. "Assessing the contribution of venture capital." *the RAND Journal of Economics,* 31(4): 674–692.

Kostovetsky, Leonard, and Alberto Manconi. 2020. "Common institutional ownership and diffusion of innovation." SSRN Working Paper 2896372.

Lerner, Josh. 1995. "Venture capitalists and the oversight of private firms." *the Journal of Finance,* 50(1): 301–318.

Lerner, Josh, and Ramana Nanda. 2020. "Venture capital's role in financing innovation: What we know and how much we still need to learn." *Journal of Economic Perspectives,* 34(3): 237–261.

Levin, RCAK, Alvin Klevorick, and R Nelson. 1987. "Appropriating the Returns from Industrial

Research and Development." *Brookings Papers on Economic Activity*, 3: 783–831.

Lindsey, Laura. 2008. "Blurring firm boundaries: The role of venture capital in strategic alliances." *The Journal of Finance*, 63(3): 1137–1168.

Li, Xuelin, Tong Liu, and Lucian A Taylor. 2023. "Common ownership and innovation efficiency." *Journal of Financial Economics*, 147(3): 475–497.

Maddala, Gangadharrao S. 1983. *Limited-dependent and qualitative variables in econometrics.* Cambridge university press.

Newham, Melissa, Jo Seldeslachts, and Albert Banal-Estanol. 2018. "Common ownership and market entry: Evidence from pharmaceutical industry."

O'Brien, Daniel P., and Steven C. Salop. 2000. "Competitive effects of partial ownership: Financial interest and corporate control." *Antitrust Law Journal*, 67(3): 559–614.

Ozcan, Pinar, and Kathleen M Eisenhardt. 2009. "Origin of alliance portfolios: Entrepreneurs, network strategies, and firm performance." *Academy of management journal*, 52(2): 246–279.

Prado, Tiago S., and Johannes M. Bauer. 2022. "Big Tech platform acquisitions of start-ups and venture capital funding for innovation." *Information Economics and Policy*, 59: 100973.

Puri, Manju, and Rebecca Zarutskie. 2012. "On the life cycle dynamics of venture-capital-and non-venture-capital-financed firms." *The Journal of Finance*, 67(6): 2247–2293.

Samila, Sampsa, and Olav Sorenson. 2011. "Venture capital, entrepreneurship, and economic growth." *The Review of Economics and Statistics*, 93(1): 338–349.

Schroth, Enrique, and Dezsö Szalay. 2010. "Cash breeds success: The role of financing constraints in patent races." *Review of Finance*, 14(1): 73–118.

Sørensen, Morten. 2007. "How smart is smart money? A two-sided matching model of venture capital." *The Journal of Finance*, 62(6): 2725–2762.

Stuart, Toby E. 2000. "Interorganizational alliances and the performance of firms: a study of growth and innovation rates in a high-technology industry." *Strategic management journal*, 21(8): 791–811.

Weigelt, Keith, and Colin Camerer. 1988. "Reputation and corporate strategy: A review of recent theory and applications." *Strategic management journal*, 9(5): 443–454.

ONLINE APPENDIX

Appendix A. A Theory of VC Financing with Startup Competition and Learning-by-investing

In what follows, I develop an analytical model, which focuses on VC's learning as a source of the selection effect. Consider the problem of a risk-neutral investor ("the VC") that has *just* invested in a startup (startup 1) operating in a certain business niche, and has to decide if and when to invest in a second startup (startup 2) operating in the same business niche, and hence potentially in competition with startup 1. I assume that any startup i has a probability of success $q_i \sim G\left[0, \bar{q}\right]$, where $G(\cdot)$ is any cumulative distribution function with $\mathbb{E}[q_i] \equiv \mu \leq \frac{1}{2}, \frac{3}{4} \leq \bar{q} \leq 1$, and $q_1 \perp q_2$. Another risk-neutral investor (C) competes with the VC to invest in startup 2. Conditionally on having eventually invested in startup 2, the VC can take different actions, which I refer to as "portfolio management strategies," to influence portfolio startups' probabilities of success and consequently the overall value of the portfolio. These capture the additional influence that only a VC with competing portfolio startups can exert, and hence, are not available to investors like C.

Competition between startups is modeled by assuming that for an investor the future return from a startup is lower if the competing startup also remains active. In particular, I assume that if a startup fails, its investor earns zero, while a startup that succeeds when the rival startup fails generates a value of R for its investor. If, instead, both startups succeed, each generates a value of $R(1-\phi)$ for its investor, with $\phi \in \left[\frac{1}{2}, 1\right]$ parametrizing the intensity of competition between startups. Thus, startup competition diminishes the value for investors, which drops to zero when $\phi = 1$, as if the startups were producing homogeneous products and engaging in Bertrand competition.

Figure A.1 summarizes the timing of the VC's problem. At $T = 1$ the VC, who has already invested in startup 1 and learned the realization of its probability of success q_1 is presented with the opportunity to invest F in startup 2. At this stage, the VC does not know the realization of q_2. If the VC invests in startup 2 at $T = 1$, then the next step concerns directly the choice of the portfolio management strategy ($T = 3$). Otherwise, the VC learns the realization of q_2 and at $T = 2$ may have a new opportunity to invest in startup 2.

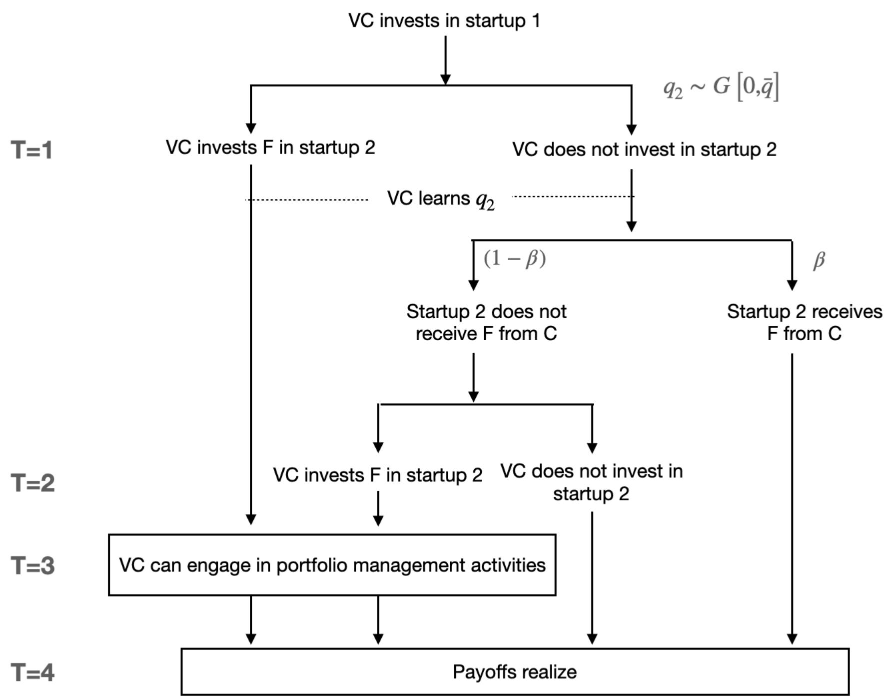


FIGURE A.1. Timing and structure of the VC's decision problem

Before this opportunity materializes, there is a probability β that startup 2 encounters the competing investor C. Since C has never invested in the business niche, I assume that it does not know the realizations of q_1 and q_2, but only their distributions. Moreover, I assume that conditional on being matched to startup 2, C is just indifferent between investing and not investing, and eventually always invests F, i.e.,

$$\mathbb{E}[q_1 q_2 R(1-\phi) + (1-q_1)q_2 R - F] = 0. \tag{A1}$$

Given that q_1 and q_2 are independent, this implies the maximum possible return from a startup can be written as $\frac{F}{R} = \mu(1 - \phi\mu)$, which is decreasing in startup competition and increasing in the average probability of success of the startup.[1] If C and startup 2 match—and hence by Equation A1 C invests in startup 2—the VC cannot take any further action and in $T = 4$ payoffs realize.

At $T = 2$, if neither the VC nor C has invested before, the VC decides whether to invest F in startup 2 knowing the realization of q_2. I assume that investors that already invested in a market in the past acquire an expertise that enables them to better assess the quality of startups. In line with this assumption, the empirical evidence indicates that more experienced VCs are typically matched with higher-quality startups (Sørensen 2007). This process is modeled by assuming that waiting to invest in startup 2 allows the VC to learn the realization of q_2 before investing. The cost of waiting to learn q_2 for the VC is that C could invest in startup 2 before $T = 2$ is reached.

Afterward, at $T = 3$, conditional on having invested in startup 2, the VC can *influence* the probability of success of portfolio startups by engaging in portfolio management activities. I begin considering three possible portfolio management strategies, and to ease exposition, I assume three specific actions the VC can undertake: (i) Increase each startup's probability of success q_i through a "knowledge transfer" $\tau \in \left[0, \frac{1}{4}\right]$.[2] For simplicity, I refer to this strategy as "symmetric knowledge sharing." (ii) Decide to transfer knowledge to only one portfolio startup i, so that the probability of success of startup i becomes $q_i + \tau$, while that of the other startup j remains q_j ("asymmetric knowledge sharing"); (iii) Adopt a passive portfolio management approach, thereby leaving portfolio startups' probabilities of success unchanged. Note that (i) and (ii) are akin to what in the main text I refer to as "coordination" and "play favorites."

Finally, at $T = 4$ payoffs realize. Table A.1 summarizes the expected payoff of the VC

[1] The simplification hinges on the assumption that the negotiations between the VC and startup 2 at $T = 1$ cannot be observed by outside investors, and hence cannot influence their beliefs about q_1 and q_2.

[2] Note that assuming $\tau \leq \frac{1}{4}$, together with $q_i \leq \frac{3}{4}$ $\forall i = 1, 2$, ensures that $q_i + \tau \leq 1$.

TABLE A.1. VC's expected payoff at $T = 2$

VC invests in startup 2	C invests in startup 2	Portfolio Management Strategy	VC's Payoff
X	✓	·	$R[q_1 q_2(1-\phi) + q_1(1-q_2)]$
X	X	·	Rq_1
✓	X	Symmetric knowledge sharing	$R[2(q_1+\tau)(q_2+\tau)(1-\phi)+$ $+(q_1+\tau)(1-q_2-\tau)+(q_2+\tau)(1-q_1-\tau)]-F$
✓	X	Favor startup i	$R[2(q_i+\tau)q_j(1-\phi)+$ $+(q_i+\tau)(1-q_j)+q_j(1-q_i-\tau)]-F$
✓	X	Passive	$R[2q_1q_2(1-\phi)+q_1(1-q_2)+q_2(1-q_1)]-F$

at $T = 2$ at each node of the problem.

Portfolio management. Proceeding backward, at $T = 3$, the VC can engage in portfolio management activities only if they have invested in two startups. Otherwise, the VC's expected payoff is simply:

$$\mathbb{E}\left[Rq_1q_2(1-\phi) + Rq_1(1-q_2)\right] = Rq_1(1-\phi q_2), \tag{A2}$$

because at this stage both probabilities of success are known to the VC. In what follows I assume without loss of generality that $q_i \geq q_j, i \neq j$. The next proposition describes the threshold rule defining the optimal portfolio management decision of the VC at $T = 3$ when choosing between engaging in knowledge sharing and being passive.

PROPOSITION A1. *When $q_j \leq \frac{1}{2\phi}$, conditional on having invested in startup 2, the VC engages in symmetric knowledge sharing iff $q_i \leq \frac{1}{2\phi} - \tau$ and in asymmetric knowledge sharing favoring startup i, otherwise. Instead, when $q_j > \frac{1}{2\phi}$, conditional on having invested in startup 2, the VC adopts a passive portfolio management approach.*

Proposition A1 shows that the VC has an incentive to favor the startup with the highest probability of success when its probability of success is large enough, both in absolute terms and relative to that of the other portfolio startup. Moreover, the threshold above which the VC favors startup i is decreasing in both ϕ and τ. When startup competition is intense, the VC has a greater incentive to favor startup i because of the loss in returns that competition would cause if both startups stayed afloat. Instead, a larger knowledge transfer increases the probability of success but also the expected loss due to competition, shrinking the region where symmetric knowledge sharing is optimal.

Proposition A1 has also important implications in terms of startup performance and the extent to which this is impacted by the VC's ability to engage in knowledge sharing. I refer to this as the *"influence effect"* of a common VC. Clearly, when the VC chooses to be passive, then they have no influence on startup performance. In the model, conditional on investing in two startups and the worst startup being not too likely to succeed, it is always optimal for the VC to share knowledge across portfolio startups, and hence the choice is only about the direction of such knowledge sharing.

PROPOSITION A2. *When the VC invests in competing startups and engages in symmetric knowledge sharing, each startup enjoys a higher payoff than in the counterfactual scenario, with a gain of* $1 - \phi(q_i + q_j + \tau)$. *Instead, when the VC invests in competing startups and engages in asymmetric knowledge sharing favoring startup i, startup i (j) enjoys a higher (lower) payoff than in the counterfactual scenario. Startup i's benefit is* $\tau(1 - \phi q_j)$, *while the loss suffered by startup* j *equals* ϕ.

Proposition A2 shows that depending on the degree of competition between startups, the size of knowledge sharing, and the relative probability of success, sharing the VC with a competitor can benefit or hurt a startup. When the VC engages in asymmetric knowledge sharing and startup i benefits at the expense of startup j, the payoff gap between startups is increasing in ϕ and decreasing in q_j and τ. By contrast, the gains from symmetric knowledge sharing the both startups enjoy are decreasing in q_i, q_j, τ and ϕ.

Second-stage investment decision. Consider now the VC's decision to invest in startup

2. At $T = 2$, the VC knows the realizations of q_1 and q_2, and can forecast what their continuation value would be if they invested and followed the optimal portfolio management strategy given $(q_1, q_2, \phi, \tau, F, R)$. Therefore, the VC chooses whether to invest by comparing q_2 to various thresholds which are endogenously determined by the optimal portfolio management strategy at the given parameters. Formally, I define the selection effect as the difference in the expected probability of success of startup 2 if financed by the VC as compared to if financed by a competing investor.

PROPOSITION A3. *Let*

$$\lambda(q_1, \phi, \tau, F, R) = \begin{cases} \frac{\frac{F}{R}-\tau}{1-2\phi(q_1+\tau)} - \tau, & \text{if} \quad q_1 < \frac{1}{2\phi} - \frac{F}{R} \\ \\ \frac{\frac{F}{R}}{1-2\phi q_1} - \tau, & \text{otherwise.} \end{cases} \tag{A3}$$

The selection effect is an increasing function of λ *and exists if and only if* $\lambda > 0$*. Moreover,* $\lambda > 0$ *if and only if* $\frac{1}{\phi} - \tau - \frac{F/R}{2\phi\tau} < q_1 < \frac{1}{2\phi}$.

While the selection effect originates from the information advantage of the VC relative to a competing investor, its magnitude depends on the intensity of startup competition, the quality of startup 1, and the size of the knowledge transfers. Having already invested in startup 1 leads to internalizing the cost that the success of both startups generates. This cost becomes larger when q_1 grows, thus increasing the selection effect. However, when the first startup initial probability of success increases above $\frac{1}{2\phi}$, the VC has no incentive to invest in an additional startup as the expected loss in returns due to competition becomes too high.[3] Overall, the VC tends to invest in startup 2 when it is better than startup 1, unless the difference between the success probabilities is so small that symmetric knowledge sharing can increase the value of the portfolio, or startup

[3] While I define the selection based on q_2, in Appendix A.1 I discuss the role of selection on q_1.

1 is very likely to succeed. This implies, as shown in Proposition A6, that asymmetric knowledge sharing favoring startup 1 can never be chosen as the optimal portfolio management strategy if the VC invest in startup 2 at $T = 2$.

First-stage investment decision. For the selection effect to arise, the VC needs time to assess startup 2's probability of success. In practice, the competitive pressure from other interested investors may prevent the VC to do so. Therefore, I now analyze the incentive of the VC to invest in startup 2 before learning q_2.

In the first stage, the VC chooses whether to invest in startup 2 without knowing q_2 or wait to learn it, running the risk that a competing investor invests in the startup. This decision is taken by comparing the expected value from investing at $T = 1$ with the expected continuation value from waiting and making the optimal decision at $T = 2$. Defining $\mathbb{E}[V^{I_t}]$ as the expected continuation value of investing at $T = t$, and p as the probability of not investing at $T = 2$, the VC invests if and only if:

$$\mathbb{E}[V^{I_1} - F] \geq (1 - \beta) \left[pq_1 R + (1 - p)\mathbb{E}[V^{I_2} - F] \right] + H(\beta, R, q_1, \phi, \mu), \tag{A4}$$

where $H(\beta, R, q_1, \phi, \mu) = \beta\mathbb{E}[Rq_1q_2(1 - \phi) + Rq_1(1 - q_2)] = \beta Rq_1 (1 - \mu\phi)$ is the expected value of the VC when a competing investor is matched to startup 2.

By increasing the cost of waiting, a larger β raises the VC's incentive to invest at $T = 1$. In particular, when $\beta = 0$, the VC is sure that they will have a second opportunity to invest in startup 2. Therefore, there is no reason to commit to an investment choice at $T = 1$, and waiting until $T = 2$ to learn q_2 is the dominant strategy.

PROPOSITION A4. *The probability of an early investment in startup 2 at T=1 is increasing in the degree of competition from other investors.*

This result is important not only for studying the interaction between investor competition and investment timing but also for understanding the practical significance of the selection effect in this context. When the VC invests in startup 2 at $T = 1$, there is no selection effect because the investment is made without knowledge of q_2, meaning that any realization in $[0, \bar{q}]$ is possible. However, model simulations indicate that investments at $T = 1$ are relatively uncommon, suggesting that strategic investments in competitors may be characterized by a significant degree of selection. This also implies that startup 1 is rarely the only one to benefit from sharing the VC. For example, when $\tau = 0.075$, $\beta = 0.5$, $\phi = 0.75$ and G is a uniform over $\left[0, \frac{3}{4}\right]$, the VC invests at $T = 1$ whenever q_1 is below the average but favoring startup 1 at $T = 3$ requires q_1 to fall within the top 21^{st} percentile of the unconditional distribution.

Overall, this model offers a straightforward analysis of how influence and selection effects shape VCs' investments in competing startups. However, it is important to address two assumptions that underlie the results. First, the VC has all the bargaining power in the negotiations with startup 2. Relaxing this assumption would not change the qualitative predictions because startup 2 tends to benefit from sharing the VC with startup 1. Moreover, in the extreme cases where the VC would be willing to finance startup 2 at $T = 1$ but later favor startup 1, increasing startup 2' s bargaining power may prevent that an agreement is reached, strengthening the conclusions of the model.

Second, I assume that the VC can control the portfolio management strategy. In practice, this might be more challenging when startups have additional investors. The alignment of incentives between the VC and startup 2 generally ensures that the predictions remain robust to cases in which startup 2 has multiple investors with no stake in startup 1. However, if the VC invested in startup 1 as part of a syndicate, this could limit its ability to favor or invest in startup 2. Consequently, in such cases, the likelihood of observing startup 2 benefiting at the expense of startup 1 might be lower than what predicted by the model.

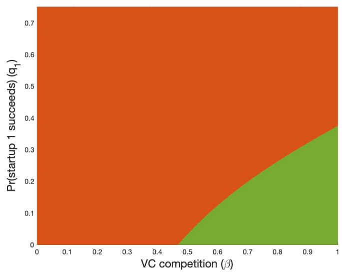
A.1. First-stage Investment, Selection on q_1 and the Relative Quality of Solo Startups

Proposition A3 defines the selection effect as the probability of success of startup 2 when invested in by the VC relative to the probability of success of startup 2 when invested in by the competing investor. When mapping the model to the data to derive testable hypotheses, I hinge on this definition to posit that startups not sharing a VC with a competitor (i.e., solo startups) are on average of lower quality (i.e., probability of success) relative to startups which are not the first investment of the VC in a business area (i.e., subsequent startups). The intuition is that at $T = 2$, the VC will only invest in startup 2 if q_2 is large enough. This definition emphasizes the role of VC learning through prior investments in determining the average inherent equilibrium quality of subsequent startups.

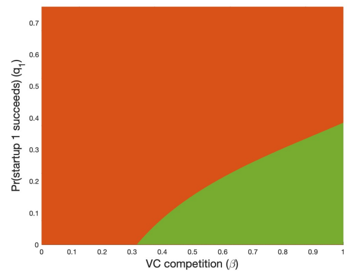
In what follows, I caution the reader about an additional source of selection that arises in the model and may as well exist in the data, i.e., the selection on q_1. While in the presentation of the model, I mainly focus on the selection on q_2 arising from the VC's learning, in the empirical analyses, I also account for this additional source of selection in the FE and IV models.

Figure A.2 plots the value of the VC from investing and not investing at $T = 1$ in the (β, q_1)–space for all the possible parametrizations implied by the combination of $\tau \in \{0, 0.075, 0.19\}$ and $\phi \in \{0.5, 0.75, 1\}$, with $\bar{q} = 0.75$. Beside allowing for several comparative statics exercises, the plots highlight that when endowed with a high–probability of success startup 1, the VC tends to avoid investing at $T = 1$. Moreover, as suggested by Figure A.3, conditional on having a new opportunity to invest in startup 2, the VC tends to avoid investing when q_1 is high.

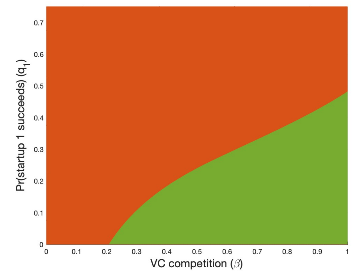
Taken together, these two facts imply that, in equilibrium, at least some of the startups not sharing a VC with a competitor may be high-quality. In other words, there may be a subset of solo startups, which are not those invested in by the competing



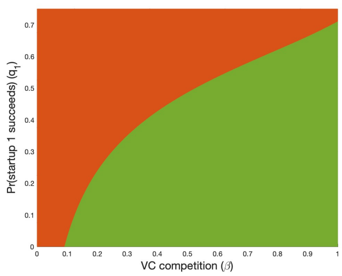
A. ϕ = 0.5, τ = 0



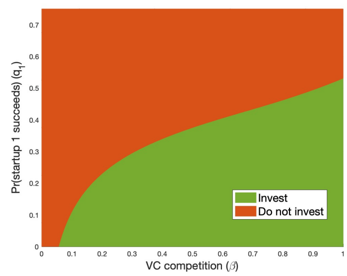
B. ϕ = 0.75, τ = 0



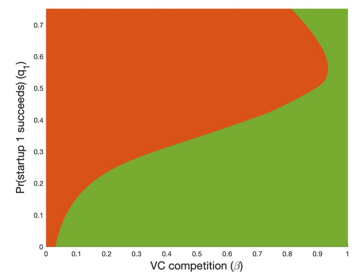
C. ϕ = 1, τ = 0



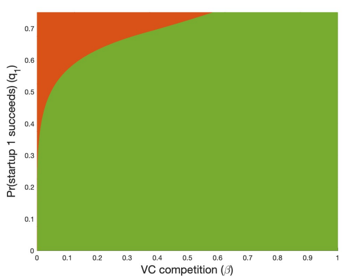
D. ϕ = 0.5, τ = 0.075



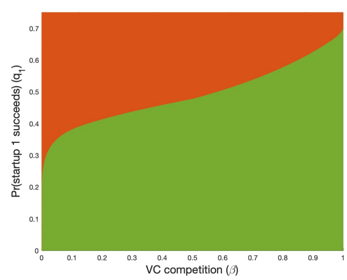
E. ϕ = 0.75, τ = 0.075



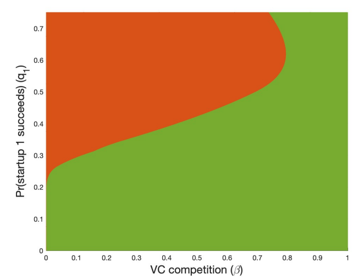
F. ϕ = 1, τ = 0.075



G. ϕ = 0.5, τ = 0.19



H. ϕ = 0.75, τ = 0.19



I. ϕ = 1, τ = 0.19

FIGURE A.2. Optimal Investment Strategy at $T = 1$ varying q_1

investor, that have average quality similar or even greater than that of subsequent startups. This means that, in theory, under certain conditions, solo startups may have on average similar or higher unobservable quality as compared to subsequent startups. This force can mitigate the size of the selection effect.

A possible explanation for my empirical findings is that first startups tend to be average startups, exactly due to the absence of business area-specific knowledge at the time of the investment. When startup 1 is an average startup, qualitatively, the model leads to the following equilibrium outcomes:

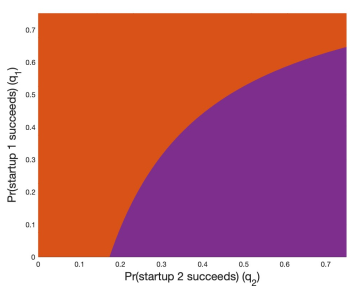
- If the VC invests at $T = 1$, then the first startup (startup 1) and the subsequent startup (startup 2) are of similar quality, on average, given that the investment in startup 2 occurs before learning the realization of q_2.

- If the VC does not invest at $T = 1$, then two possibilities can materialize:

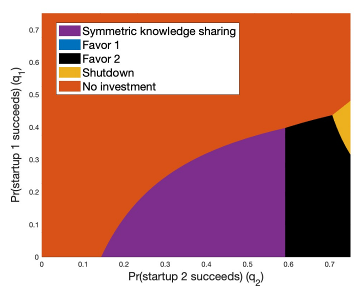
  (a) The outside investor funds startup 2 without knowing the realization of q_2. In this case, startup 1 and 2 are two solo startups with the same quality, on average.

  (b) The VC invests in startup 2 knowing q_2. This implies that the investment tends to occur when startup 2 has quality above the average. Thus, in this case the subsequent startup has inherently greater quality than the first one.

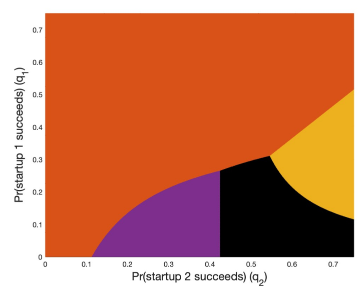
Therefore, subsequent startups should be on average of greater inherent quality relative to solo startups, which in turn should be similar to first startups.



A. $\phi = 0.5, \tau = 0.075$



B. $\phi = 0.75, \tau = 0.075$



C. $\phi = 1, \tau = 0.075$

FIGURE A.3. Optimal Investment Strategy at $T = 2$ varying q_1

A.2. Startup Shutdown

In this section, I extend the model to allow for startup shutdown. At $T = 3$, a common VC can be passive, share knowledge across portfolio startups, or discontinue one of the two. In this case, if startup j is discontinued, the expected payoff of the VC is $q_i R$. The next result describes the optimal portfolio management strategy.

PROPOSITION A5. *Conditional on having invested in startup 2, the VC engages in:*

(i) Symmetric knowledge sharing iff $q_i \leq \frac{1}{2\phi} - \tau$.

(ii) Asymmetric knowledge sharing favoring startup i iff $\frac{1}{2\phi} - \tau < q_i \leq \frac{q_j+\tau}{2\phi q_j} - \tau$.

(iii) Shutdown startup j iff $q_i > \frac{q_j+\tau}{2\phi q_j} - \tau$.

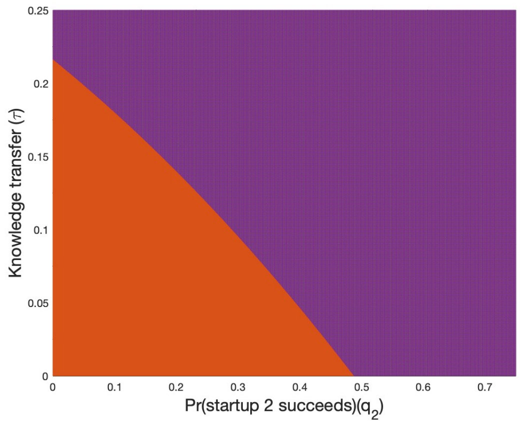
Proposition A5 illustrates how shutting down startup j can be optimal only in contexts characterized by a high degree of competition between startups and by a large enough gap in the probability of success.

Next, I examine the investment decision of the VC at $T = 2$, when both q_1 and q_2 are known. It is easy to see that when $q_1 > q_2$ investing in startup 2 to shut it down generates the same value as not investing but requires the VC to bear the investment cost F, and hence is dominated. Thus, when $q_1 > q_2$, the VC either invests to engage in symmetric knowledge sharing or does not invest. Instead, if $q_2 \geq q_1$, the VC invests in startup 2 and discontinues startup 1 if and only if $q_2 > \max\left\{q_1 + \frac{F}{R}, \frac{q_1+\tau}{2\phi q_1} - \tau\right\}$.

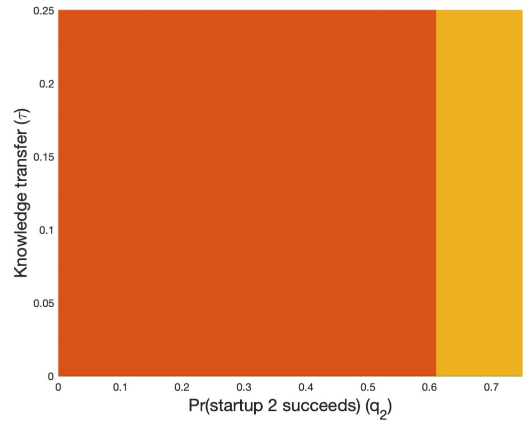
Figure A.4 illustrates the optimal strategy of the VC as a function of τ and q_2, for different levels of startup competition $\phi \in \left\{\frac{1}{2}, \frac{3}{4}, 1\right\}$ when G is any distribution over $\left[0, \frac{3}{4}\right]$ with mean at the midpoint of the interval. Moreover, to emphasize the selection effect on the second startup, which is a focus of this paper, I assume that startup 1 is an *average startup*.[4] The red area represents the values of τ and q_2 for which the VC does not invest, thus identifying the selection effect. The selection effect is decreasing in τ and is larger when startup competition is more intense.

When competition is weak ($\phi = 0.5$ in Figure A.4A), the two startups are differentiated enough that a VC with an average portfolio startup will always engage in symmetric knowledge sharing conditional on investing in a new startup. However, the selection

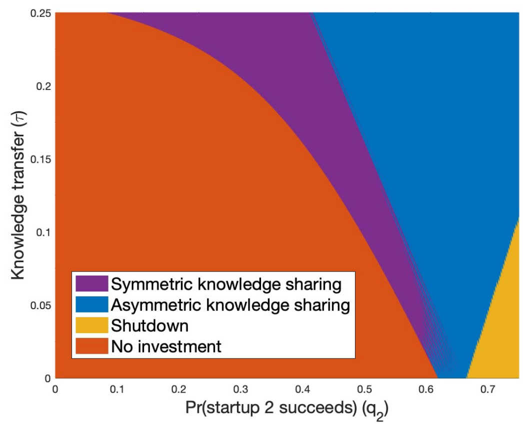
[4] The key insights of the model as well as its qualitative implications are robust to considering a continuous $\phi \in \left[\frac{1}{2}, 1\right]$.



A. Weak competition (ϕ = 0.5)



B. Intense competition (ϕ = 1)



C. Moderate competition (ϕ = 0.75)

FIGURE A.4. Optimal Investment and Portfolio Management Strategy at T = 2

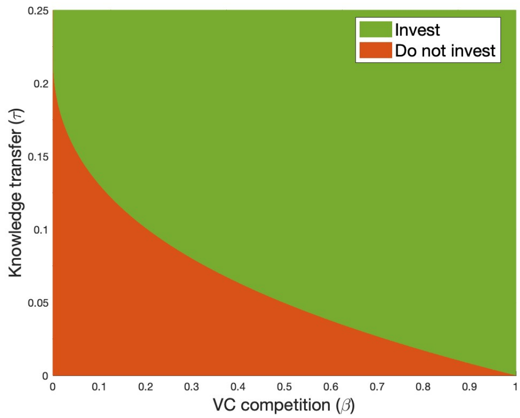
effect is still quite strong, especially for values of τ that are not too large. For example, when τ = 0.05, meaning that the VC can increase an average startup probability of success by more than 13%, the VC needs to encounter a startup that is well above the average to invest. Conversely, when competition is intense (ϕ = 1, Figure A.4B), the VC receives no returns from having two successful startups in its portfolio, making it always optimal to discontinue the startup with the lower probability of success. Since investment in startup 2 only occurs when q_2 is in the top 20^{th} percentile of the distribution, when the VC invests in startup 2, startup 1 is shut down. Figure A.4C illustrates the case of moderate competition (ϕ = 0.75). Conditional on investing, the largest area in the graph is the one where the VC favors startup 2. This becomes more evident when the probability of success of startup 2 and the size of the knowledge transfer increase.

First-stage investment decision. Consistently with Proposition A4, all the graphs in Figure A.5 display that greater investor competition increases the probability of observing the VC investing at $T = 1$. Note that this implies that selection tends to be less severe in contexts where competition between startups is weak. Figures A.5A, A.5B and A.5C also show that the size of the investment region increases with τ, fixing $q_1 = \mu = \frac{3}{8}$. Intuitively, a relatively low draw of q_2 may be compensated through knowledge sharing when τ is large. Moreover, when competition increases from weak to moderate, the area where the VC invests shrinks significantly.

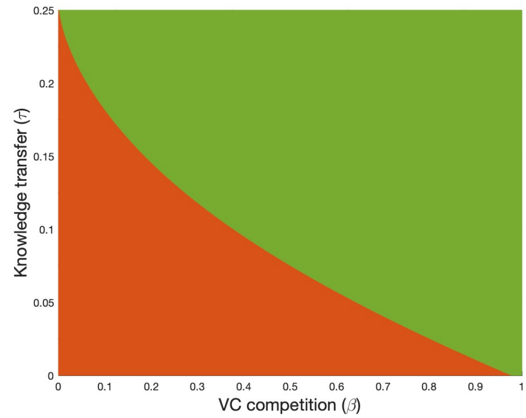
Interestingly, when ϕ increases up to 1, Figure A.5C shows that the shape of the no investment region changes. This is because, conditionally on investing in startup 2, favoring the best startup (via knowledge sharing or by discontinuing the other) becomes more attractive for the VC. In particular, the VC now prefers to not invest for very low β even when τ is very large, while investment is preferred with high β even when $\tau \to 0$.

Lastly, Figure A.5D plots the VC's values from investing and not investing at $T = 1$ fixing $\tau = 0.075$ and letting q_1 vary. Two facts are noteworthy: (i) the VC is more likely to invest when startup 1 has a lower probability of success.[5] (ii) If β is large, investment at $T = 1$ can also occur when q_1 is high because the VC has an incentive to invest in startup 2 to favor startup 1, either via discontinuing startup 2 or asymmetric knowledge sharing. The reason is that by not investing at $T = 1$, the VC leaves open the possibility that the outside investor invests in startup 2. Therefore, when startup 1 is very likely to succeed, the VC is willing to invest in startup 2 only to preempt a competing investor from funding startup 2. This decision is made even more appealing by the high degree

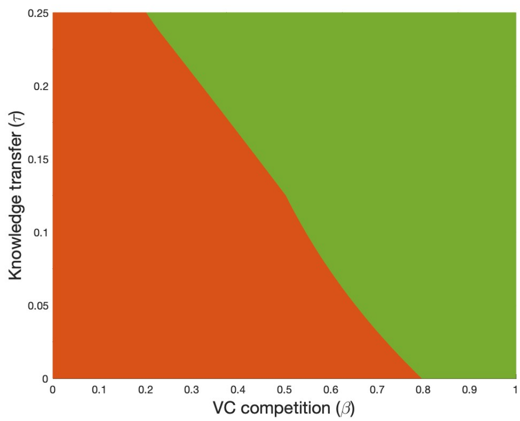
[5] This is true for any ϕ and endogenously determines the types of startups that are more likely to reach $T = 2$. Appendix A.1 discusses how the size of q_1 affects the equilibrium inherent probability of success of subsequent startups relative to solo ones.



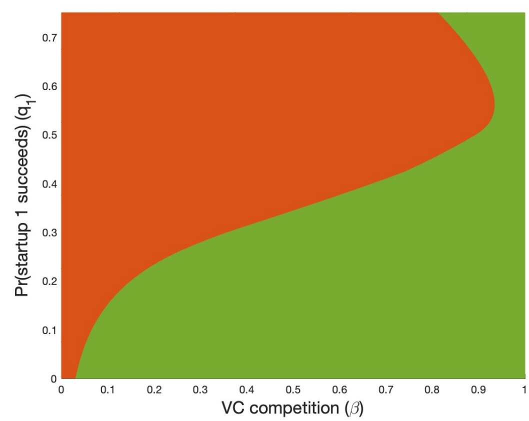
A. Weak competition (ϕ = 0.5)



B. Moderate competition (ϕ = 0.75)



C. Intense competition (ϕ = 1)



D. Intense competition (ϕ = 1) and τ = 0.075

FIGURE A.5. Optimal Investment Strategy at $T = 1$

of startup competition, which lowers the cost of investing F.

Hence, this model provides a theoretical foundation for VCs investing in startups with the intent to preempt competition. At the same time, however, the model suggests that this may only occur in cases where startup competition is extremely intense.

A.3. Proofs and additional theoretical results

Proof of Proposition A1.

PROOF. The expected payoff from symmetric knowledge sharing is:

$$V^S = R\left[2(q_i+\tau)(q_j+\tau(1-\phi)+(q_i+\tau)(1-q_j-\tau)+(q_j+\tau)(1-q_i-\tau)\right].$$

The expected payoff from favoring i is:

$$V^{F^i} = R\left[2(q_i+\tau)q_j(1-\phi)+(q_i+\tau)(1-q_j-\tau)+q_j(1-q_i-\tau)\right].$$

The expected payoff from being passive is:

$$V^P = R\left[2q_iq_j(1-\phi)+q_i(1-q_j)+q_j(1-q_i)\right]$$

First, notice that—conditionally on engaging in asymmetric knowledge sharing—the VC always favors the startup with the highest probability of success, i.e. $V^{F^i} > V^{F^j} \iff q_i > q_j$. Moreover, it is easy to show the following facts:

(a) $V^S \geq V^{F^i} \iff q_i \leq \frac{1}{2\phi} - \tau$.

(b) $V^S \geq V^P \iff q_i \leq \frac{1}{\phi} - q_j - \tau$.

(c) $V^P > V^{F^i} \iff q_j > \frac{1}{2\phi}$.

Combining (a) and (b), it follows that symmetric knowledge sharing is optimal if and only if:

(A5) $$q_i \leq \min\left\{\frac{1}{2\phi}-\tau, \frac{1}{\phi}-q_j-\tau\right\} = \begin{cases} \frac{1}{2\phi}-\tau, & \text{if } q_j \leq \frac{1}{2\phi} \\ \frac{1}{\phi}-q_j-\tau, & \text{else.} \end{cases}$$

Therefore, suppose first that $q_j \leq \frac{1}{2\phi}$. Then, by A5 and (c), it follows that the VC engages in symmetric knowledge sharing iff $q_i \leq \frac{1}{2\phi} - \tau$ and in asymmetric knowledge sharing favoring startup i, otherwise. Suppose now $q_j > \frac{1}{2\phi}$. By (c), the VC always prefers being passive to favor startup i. Expression A5 implies that symmetric knowledge sharing are preferred when $\frac{1}{\phi} - q_j - \tau$. However, this implies that:

$$\frac{1}{2\phi} < q_j \leq q_i \leq \frac{1}{\phi} - q_j - \tau$$

$$\frac{1}{2\phi} < \frac{1}{\phi} - q_j - \tau,$$

a contradiction because it requires $q_j < \frac{1}{2\phi} - \tau$. Hence, when $q_j > \frac{1}{2\phi}$, the VC always prefers being passive to symmetric knowledge sharing. □

Proof of Proposition A2.

PROOF. Fix q_i and q_j, where without loss of generality $q_i \geq q_j$. I focus on cases in which an influence effect exists, i.e., whenever $q_j < \frac{1}{2\phi}$. The payoff accruing to startup $k = i, j$ in the counterfactual scenario is:

$$V_k^{\text{cf}} = R(1-\phi)q_k q_{-k} + q_k(1-q_{-k})R.$$

Suppose $q_i \leq \frac{1}{2\phi} - \tau$. Then, a common VC chooses to engage in symmetric knowledge sharing. Then, startup i obtains:

$$V_i^S = R(1-\phi)(q_i+\tau)(q_j+\tau) + (q_i+\tau)(1-q_j-\tau)R.$$

Note that the benefit from sharing the VC in this case can be quantified as:

$$V_i^S - V_i^{cf} = 1 - \phi(q_i + q_j + \tau).$$

Note that since $q_i \leq \frac{1}{2\phi} - \tau$ and $q_i \geq q_j$, a sufficient condition for this expression to be positive is:

$$1 \geq \phi \left(\frac{1}{2\phi} + \frac{1}{2\phi} - \tau \right) = 1 - \tau\phi,$$

which is always satisfied.

Suppose now $q_i > \frac{1}{2\phi} - \tau$. Then, the VC favors startup i. startup i obtains:

$$V_i^{A_i} = R(1-\phi)(q_i + \tau)q_j + (q_i + \tau)(1 - q_j)R,$$

while startup j obtains:

$$V_j^{A_i} = R(1-\phi)q_j(q_i + \tau) + q_j(1 - q_i - \tau)R.$$

Therefore, the benefit for startup i can be computed as:

$$V_i^{A_i} - V_i^{\text{cf}} = \tau(1 - \phi q_j) > 0.$$

On the other hand, the loss for startup j is:

$$V_j^{A_i} - V_j^{\text{cf}} = -\phi < 0.$$

□

LEMMA A1. *In equilibrium, it is never optimal for the VC to invest in startup 2 at $T = 2$ and then adopt a passive portfolio management approach.*

PROOF. Suppose by contradiction it is optimal to invests in startup 2 at $T = 2$ and then adopt a passive portfolio management approach. Then, by Proposition A1, $q_i \geq q_j \geq \frac{1}{2\phi}$. Moreover, at $T = 2$, for the VC to invests and then do not engage in any sort of knowledge sharing, it must be:

$$Rq_iq_j(1-\phi) + Rq_i(1-q_j) + Rq_j(1-q_i) - F > q_jR \iff q_i(1-2\phi q_j) > \frac{F}{R},$$

a contradiction because $q_j \geq \frac{1}{2\phi}$ and hence $1-2\phi q_j < 0$. $\square$

LEMMA A2. *If $q_1 \leq q_2 < \frac{1}{2\phi} - \tau$, conditional on investing, the VC chooses symmetric knowledge sharing at $T = 3$. Therefore, the VC invests at $T = 2$ if and only if:*

$$q_2 \geq \frac{\frac{F}{R} - \tau}{1-2\phi(q_1+\tau)} - \tau \equiv \sigma(q_1, \phi, \tau, F, R) \tag{A6}$$

If $q_2 > \max\left\{\frac{1}{2\phi} - \tau, q_1\right\}$ and $q_1 < \frac{1}{2\phi}$, conditional on investing, the VC chooses asymmetric knowledge sharing favoring startup 2 at $T = 3$. Therefore, the VC invests at $T = 2$ if and only if:

$$q_2 \geq \frac{\frac{F}{R}}{1-2\phi q_1} - \tau \equiv \bar{\sigma}(q_1, \phi, \tau, F, R) \tag{A7}$$

PROOF. Suppose first $q_2 \geq q_1$. Depending on how large q_2 is, VC will choose to engage in symmetric or asymmetric knowledge sharing. If $q_1 \leq q_2 < \frac{1}{2\phi} - \tau$, VC invests in startup 2 *iff*:

$$R[(q_1+\tau)(q_2+\tau)(1-\phi) + (q_1+\tau)(1-q_2-\tau) + (1-q_1-\tau)(q_2+\tau)] - F \geq q_1R \iff$$

$$(q_2+\tau)\left[1-2\phi(q_1+\tau)\right] \geq \frac{F}{R} - \tau \iff$$

$$q_2 \geq \frac{\frac{F}{R} - \tau}{1-2\phi(q_1+\tau)} - \tau \equiv \sigma(q_1, \phi, \tau, F, R).$$

On the other hand, when $q_2 > \frac{1}{2\phi} - \tau$ and $q_1 < \frac{1}{2\phi}$, the VC invests in startup 2 *iff*:

$$R[(q_2+\tau)q_1(1-\phi) + (q_2+\tau)(1-q_1) + (1-q_2-\tau)q_1] - F \geq q_1R \iff$$

$$q_2 \geq \frac{\frac{F}{R}}{1-2\phi q_1} - \tau \equiv \bar{\sigma}(q_1, \phi, \tau, F, R).$$

□

LEMMA A3. *If $q_1 > q_2$ the VC will either invest to engage in symmetric knowledge sharing, or otherwise they will not invest at all.*

PROOF. By Lemma A1, a passive behavior is never optimal. Therefore, showing that when $q_1 > q_2$ investing and engaging in asymmetric knowledge sharing favoring startup 1 is not optimal proves the statement. Suppose by contradiction that this is the case. Then, it must be that:

$$R\left[(q_1+\tau)q_2(1-\phi) + (q_1+\tau)(1-q_2) + (1-q_1-\tau)q_2\right] - F \geq q_1 R \iff$$

$$\frac{F}{R} < q_2\left[1-2\phi\left(q_1+\tau\right)\right].$$

A necessary condition for this to hold is $1-2\phi\left(q_1+\tau\right) > 0$ or $q_1 < \frac{1}{2\phi} - \tau$. However, this contradicts Proposition A1 which states that conditional on investment favoring startup 1 is optimal if and only if $q_1 > \frac{1}{2\phi} - \tau$. □

Proof of Proposition A3.

PROOF. Notice first that:

$$\bar{\sigma}(q_1, \phi, \tau, F, R) > \sigma(q_1, \phi, \tau, F, R) \iff q_1 < \frac{1}{2\phi} - \frac{F}{R}.$$

Therefore, λ is the threshold above which the VC decides to invest in startup 2.

I now show that a positive selection effect exists for $\lambda > 0$ and is increasing in λ. By definition, the selection effect is: $\mathbb{E}\left[q_2 | q_2 > \lambda(q_1, \phi, \tau, F, R)\right] - \mathbb{E}\left[q_2\right]$, which implies that when $\lambda = 0$, the selection effect is zero by construction. To see that the selection effect is increasing in λ, one can simply rewrite it as:

$$\begin{aligned}&\mathbb{E}\left[q_2|q_2 > \lambda(q_1, \phi, \tau, F, R)\right] - \mathbb{E}\left[q_2\right]\\&= \int_{\lambda}^{\bar{q}} \frac{g(x)}{(1-G(\lambda))} x dx - \mu\end{aligned}$$

where $g(\cdot)$ and $G(\cdot)$ are the probability density and the cumulative distribution functions of q_2, respectively, and $\frac{g(x)}{(1-G(\lambda))}$ is the conditional probability density function of $q_2|q_2 > \lambda$. Since by the Leibniz Integral Rule,

$$\frac{\partial}{\lambda}\left[\int_{\partial\lambda}^{\bar{q}} g(x) x dx\right] = -g(\lambda),$$

it follows that the derivative of the selection effect w.r.t. λ equals:

$$\frac{g(\lambda)}{\left[1-G(\lambda)\right]^2}\left[\int_{\lambda}^{\bar{q}} x g(x) dx - \lambda\left(1-G(\lambda)\right)\right],$$

which is positive if and only if,

$$\mathbb{E}\left[X|X > \lambda\right] = \int_{\lambda}^{\bar{q}} \frac{g(x)}{1-G(\lambda)} x dx \geq \lambda,$$

which is always true.

Next, I derive necessary and sufficient conditions for a selection effect on startup 2 to exist by studying where $\lambda > 0$.

When $q_1 < \frac{1}{2\phi} - F/R$, There are two possible scenarios:

$$(a)\;\; q_1 \leq \frac{1}{2\phi} - \tau: \;\; \lambda > 0 \iff \frac{1}{\phi} - \tau - \frac{F/R}{2\phi\tau} \leq q_1 < \min\left\{\frac{1}{2\phi} - F/R, \frac{1}{2\phi} - \tau\right\}.$$

$$(b)\ \ q_1 > \frac{1}{2\phi} - \tau : \ \ \lambda > 0 \iff \frac{1}{2\phi} - \tau \leq q_1 < \min\left\{\frac{1}{2\phi} - F/R, \frac{1}{\phi} - \tau - \frac{F/R}{2\phi\tau}\right\}.$$

Thus, we need to distinguish two cases:

(a.i) If $\frac{F/R}{\tau} \geq 1$, then $\lambda > \iff \frac{1}{\phi} - \tau - \frac{F/R}{2\phi\tau} < q_1 < \frac{1}{2\phi} - F/R$.

(a.ii) If $\frac{F/R}{\tau} < 1$, then $\lambda > 0 \iff \frac{1}{\phi} - \tau - \frac{F/R}{2\phi\tau} < q_1 < \frac{1}{2\phi} - \tau$. However, this leads to a contradiction because when $\frac{F/R}{\tau} < 1$, $\frac{1}{\phi} - \tau - \frac{F/R}{2\phi\tau} > \frac{1}{2\phi} - \tau$.

(b.i) If $\frac{F/R}{\tau} \geq 1$, then $\lambda > 0 \iff \frac{1}{2\phi} - \tau < q_1 < \frac{1}{\phi} - \tau - \frac{F/R}{2\phi\tau}$, which leads to a contradiction because when $\frac{F/R}{\tau} \geq 1$, $\frac{1}{\phi} - \tau - \frac{F/R}{2\phi\tau} < \frac{1}{2\phi} - \tau$.

(b.ii) If $\frac{F/R}{\tau} < 1$, then $\lambda > 0 \iff \frac{1}{2\phi} - \tau \leq q_1 < \frac{1}{2\phi} - F/R$. However, this implies $\lambda < 0$, a contradiction.

Therefore, the selection effect exists if and only if

$$\frac{1}{\phi} - \tau - \frac{F/R}{2\phi\tau} < q_1 < \frac{1}{2\phi} - F/R$$

Instead, when $q_1 \geq \frac{1}{2\phi} - F/R$, it is easy to see that the selection effect exists if and only if $q_1 < \frac{1}{2\phi}$ and $q_1 \geq \frac{1}{2\phi} - \frac{F/R}{\tau}$. Hence, it follows that the selection effect exists if and only if

$$\frac{1}{2\phi} - F/R \leq q_1 < \frac{1}{2\phi}.$$

Combining the two results, it is possible to conclude that the selection effect exists if and only if $\frac{1}{\phi} - \tau - \frac{F/R}{2\phi\tau} < q_1 < \frac{1}{2\phi}$.

□

In what follows, I restrict attention to the cases in which the selection effect exists.[6]

[6]Note that this assumption is not too restrictive as I still consider cases wherein $q_1 > \mu$.

PROPOSITION A6. *When $q_2 < q_1$, the VC invests in startup 2 if and only if $q_2 \geq \sigma(q_1, \phi, \tau, F, R)$ and $q_1 < \frac{1}{2\phi} - \frac{F}{R}$. Moreover, conditional on investment, the VC engages in symmetric knowledge sharing. If instead $q_2 \geq q_1$, in the second-stage, the VC behaves as follows:*

(i) If q_1 is low ($q_1 < \frac{1}{2\phi} - \frac{F}{R}$) and $\tau > \frac{1}{2\phi} - \bar{q}$, then the VC will invest if and only if $q_2 \geq \sigma(q_1, \phi, \tau, F, R)$. Moreover, they will engage in symmetric knowledge sharing whenever $q_2 \leq \frac{1}{2\phi} - \tau$, and in asymmetric knowledge sharing favoring startup 2 otherwise.

(ii) If q_1 is larger, i.e., $\frac{1}{2\phi} - \frac{F}{R} \leq q_1 < \frac{1}{2\phi} - \frac{F}{R}\left[\frac{1}{2\phi(\bar{q}+\tau)}\right]$ and $\tau > \frac{1}{2\phi} - \bar{q}$, then the VC will invest engage in asymmetric knowledge sharing favoring startup 2 if and only if $q_2 \geq \bar{\sigma}(q_1, \phi, \tau, F, R)$.

(iii) In all the other cases the VC will invest and engage in symmetric knowledge sharing whenever $q_2 \geq \sigma(q_1, \phi, \tau, F, R)$, and will not invest otherwise.

Proof of Proposition A6.

PROOF. Suppose first $q_2 < q_1$. By Lemma A3 in this case it is optimal to invest only if the VC plans to engage in symmetric knowledge sharing, which is the case if and only $q_1 < \frac{1}{2\phi} - \tau$. Moreover, symmetric knowledge is preferred to no investment at $T = 2$ whenever $q_2 \geq \sigma$. This implies that investment followed by symmetric knowledge sharing occurs if and only if:

$$\sigma \leq q_2 < q_1 < \frac{1}{2\phi} - \tau.$$

Thus, it is necessary that $\sigma < \frac{1}{2\phi} - \tau$. This occurs if and only if $q_1 < \frac{1}{2\phi} - \frac{F}{R}$. Otherwise the VC does not invest.

Consider now the case in which $q_2 \geq q_1$. By Lemma A2, conditional on investment, asymmetric knowledge sharing occurs if and only if $q_2 \geq \frac{1}{2\phi} - \tau$. Since

$$\frac{F/R}{1-2\phi q_1} - \tau < \frac{1}{2\phi} - \tau \iff q_1 < \frac{1}{2\phi} - \frac{F}{R},$$

the VC engages in asymmetric knowledge sharing if and only if:

- $q_2 > \frac{1}{2\phi} - \tau$ when $q_1 < \frac{1}{2\phi} - \frac{F}{R}$,
- $q_2 > \frac{F/R}{1-2\phi q_1} - \tau$ when $q_1 > \frac{1}{2\phi} - \frac{F}{R}$.

A necessary condition for a region where asymmetric knowledge sharing occurs exists is that the above threshold is below $\bar{q}$. This is the case whenever:

- $\tau > \frac{1}{2\phi} - \bar{q}$ if the relevant threshold is $\frac{1}{2\phi} - \tau$.
- $q_1 < \frac{1}{2\phi} - \frac{F}{R}\left[\frac{1}{2\phi(\bar{q}+\tau)}\right]$ if the relevant threshold is $\frac{F/R}{1-2\phi q_1} - \tau$.

Lastly, noting that:

$$\frac{1}{2\phi} - \frac{F}{R} < \frac{1}{2\phi} - \frac{F}{R}\left[\frac{1}{2\phi\left(\bar{q}+\tau\right)}\right] \iff \tau > \frac{1}{2\phi} - \bar{q},$$

and combining all the thresholds derived leads to the result. □

Proof of Proposition A4.

PROOF. Using inequality A4, it is enough to show that the derivative of the right-hand side with respect to β is decreasing, i.e.:

$$Rq_1\left(1-\mu\phi\right) - \left[pq_1R + (1-p)\mathbb{E}[V^{I_2} - F]\right] \leq 0.$$

This is always the case because:

$$
\begin{aligned}
pq_1R + (1-p)\mathbb{E}[V^{I_1} - F] &\geq Rq_1 \\
&\geq Rq_1\left(1 - \mu\phi\right),
\end{aligned}
$$

where the first inequality follows from the fact that at $T = 2$, the VC can always decide not to invest, and the last inequality from the fact that $(1 - \mu\phi) < 1$ for any $\phi \in \left[\frac{1}{2}, 1\right]$. □

Proof of Proposition A5.

PROOF. Define $V^K = Rq_i$ given that the VC will shutdown the startup with the lowest probability of success. Note that $V^K > V^P \iff q_i > \frac{1}{2\phi}$. Proposition A1 shows that a passive approach is preferred to sharing knowledge if and only $q_i \geq q_j > \frac{1}{2\phi}$. However, when discontinuing startup j is an option, the VC would prefer doing that in this case. It follows that a adopting a passive management approach is never optimal. Note that:

- $V^K > V^S \iff q_i > \frac{q_j+\tau}{2\phi q_j} - \tau$.
- $V^K > V^{F^i} \iff q_i > \frac{q_j+2\tau}{2\phi(q_j+\tau)} - \tau$.

This implies that discontinuing startup j is optimal when

$$
q_i > \max\left\{\frac{q_j + \tau}{2\phi q_j} - \tau, \frac{q_j + 2\tau}{2\phi(q_j + \tau)} - \tau\right\} = \frac{q_j + \tau}{2\phi q_j} - \tau,
$$

for any $\tau \geq 0$, $\phi \geq 0$ and $q_i \geq q_j$. □

Appendix B. Taxonomy Extrapolation

In this section, I describe the procedure used to extrapolate the S&P taxonomy to the investment data. My approach leverages the information available (CB's business descriptions and keywords, and S&P's BNs) for the subset of companies that were acquired, to match each startup recorded only in CB to a unique BN. For this purpose, I rely on the k-Nearest Neighbors (k-NN) classifier, which is a simple and intuitive non-parametric and instance-based machine learning method used for both classification and regression tasks. The main idea is that data points belonging to the same class tend to be close to each other in the feature space. The algorithm proceeds in four steps:

(1) *Organize and clean the data.* Since the ICET sector covered by S&P is a subset of the space in which the startups recorded in CB operate, I manually scrutinize each of the almost 800 keywords associated by CB to startups and I use this to exclude companies not belonging to the ICET sector in order to ensure a matching between the portion of the technology space covered by the two datasets.[7] Then, for each startup, I construct and clean a string that includes the startup business description and the CB-assigned keywords.[8]

(2) *Define the training sample.* I identify startups that were acquired, and hence for which BNs are available, by merging CB with S&P.[9] These startups–which are roughly the 5% of the sample—span almost all BNs.[10] This constitutes the "training sample."

(3) *Text vectorization.* Since each startup is characterized by a set of words, one can construct a vocabulary, i.e. the collection of all the words describing the startups,

[7]This operation in practice mainly consists of excluding Life Sciences startups which are easily distinguishable by keywords such as "Biotech" or "Medical."

[8]Cleaning involves: tokenize each string, lemmatize each token, and remove non-alphabetic tokens and stop words such as 'a,' 'what,' 'when,' 'where,' 'which,' 'while,' etc.

[9]I do the merge using startups' names (fuzzy merge) and URLs, both available in CB and S&P.

[10]Since some BNs have very few matched startups, I collapse them into other BNs belonging to the same tech category.

and compute the term frequency-inverse document frequency (TF-IDF) values.[11] Then, each startup i is represented by a vector S_i, with each element being populated by a weight measuring the relative importance of that particular word in the string.

(4) *Implement k-NN classifier.* The k-NN classifier relies on a distance metric to measure the similarity between data points in the feature space. I compute the cosine similarity between any startup in the training sample and any query startup. Given each vector representing a startup S_i, the cosine similarity between any pair of startups (i, j) is simply:

$$pairwise\_cosine_{ij} = \frac{\boldsymbol{S_i} \cdot \boldsymbol{S_j}}{||\boldsymbol{S_i}|| \; ||\boldsymbol{S_j}||}.$$

Finally, I assign each query startup to a BN by using majority vote among the 'k' nearest neighbors. In this way, the BN with the most frequent occurrence among the 'k' neighbors is assigned to the query point.[12]

Intuitively, if I selected $k = 1$, then the algorithm would simply compute all the pairwise cosine similarities between any startup in the training sample and any query startup and assign query startups to the same BN as the most similar startup in the training sample. In practice, k is a hyperparameter that needs to be set before applying the k-NN algorithm. Therefore, I eventually select the $k \in \{1, ..., 50\}$ that maximizes the accuracy of the prediction, i.e. $k = 10$.

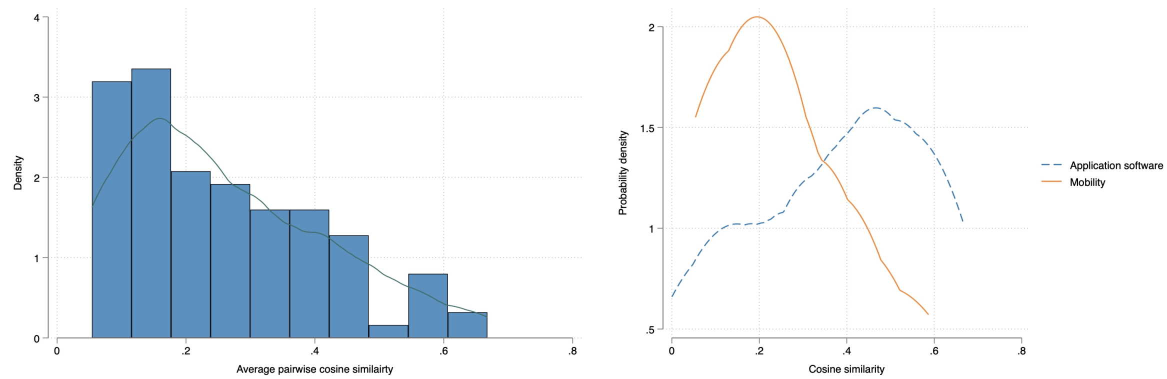
Next, I evaluate the performance of the classifier used.

Performance of the k-NN Classifier. I begin by computing the cosine similarity between any pair of startups belonging to the same BN. Ideally, these values should be high reflecting that similar companies are classified in the same BN by the algorithm. Figure B.1A illustrates the distribution of these cosine similarities across all BNs, while

[11] This step is performed using the *TfidfVectorizer* in the Python package *scikit-learn*.

[12] In practice, all these steps are implemented via the *sklearn.neighbors* module in the Python package *scikit-learn*.

Figure B.1B plots the same distribution separately for BNs within two large tech categories (Application software and Mobility), showing a substantial heterogeneity in the distributions. To provide a benchmark for the values of the similarity scores displayed in Figure B.1, in Table B.1, I compute the cosine similarity matrix—constructed using CB keywords and business descriptions—for a group of well-known tech companies. Most of these companies belong to Application software and Mobility. Not surprisingly, Uber and Lyft are the most similar with a score of 0.531, while WeWork, which S&P categorizes as a Non-tech company, is in fact very different from all other companies in the matrix. Comparing the scores in the matrix with the distributions in Figure B.1 suggests that the algorithm is able to cluster together similar startups.



A. All BNs

B. BNs in Application software and Mobility

FIGURE B.1. Within BN average pairwise cosine similarity

Notes: The left figure plots the distribution of cosine similarity between any pair of startups belonging to the same BN across all BNs. The right figure plots the same distribution separately for BNs within two large tech categories (Application software and Mobility).

A commonly used tool to evaluate the performance of a classifier is the receiver operating characteristic curve, or ROC curve. The ROC curve is a graphical plot that illustrates the diagnostic ability of a binary classifier system by plotting the True Positive Rate against the False Positive Rate at various threshold settings for the classifier. However, the extrapolation of the S&P taxonomy is a very complex non-binary classification problem involving hundreds of BNs. Hence, to plot the ROC curve, I focus on

TABLE B.1. Cosine similarity matrix for some well-known tech companies

	Uber	WeWork	Grab	Delivery Hero	Lyft	DoorDash	Whatsapp	Instagram
Uber	1.000	0.000	0.473	0.000	0.531	0.115	0.037	0.149
WeWork	0.000	1.000	0.000	0.000	0.000	0.031	0.027	0.000
Grab	0.473	0.000	1.000	0.171	0.267	0.280	0.000	0.148
Delivery Hero	0.000	0.000	0.171	1.000	0.000	0.351	0.000	0.000
Lyft	0.531	0.000	0.267	0.000	1.000	0.091	0.043	0.120
DoorDash	0.115	0.031	0.280	0.351	0.091	1.000	0.053	0.019
Whatsapp	0.037	0.027	0.000	0.000	0.043	0.053	1.000	0.053
Instagram	0.149	0.000	0.148	0.000	0.120	0.019	0.053	1.000

tech categories (level-1s) and I treat each tech category as a separate binary classification problem. Figure B.2 illustrates the ROC curves for each tech category separately. Ideally, one would like, for each class, a ROC curve that is as close as possible to the upper left corner of the graph, where the true positive rate is one 1 and the false positive rate is 0. In practice, a good ROC curve should be curved away from the diagonal line (which would be the ROC curve of a random guess) and should be steep, especially near the top-left corner. This steepness implies that the classifier achieves high true positive rates while keeping false positive rates low. These things generally hold for the ROC curves displayed in Figure B.2, although the graph also suggests the presence of some heterogeneity in the quality of prediction across level-1s.

To provide further evidence in favor of the goodness of the 10-NN classifier chosen to perform the taxonomy extrapolation, in Table B.2, I compare its performance with that of two alternative classifiers: (i) the Multinomial Naive Bayes; (ii) the XGBoost.

The Multinomial Naive Bayes is a variant of the Naive Bayes algorithm used for classification tasks, particularly in cases where the features are discrete and represent counts or frequencies of occurrences. It is commonly applied to text classification problems where each document is represented by word frequencies. The algorithm assumes that each startup is a document, i.e. a set of words belonging to one of the predefined classes (BNs). The first step entails computing the prior probabilities of each class, which are the probabilities of randomly selecting a startup from each BN.

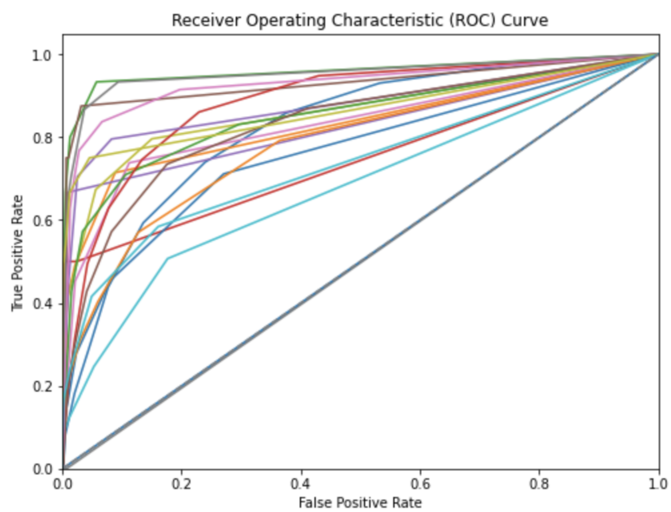


FIGURE B.2. Validation of the extrapolation procedure: ROC Curve

Notes: Each curve in the figure represents a tech category and it is drawn by treating each tech category as a separate binary classification problem.

Afterward, the algorithm computes the probability of a term appearing in a startup's string given the class it belongs to. The key assumption is that words are conditionally independent given the BN label. This simplifies the computation by assuming that the occurrence of each term in a document is not influenced by the presence or absence of other terms. In the next step, the algorithm computes the conditional probability for each word given the BN. It then multiplies these probabilities for all the words in the document and scales them by the prior probability of each class. Finally, prediction can be made simply by assigning the startup to the BN with the highest probability.

The XGBoost (Extreme Gradient Boosting) classifier is a highly efficient and scalable implementation of gradient boosting for supervised learning tasks. It builds an ensemble of decision trees in a sequential manner, where each tree corrects the errors of its predecessors by focusing on the misclassified instances. Additionally, the XGBoost classifier allows users to specify the objective function according to the specific problem type. As common for classification tasks in which there are multiple classes to predict, I use the "multi:softmax" objective.

TABLE B.2. Algorithms comparison

	Level-1		Level-2	
	Accuracy	F1-score	Accuracy	F1-score
XGBoost	0.56	0.53	0.29	0.27
Multinomial Naive Bayes	0.47	0.53	0.19	0.17
10-NN	0.54	0.52	0.31	0.29

In terms of metrics used to evaluate the performance of the algorithm, I rely on accuracy and F1-score. The accuracy measures the number of correct predictions divided by the total number of predictions. On the other hand, the F-1 score combines both precision (i.e., the ratio of true positive predictions to the total predicted positives) and recall (i.e., the ratio of true positive predictions to the total actual positives) into a single score, using the following formula:[13]

$$F1 - score = \frac{2 \times (precision * recall l)}{(precision + recall l)}$$

The F1-score provides a balanced assessment of a classifier's performance: the larger the F1-score, the better the balance of precision and recall, meaning that the classifier performs better on both positive and negative classes.

Table B.2 compares the performance of the three algorithms. All algorithms perform well in predicting level-1s while the 10-NN outperforms the other in the prediction of level-2s. Overall, the quality of the prediction decreases for all algorithms when predicting level-2s. This is because predicting level-2s is a significantly more complex prediction problem which involves roughly two-hundred classes, as compared to the less than twenty classes involved in the level-1s' extrapolation. Nonetheless, the accuracy achieved by the preferred algorithm in the prediction of level-2s (31%) represents a substantial progress over the baseline model or random guessing, which has an accuracy of 0.5%.

[13] The F1-score is especially useful in my setting because some classes have significantly more instances than others.

Appendix C. Additional Tables and Figures

TABLE C.1. Summary Statistics

	Linked startups						Solo startups			Full sample		
	First			Subsequent								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
VARIABLES	N	mean	sd	N	mean	sd	N	mean	sd	N	mean	sd
Size first round of VC financing ($, in logs)	3,410	10.42	7.16	6,328	10.79	7.19	24,058	10.65	7.03	33,796	10.66	7.07
$\mathbb{1}${Serial entrepreneur}	426	0.24	0.43	3,137	0.23	0.42	11,499	0.21	0.41	15,062	0.22	0.41
VC_experience	3,410	57.17	103.0	6,328	121.8	167.6	24,058	26.64	73.00	33,796	47.54	107.1
VC_age	3,319	14.15	16.71	6,218	17.26	16.88	20,826	14.65	21.82	30,363	15.13	20.41
$\mathbb{1}${Syndicated round}	3,410	0.426	0.495	6,328	0.523	0.500	24,058	0.409	0.492	33,796	0.432	0.495
Max_non-leadVC_experience	3,410	51.70	179.0	6,328	86.97	248.9	24,058	40.26	166.4	33,796	50.16	186.7
Linked	3,410	1	0	6,328	1	0	24,058	0	0	33,796	0.288	0.453
VC-venture_Harvesine_distance	2,773	5.284	3.483	5,302	5.503	3.457	18,026	5.089	3.508	26,101	5.194	3.499
investors_count	3,410	2.112	2.019	6,328	2.523	2.400	24,058	2.022	2.024	33,796	2.125	2.107
Startup_year_founded	3,410	2,010	5.459	6,328	2,011	5.424	24,058	2,010	5.973	33,796	2,010	5.845
$\mathbb{1}${M&A}	3,410	0.124	0.329	6,328	0.100	0.300	24,058	0.116	0.320	33,796	0.114	0.317
$\mathbb{1}${IPO}	3,410	0.024	0.153	6,328	0.028	0.166	24,058	0.036	0.187	33,796	0.035	0.184
$\mathbb{1}${Shutdown}	3,410	0.037	0.153	6,328	0.020	0.156	24,058	0.025	0.156	33,796	0.024	0.153
VC_past_SIC_in_other_BN	34,327	0.155	0.362	57,269	0.405	0.491	228,595	0.0797	0.271	320,191	0.146	0.353
ln(1+$ raised)	34,327	2.952	6.120	57,269	3.353	6.445	228,595	2.756	5.885	320,191	2.883	6.018
$\mathbb{1}${round raised}	34,327	0.255	0.436	57,269	0.286	0.452	228,595	0.241	0.428	320,191	0.250	0.433
$\mathbb{1}${executive hired}	34,327	0.833	0.373	57,269	0.827	0.378	228,595	0.824	0.381	320,191	0.825	0.380
$\mathbb{1}${leaving executives}	34,327	0.363	0.481	57,269	0.333	0.471	228,595	0.335	0.472	320,191	0.338	0.473
$\mathbb{1}${new board memebrs}	34,327	0.515	0.500	57,269	0.500	0.500	228,595	0.480	0.500	320,191	0.487	0.500
$\mathbb{1}${leaving board members}	34,327	0.182	0.386	57,269	0.168	0.374	228,595	0.181	0.385	320,191	0.179	0.383
BN_competition_index	34,327	0.568	0.138	57,269	0.593	0.130	228,595	0.480	0.185	320,191	0.510	0.178
BN_maturity	34,327	4.584	1.039	57,269	4.779	0.954	227,879	3.982	1.326	319,475	4.189	1.282
BN_active_VCs	34,327	6.617	0.905	57,269	6.792	0.834	228,595	5.972	1.259	320,191	6.188	1.209
BN_tightness	34,327	8.227	6.162	57,269	6.053	3.605	228,595	7.531	5.851	320,191	7.341	5.590

Notes: The table reports summary statistics (number of observations, mean and standard deviation) for all the variable considered in the analyses. The last three columns refer to the full sample, while the other separately describe each group considered (first and subsequent startups, and solo startups). As it is clear from the number of observations, the statistics in the last eleven rows are at the startup-year level, while the others are at the startup level.

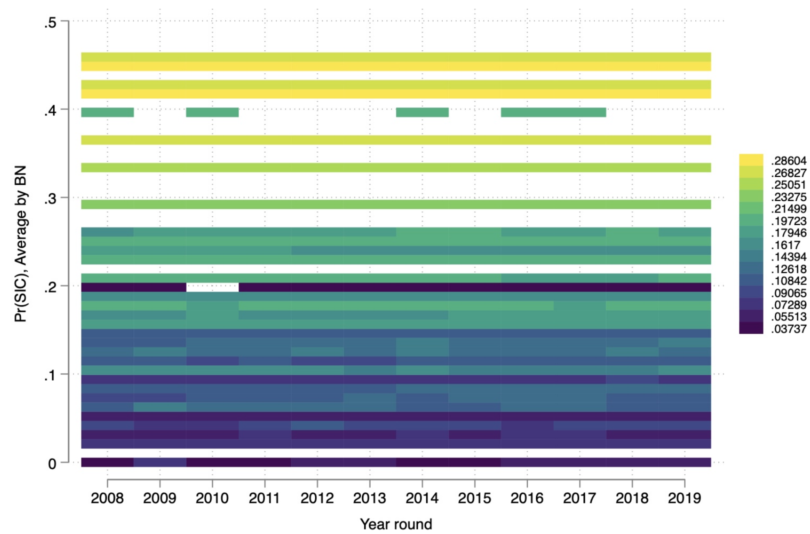
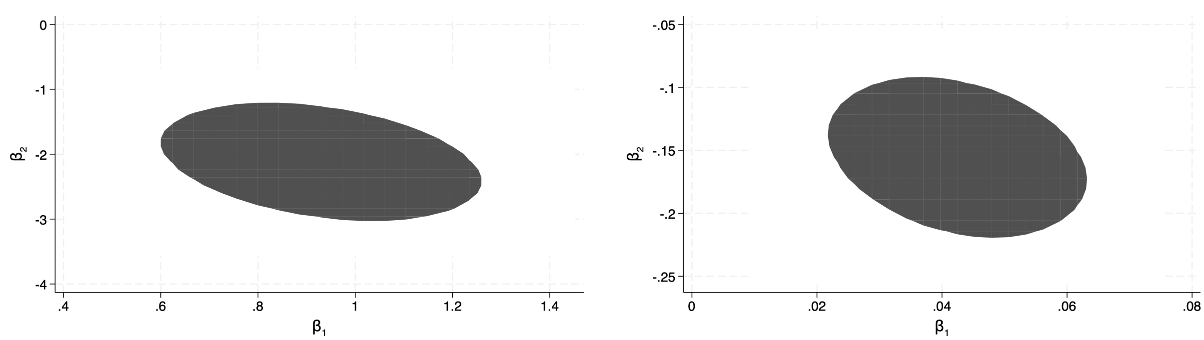


FIGURE C.1. Correlation between being linked and the instrument

Notes: The figure illustrates the correlation between the average probability that a startup shares a VC with a competitor across BNs and the same average for the IV over time. Darker colors indicate a lower correlation.



A. ln(1+$ raised)

B. 𝟙{round raised}

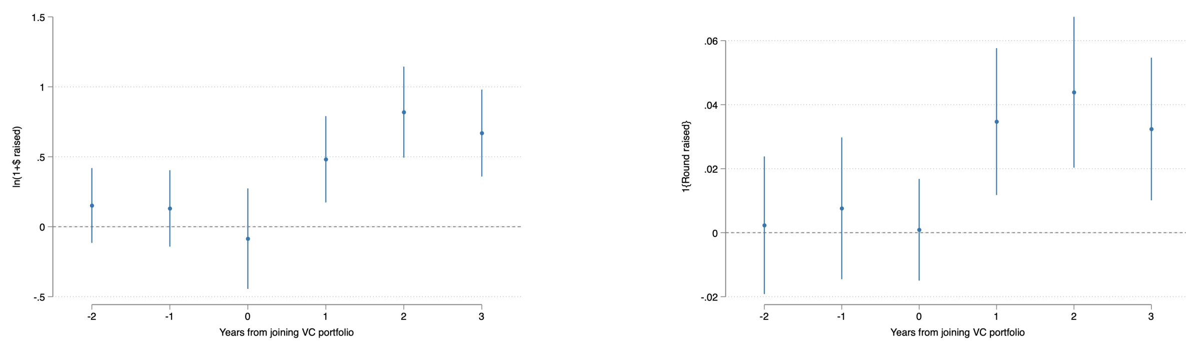
FIGURE C.2. Robustness check: Weak-IV robust confidence sets

Notes: The figure illustrates 95% confidence set for the IV estimates of β_1 and β_2 in Equation 1 that are robust to the case in which the instruments are weak. The dependent variables are the logarithm of the amount of VC raised (Figure A) and likelihood of raising an additional round (Figure B). The shaded area represents the range of the estimates of β_1 and β_2 such that the rejection probability (i.e., 1 − *pval ue*) is below 95%.

TABLE C.2. First Stage Regression

	(1) SharedVC	(2) First × SharedVC	(3) SharedVC	(4) First × SharedVC
𝟙{*VC_past_SIC_in_other_BN*}	0.189***	-0.003***	0.891***	-0.006***
	(0.003)	(0.000)	(0.003)	(0.001)
First × 𝟙{*VC_past_SIC_in_other_BN*}	0.021***	0.214***	-0.305***	0.594***
	(0.005)	(0.004)	(0.009)	(0.009)
Post	0.146***	-0.031***	0.045***	-0.047***
	(0.003)	(0.001)	(0.003)	(0.001)
First × *Post*	0.594***	0.782***	0.578***	0.682***
	(0.005)	(0.004)	(0.007)	(0.006)
Linked	0.641***	-0.000		
	(0.003)	(0.000)		
First	-0.485***	0.005***		
	(0.005)	(0.000)		
Observations	285,759	285,759	285,630	285,630
R-squared	0.775	0.833	0.888	0.871
BN × Year FE	✓	✓	✓	✓
Startup FE			✓	✓

Notes: *** p<0.01, ** p<0.05, * p<0.1. The table reports the results of the first-stage regressions estimated via OLS. All regressions include controls for the cumulative funds and number of rounds raised by the startup up to $t-1$, as well as the stage reached at any year before the first round of VC financing. Standard errors are reported in parentheses and are clustered at the startup level.



A. ln(1+$ raised)   B. 𝟙{Round raised}

FIGURE C.3. Dynamic correlation between being linked and startup outcomes

Notes: The figure illustrates the comparison between subsequent and solo startups within 3 years before and after their first round of venture capital financing using a DiD methodology, where the time variable is delineated by the years leading up to and following the first round of venture capital financing. Before implementing the DiD design, the sample is selected by dropping first startups and matching the remaining units via PSM on the number of rounds and the amount of funding raised before the first round of venture capital financing, as well as the year of this round.

Table C.3. Effect of investing in competitors on the probability of VC follow-up

	(1) (OLS)	(2) (OLS)	(3) (IV)
Linked	0.009***		
	(0.002)		
First	-0.013***		
	(0.003)		
Post	0.370***	0.652***	0.646***
	(0.002)	(0.002)	(0.003)
First × *Post*	0.235***	0.121***	0.133***
	(0.007)	(0.007)	(0.017)
SharedVC	0.038***	0.027***	0.056***
	(0.004)	(0.005)	(0.007)
First × *SharedVC*	-0.334***	-0.188***	-0.224***
	(0.008)	(0.008)	(0.021)
Observations	286,321	286,192	286,192
Adj. R-sq	0.200	0.381	
BN Year FE	✓	✓	✓
Startup FE		✓	✓

Notes: *** p<0.01, ** p<0.05, * p<0.1. In columns (1) ((2)), the table reports the results of the Baseline (FE) model when the outcome is a binary variable which equals one if the lead VC of the first round of venture capital financing provides funds to the startup in any given year. In columns (3), the table reports the results of the IV model estimated via 2SLS. All regressions include controls for the cumulative funds and number of rounds raised by the startup up to $t-1$, as well as the stage reached at any year before the first round of VC financing. Standard errors are reported in parentheses and are clustered at the startup level.

Table C.4. Robustness check: Two-step Heckman estimation

a. Switching regressions with endogenous switching

	First stage	Second stage			
DEP. VAR.	Linked	ln(1+$ raised)		𝟙{round raised}	
	(1)	(2) (Linked)	(3) (Solo)	(4) (Linked)	(5) (Solo)
𝟙{VC past SIC in other BN}	1.787***				
	(0.0211)				
startup_age	0.00334*	-0.173***	-0.215***	-0.0103***	-0.0148***
	(0.00198)	(0.0175)	(0.00938)	(0.00152)	(0.000574)
rounds_raised_before	-0.0250	-0.129	0.935***	0.0123	0.0803***
	(0.0514)	(0.481)	(0.284)	(0.0275)	(0.0152)
funds_raised_before	-0.00695	0.0383	0.0990***	-0.00156	0.00413**
	(0.00629)	(0.0948)	(0.0295)	(0.00476)	(0.00191)
1.serial	-0.0370	0.0237	1.554***	-0.000158	0.0622***
	(0.0349)	(0.289)	(0.223)	(0.0218)	(0.0135)
2.serial	0.0395*	-2.858***	-2.825***	-0.169***	-0.173***
	(0.0212)	(0.280)	(0.114)	(0.0204)	(0.00686)
Inverse mills ratio		0.509**	-0.643***	0.0386**	-0.0450***
		(0.252)	(0.130)	(0.0168)	(0.00805)
Observations	32,047	5,597	25,719	5,597	25,719
R-squared		0.360	0.107	0.343	0.103
BN FE	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓

b. Counterfactual Analyses

	ln(1+$ raised)		𝟙{round raised}	
	Linked (Mean)	Solo (Mean)	Linked (Mean)	Solo (Mean)
Actual after first round financing	6.598	5.436	0.466	0.398
Hypothetical after first round financing	5.635	6.918	0.412	0.492
Difference	0.207**	-1.508***	0.003	-0.096***

Notes: *** p<0.01, ** p<0.05, * p<0.1. The tables summarize the results of a two-step Heckman selection model, employing a switching regression with endogenous switching methodology to distinguish selection and influence effect. The relevant sample is the cross-section of subsequent and solo startups. Column (1) of panel (a) displays the first-stage regression using the usual IV along with other relevant covariates, while the other columns show the results of the second-stage regressions run separately for linked and solo startups. The second stage also includes the inverse mills ratio computed after the first stage. In panel (a), robust standard errors are reported in parentheses. Panel (b) shows the results of "what-if" analyses based on the results of the switching regression model in panel (a). It reports the actual and counterfactual changes in the dependent variables after the first round of venture capital financing. For example, for a linked startup, the counterfactual scenario (row 2) predicts what would have happened to startup performance if the startup was not linked. The last row displays the t–test of mean difference.

TABLE C.5. Robustness check: Subsample with first two investments only

	ln(1+$ raised)		𝟙{round raised}		𝟙{Shutdown}	
	(1) (OLS)	(2) (IV)	(3) (OLS)	(4) (IV)	(5) (OLS)	(6) (IV)
SharedVC	0.209**	0.936***	0.011**	0.037***	-0.001	-0.000
	(0.080)	(0.124)	(0.006)	(0.009)	(0.001)	(0.001)
First × *SharedVC*	-1.209***	-2.073***	-0.126***	-0.145***	0.003**	0.010***
	(0.121)	(0.269)	(0.008)	(0.019)	(0.001)	(0.003)
Observations	263,804	263,928	263,804	263,928	263,804	263,928
Adj. R-sq	0.348		0.382		0.118	
Startup FE	✓	✓	✓	✓	✓	✓
BN × Year FE	✓	✓	✓	✓	✓	✓

Notes: *** p<0.01, ** p<0.05, * p<0.1. The table shows the results of the FE and IV models excluding from the sample linked startups that were the third or later investment by the VC in the same BN. Standard errors are reported in parentheses and are clustered at the startup level.

TABLE C.6. Robustness Check: Investor Fixed Effects

OLS MODEL	(1) ln(1+$ raised)	(2) 𝟙{round raised}	(3) 𝟙{Shutdown}
Linked	0.204***	0.025***	-0.000
	(0.068)	(0.005)	(0.000)
First	-0.297***	-0.024***	0.000
	(0.085)	(0.007)	(0.000)
Post	4.004***	0.370***	0.003***
	(0.049)	(0.003)	(0.000)
First × *Post*	1.917***	0.161***	-0.004***
	(0.139)	(0.009)	(0.000)
SharedVC	0.254***	0.008	-0.001*
	(0.075)	(0.005)	(0.000)
First × *SharedVC*	-2.840***	-0.239***	0.005***
	(0.144)	(0.009)	(0.001)
Observations	286,294	286,294	286,294
Adj. R-sq	0.177	0.206	0.031
BN × Year FE	✓	✓	✓
Investor FE	✓	✓	✓

Notes: *** p<0.01, ** p<0.05, * p<0.1. Standard errors are reported in parentheses and are clustered at the startup level. The table shows the results of the Baseline model with the inclusion of (lead) VC fixed effects.

Table C.7. Robustness Check: Investor Characteristics

	ln(1+$ raised)		𝟙{round raised}	
	(1) (OLS)	(2) (IV)	(3) (OLS)	(4) (IV)
SharedVC	0.241**	0.669***	0.015**	0.030***
	(0.101)	(0.146)	(0.006)	(0.009)
First × *SharedVC*	-1.330***	-2.100***	-0.135***	-0.155***
	(0.157)	(0.370)	(0.010)	(0.026)
Observations	265,891	265,891	265,891	265,891
Adj. R-sq	0.351		0.382	
BN × Year FE	✓	✓	✓	✓
Startup FE	✓	✓	✓	✓
VC characteristics × *Post*	✓	✓	✓	✓

Notes: *** p<0.01, ** p<0.05, * p<0.1. Standard errors are reported in parentheses and are clustered at the startup level. VC characteristics include: age and experience of the lead VC, and the experience of the most experienced non-lead VC.

Table C.8. Robustness check: Post first-round-financing subsample

	ln(1+$ raised)		𝟙{round raised}	
	(1) (OLS)	(2) (IV)	(3) (OLS)	(4) (IV)
SharedVC	0.350***	0.298***	0.034***	0.054***
	(0.048)	(0.106)	(0.003)	(0.007)
First × *SharedVC*	-0.859***	-1.453***	-0.083***	-0.132***
	(0.054)	(0.098)	(0.004)	(0.007)
Observations	209,537	209,630	209,537	209,630
Adj. R-sq	0.248		0.267	
BN × Year FE	✓	✓	✓	✓
Investor FE	✓		✓	

Notes: *** p<0.01, ** p<0.05, * p<0.1. Standard errors are reported in parentheses and are clustered at the startup level. This specification excludes from the sample for each startup years before the first round of venture capital financing.

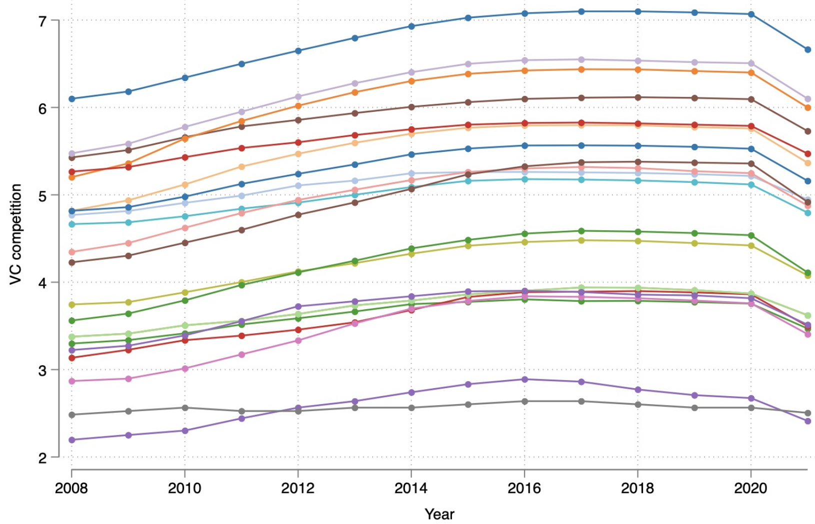


FIGURE C.4. Average VC competition over time across tech categories

Notes: The figure illustrates the average trend in VC competition (as measured by *BN_active_VCs*) within each tech category between 2008 and 2021.

TABLE C.9. Operational impact of VCs investing in competitors

	𝟙{new board members}		𝟙{leaving board members}		𝟙{ executive hired}		𝟙{leaving executives}	
	(1) (OLS)	(2) (IV)	(3) (OLS)	(4) (IV)	(5) (OLS)	(6) (IV)	(7) (OLS)	(8) (IV)
SharedVC	-0.007	-0.004	0.012***	0.019***	0.007	0.019***	0.017***	0.024***
	(0.005)	(0.006)	(0.003)	(0.005)	(0.005)	(0.006)	(0.006)	(0.008)
First × *SharedVC*	-0.001	-0.002	-0.007	-0.027	0.001	-0.019	-0.015	-0.053
	(0.010)	(0.026)	(0.008)	(0.024)	(0.010)	(0.025)	(0.013)	(0.039)
Observations	220,049	220,049	220,049	220,049	220,049	220,049	220,049	220,049
Adj. R-sq	0.909		0.856		0.808		0.808	
BN × Year FE	✓	✓	✓	✓	✓	✓	✓	✓
Startup FE	✓	✓	✓	✓	✓	✓	✓	✓

Notes: *** p<0.01, ** p<0.05, * p<0.1. The table shows the results of the FE and IV models. All regressions control for the VC-startup distance, measured by the Harvesine formula (in logs), as well as for the interaction term between *First* × *SharedVC* and this distance. This is because the operational impact of a VC may manifest more strongly for startups that are headquartered closer to the VC's main office (Bernstein, Giroud and Townsend 2016). Standard errors are reported in parentheses and clustered at the startup level.