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

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I examine how venture capitalists' (VCs) investments in competing startups affect the performance of those startups. Using a new analytical framework, I highlight two effects. First, VCs internalize the competition among portfolio startups, and this impacts their incentives to engage in activities that *influence* startups' outcomes. Second, by investing in a business area, VCs learn to select better startups within that business area. This *selection* effect incentivizes VCs with competing portfolio startups to take actions enhancing the outcomes of the subsequent startup invested in the business area at the expense of the first one. To test the hypotheses, I combine venture investment data from Crunchbase (2008-2021) with S&P 451 Research, a tech M&A database that classifies startups according to a unique hierarchical technology taxonomy. I find that the first of the competing startups invested by a VC exhibits poorer performance after the VC invests in a competitor, as compared to startups that do not share any VC with a competitor. In contrast, subsequent startups invested by the VC in the same business area outperform startups not sharing a VC with a competitor, by securing at least 39% more venture capital and enjoying a 2-4% higher likelihood of raising a venture round each year after receiving funding from the VC. While these results are partly attributable to the selection effect, they also indicate that investing in competitors enables VCs to exert additional influence on their portfolio startups, favoring startups invested subsequently over those invested first.

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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, underscoring the importance of venture capitalists (VCs) in shaping the development and market success of new technologies (Kortum and Lerner 2000; Samila and Sorenson 2011; Chemmanur, Krishnan and Nandy 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 VCs' role extends beyond mere screening and financing to encompass monitoring activities that can significantly impact startups' growth (Kaplan and Strömberg 2001; Bernstein, Giroud and Townsend 2016) a fundamental question arises: How does sharing a VC with a competitor affect startup performance through these VCs' activities?

The presence of competing startups in the portfolio can influence a VC's monitoring activities.[2] 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.[3] In theory, there could even be cases where such competition-driven dynamics lead to the discontinuation of a startup (Fulghieri and 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 portfolio 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 could enhance the ability of startups to coordinate in the product market and relax competition (Azar, Schmalz and Tecu 2018).

[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] Monitoring is broadly defined to encompass any action a VC can take to increase the value of a portfolio startup. Examples include mentoring and providing access to their network of experts and firms.

[3] 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."

Nonetheless, it is important to consider that VCs strategically assess how a startup interfaces with the rest of their portfolio in the product market when making investment decisions.[4] This screening process not only impacts the types of startups that will share a VC with a competitor in equilibrium, but also shapes the monitoring activities that a VC undertakes to maximize the overall value of the portfolio.

This paper introduces a novel framework to interpret the motives and consequences of VCs' strategic investments in competing startups, while also delving into the interplay between VCs' screening and monitoring activities in determining the outcomes of competing portfolio startups. In particular, the paper's analytical framework identifies two effects. First, the internalization of competition among portfolio startups influences the monitoring activities of VCs, and hence startups' performance (the "influence effect"). Second, the expertise acquired by VCs through prior investments in a specific business area enables them to identify startups with better prospects in the future.[5] This aspect, the "selection effect," implies that the first startup invested by a VC in a business area will be of lower quality as compared to the subsequent startups funded in that same business area. In turn, this provides VCs with an incentive to take actions to enhance the performance of these subsequent startups at the expense of those invested first. Under certain conditions, the model also rationalizes the discontinuation of the first startup invested in the business area. In contrast, when selection is absent or weak, or when the intensity of competition between startups is low, the model demonstrates that sharing a VC with a competitor can benefit each of the startups.

To test the predictions derived from the analytical framework, I utilize venture investment data from Crunchbase (2008-2021), in combination with 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 other researchers have used to study the technology space (Jin, Leccese and Wagman 2022, 2023; Cheng et al. 2023). 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 VCs investing in startups in the same busi-

[4] Hellmann (2002) shows analytically that a VC's monitoring of a startup is influenced by that startup's complementarity or substitutability to another asset owned by the VC. In turn, this affects the ex-ante probability that the VC invests in the startup.

[5] Sørensen (2007) shows that in a two-sided matching model, more experienced VCs are matched in equilibrium with inherently better startups.

ness 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 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 analyses, addressing the selection effect requires making assumptions on the inherent unobserved startup quality, which is a source of endogeneity. If, as in the analytical model, this is time-invariant, a model with startup fixed effects can account for the selection effect. If, instead, one allows a startup's unobserved quality to change over time, then an instrumental variable approach is needed. To that end, I instrument whether a startup shares a VC with a competitor using a binary variable which equals one if the VC has invested in competing startups within other business niches in the past. Given that the instrument is based on an investor's past investment strategies, it should be correlated with the endogenous variable.[6] It also satisfies the exclusion restriction because it is uncorrelated with the VC's specialized expertise within the focal business niche where they consider investing in competing startups.

I find that the first startups invested in a particular business niche, following their VC's investment in a competing startup, exhibit poorer performance compared to startups that do not share any VC with a potential competitor ("solo startups"). In contrast, subsequent startups invested by the VC in the same business niche outperform solo startups. On average, these subsequent startups secure a minimum of 39% 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 positive influence is primarily directed towards subsequent startups, while first startups invested are hurt. Moreover, I delve into various heterogeneous effects guided by the predictions of the analytical model. Notably, I demonstrate that when two competing startups receive funds from the same VC within a short time lag, and hence the selection effect is weak, each startup benefits from sharing the VC.

This paper contributes to the burgeoning literature studying the implications for startup growth of VCs' investments in competitors. Li, Liu and Taylor (2023) find that VCs

[6] In general, because of inertia in resources, capabilities, and internal processes, firms tend to behave consistently over time, so their past actions are considered a credible signal of future behavior (Weigelt and Camerer 1988).

investing in competing pharmaceutical startups tend to withhold funding from projects that are lagging behind.[7] However, countering this viewpoint, Eldar and Grennan (2023) show that same industry startups inside VC portfolios raise more capital, fail less, and exit more successfully. My findings reconcile this seemingly conflicting evidence by leveraging the interplay between the selection and influence effects. The origin of this interaction lies in the learning process VCs undergo from their prior investments. This directs my analyses towards investigating how the influence effect varies across the chronological order in which portfolio startups were funded, a dimension not explored in Li, Liu and Taylor (2023) nor Eldar and Grennan (2023). This unique facet of my analysis allows me to discern the adverse performance consequences associated with sharing a VC with a competitor for startups which are the VC's first investment in the business niche. Furthermore, within my framework, the sign and the magnitude of the influence effect depend on the degree of product market competition among portfolio startups. Consistently, 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 observation implies that the varying degrees of competition present across the industries examined in the existing literature could contribute to the divergent findings.[8]

Furthermore, by studying the decision-making process and the implications for value-adding activities of VCs' investments in competing startups, this paper adds to the existing body of research that focuses on understanding VCs' investment decisions, their screening and monitoring practices, and the intricate interplay between these aspects (Lerner 1995; Kaplan and Strömberg 2001; Hellmann and Puri 2002; Kaplan and Strömberg 2004; Sørensen 2007; Puri and Zarutskie 2012; Bernstein, Giroud and Townsend 2016; Ewens, Nanda and Rhodes-Kropf 2018; Gompers et al. 2020).

My results have also important practical implications for entrepreneurs. In contrast to a literature emphasizing the advantages of connecting with other entrepreneurs in the same industry (Baum, Calabrese and Silverman 2000; Stuart 2000; Ozcan and Eisenhardt 2009), I show that when such connections are via a shared VC, there might

[7] Cox Pahnke et al. (2015) focus more generally on the potential risk for entrepreneurs of being connected to competitors via shared investors. Their findings indicate that for startups operating in the minimally invasive surgical device segment, a higher number of common investors with competitors is associated with a reduced likelihood of introducing a new product to the market.

[8] For instance, the investigation by Li, Liu and Taylor (2023) centers around 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 (2023) studies startups spanning all sectors of the economy.

be negative consequences for the first entrepreneur to form the connection with the VC. For this entrepreneur, the complexity lies in the fact that, at the time of establishing the tie, they lack knowledge about whether the VC will invest in a competitor, and such aspects typically cannot be contracted upon. Given that larger and more experienced VCs are more likely to engage in this investment behavior, my framework offers a rationale for why entrepreneurs should be cautious when accepting funds from such VCs. Conversely, when offered the possibility, entrepreneurs should accept to become part of a VC's portfolio that already includes a competitor because they are likely to gain from this relationship.

Finally, my work contributes to the literature on the impact of institutional investors' common ownership of public companies on innovation (He and Huang 2017; Kostovetsky and Manconi 2020; Antón et al. 2021).[9,10] Firstly, I complement this line of research by studying a different institutional setting, whose advantages lie in the more significant control rights of VCs relative to institutional investors (Gompers et al. 2020), and in the existence of clear 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).[11] Secondly, I contribute to this literature by examining the outcomes of startups instead of public companies' patenting activity. From a policy standpoint, this outcome is particularly relevant because technology startups not only affect the pipeline of new innovations, but can also determine changes in market structure by entering product markets and competing with established incumbents. On the one hand, VCs' investments in competitors negatively affect the first startup invested in a particular business niche, potentially leading to reduced innovation and future market competition. On the other hand, this enhances the performance of the startups subsequently invested in that business niche. While this paper does not conclusively determine the average net effect on welfare, the results underscore the importance for policymakers to assess

[9] López and Vives (2019) develop a theoretical model showing that common ownership can increase R&D and welfare by enabling the common investor to internalize positive R&D spillovers between portfolio firms.

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

[11] Notably, Antón et al. (2023) show that a formal direct mechanism is not necessary for common ownership to have anti-competitive effects so long as common owners are involved in setting managers' compensation.

the potential consequences of VCs' investments in competing startups.[12]

The rest of the paper is organized as follows. Section 2 introduces the analytical model and discusses its main predictions. Section 3 provides an overview of the data and outlines the procedure to construct the final sample. In Section 4, the empirical framework is detailed, along with the primary analysis concerning the overall effect of sharing a VC with a competitor on startup outcomes. Section 5 explores heterogeneous effects around key comparative statics of the analytical model, while a conclusion is offered in Section 6.

2. A Theory of VC Financing with Startup Competition

Consider the problem of a risk-neutral investor ("the VC") that has *just* invested in a startup (startup 1) with probability of success $q_1 \sim \mathcal{U}\left[0, \frac{3}{4}\right]$ operating in a certain business niche. The VC has to decide if and when to invest in a second startup (startup 2) with probability of success $q_2 \sim \mathcal{U}\left[0, \frac{3}{4}\right]$, $q_1 \perp q_2$, operating in the same business niche, and hence potentially in competition with startup 1. 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.[13]

Competition between startups is modelled by assuming that for an investor the future return from a startup are lower if the competing startup also remains active.[14] 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.[15]

[12] Public companies' common ownership by institutional investors has already attracted the attention of antitrust agencies in the U.S. and the E.U. See, for example, the hearings hosted by the Federal Trade Commission in 2018, available at: https://www.ftc.gov/system/files/documents/public_events/1422929/ftc_hearings_session_8_transcript_12-6-18_.pdf, or the European Commission's decision "M.7932 – Dow/DuPont," available at: https://ec.europa.eu/competition/mergers/cases/decisions/m7932_13668_3.pdf.

[13] I focus on the additional influence that a VC with competing portfolio startups can generate. Hence, C cannot engage in portfolio management activities.

[14] 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."

[15] One can interpret R as the potential market demand for the product. When $\phi = \frac{1}{2}$, the two products are differentiated enough that each startup serves half of the market. When $\phi = 1$, the two products are

I model the VC's problem as a four-stage game, and Figure 1 summarizes the timing. 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 game directly moves to the portfolio management strategy decision by the VC ($T = 3$). Otherwise, the game moves to next stage, where the VC learns the realization of q_2 and may have a new opportunity to invest in startup 2.

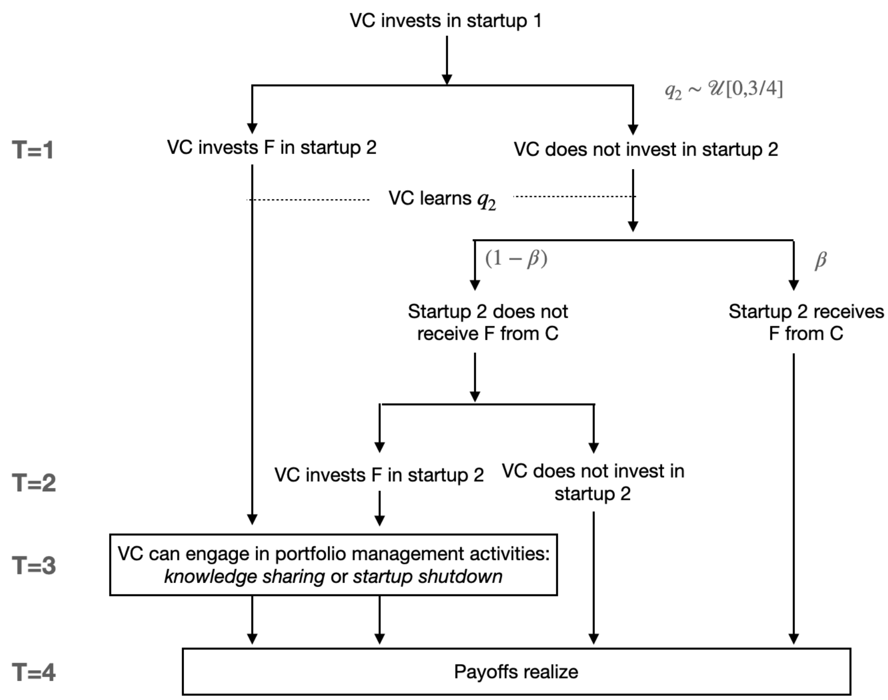


FIGURE 1. Timing and Structure of the Game

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.,

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

Since q_1 and q_2 are assumed to be independent, this condition allows to write the

homogeneous generating a zero payoff, as if the two startups engaged in Bertrand competition.

investment cost relative to the investor's maximum possible return from a startup as a decreasing function of startup competition, i.e., $\frac{F}{R} = \frac{3}{8} - \frac{9\phi}{64}$.[16] If C and startup 2 match—and hence by Equation 1 C invests in startup 2— the game moves to the last stage of the game ($T = 4$) where payoffs realize.

At $T = 2$, if neither the VC nor C have invested before, the VC decides whether to invest F in startup 2 knowing the realization of q_2.[17] The underlying assumption is that investors that already invested in a market in the past acquire an expertise that allows them to better infer startups' quality. This process is modelled 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.

Afterwards, 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. Importantly, I focus on the additional value that a common VC, i.e. a VC entering this stage with two competing startups in the portfolio, can generate relative to an investor that only made one investment in the market.[18] I consider three possible portfolio management strategies.[19]

First, a common VC could increase the value of both startups by favoring exchanges of innovation resources within the portfolio (González-Uribe 2020). I model this strategy by assuming that a common VC is able to increase each startup's probability of success q_i through a "knowledge transfer" $\tau \in \left[0, \frac{1}{4}\right]$.[20,21] For simplicity, I refer to this strategy as "symmetric knowledge sharing."[22] Second, a common VC could *"play favorites,"* and only share knowledge with one of the two startups ("asymmetric knowledge sharing"). Thus, I assume that a common VC can 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

[16] 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.

[17] This assumes that the VC has all the bargaining power. Since I will show that, in equilibrium, startup 2 tends to benefit from sharing the VC with startup 1, the model predictions are generally robust to increasing entrepreneur's bargaining power.

[18] Recall that at this stage, whatever the stage in which the VC invested in startup 2, q_2 is known.

[19] Following Hellmann (2002), I assume that these actions cannot be contracted upon when the investment is made.

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

[21] Dessí and Yin (2015) model knowledge transfers from VCs to a portfolio startup in a similar way to study the conditions under which entrepreneurs prefer venture capital over other forms of finance, and its implications for startups' performance.

[22] Note that the model is agnostic about the content of the information that a VC can share across portfolio startups. This implies that symmetric knowledge sharing can enhance the performance of both startups via channels other than the sharing innovation resources, such as the implementation of conducts that relax product market competition (Azar, Schmalz and Tecu 2018).

TABLE 1. VC's Payoff

VC invests in startup 2	C invests in startup 2	Portfolio Management Strategy	VC's Payoff
X	✓	·	$R[q_1q_2(1-\phi)+q_1(1-q_2)]$
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	Shutdown of startup j	Rq_i-F

other startup j remains q_j. Third, a VC may also choose to adopt a passive portfolio management approach, thereby leaving portfolio startups' probabilities of success unchanged. Which of the portfolio management strategies is optimal in equilibrium is a function of startups' probability of success, the intensity of startup competition and the size of the knowledge transfer.

In addition to these three mechanisms, I also consider a version of the model in which I allow the VC to discontinue their portfolio startups. While this may seem an extreme approach to portfolio management, other theoretical papers (e.g., Fulghieri and Sevilir (2009)) have studied this channel and Li, Liu and Taylor (2023) have shown how it can be empirically relevant in the context of competing pharmaceutical startups.[23]

Finally, at $T=4$ payoffs realize. Table 1 summarizes the VC's payoff in each node of the game, including also the payoff from shutting down a portfolio startup at $T=3$.

2.1. Portfolio Management

I proceed by solving the model backward, and I use the Subgame Perfect Equilibrium (SPE) as equilibrium concept. 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:

$$\mathbb{E}\left[Rq_1q_2(1-\phi)+Rq_1(1-q_2)\right]=Rq_1(1-\phi q_2), \tag{2}$$

[23]The model assumes that the VC can dictate portfolio strategy. In practice, startup 2 may have additional investors, possibly with no stake in startup 1. This may limit the VC's ability to engage in monitoring activities that maximize only its own portfolio value. I will show that startup 2 typically benefits from the VC's monitoring in equilibrium, making model predictions generally robust to cases wherein the VC invests in startup 2 as part of a syndicate. However, if startup 1 has multiple investors, this could reduce the likelihood of VC favoring startup 2 or funding it, compared to what predicted by the model.

since 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 1. *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 1 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 they internalize the loss in portfolio returns due to market competition that would arise if both startups stayed afloat. For what concerns τ, an increase in the size of the knowledge transfer has two opposite effects. On the one hand, it increases expected returns by increasing the probability of success. On the other hand, a larger τ decreases the expected payoff of the VC because it makes the return loss due to competition more likely to realize. This cost is larger with symmetric knowledge sharing. In net, this second effect dominates and hence a larger τ makes it more likely that a common VC engages in asymmetric knowledge sharing, ceteris paribus.

Proposition 1 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. To evaluate the impact of the VC's decision to invest in competitors, one needs to compare a startup's payoff when sharing the VC with a competitor (*actual scenario*) against what would have been that same startup payoff if it did not share the VC with a competitor (*counterfactual scenario*).[24]

PROPOSITION 2. *When the VC invests in competing startups and engages in symmetric knowledge sharing, each startup enjoys a higher payoff than in the counterfactual scenario,*

[24]The counterfactual scenario is also equivalent to a passive behavior of the common VC.

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 2 shows that depending on the degree of competition between startups, the size of knowledge sharing and relative probability of success, sharing the VC with a competitor can benefit or hurt a startup. This is because, when for the VC it is optimal to engage in asymmetric knowledge sharing, only the startup towards which knowledge is directed benefits, while the other is worse off relative to the counterfactual scenario. In addition, it is easy to see that the startup's gain from symmetric knowledge sharing is decreasing in q_1, q_2, τ and ϕ. The intuition is that this portfolio management strategy increases the probability that both startups succeed and competition occurs.

When the VC engages in asymmetric knowledge sharing, the benefit enjoyed by startup i is decreasing in ϕ. While a more intense competition makes the VC more likely to favor i, this also increases the likelihood that both startups are successful and compete leading to a greater loss in portfolio value. This second effect dominates.[25] However, in net, since the loss suffered by startup j is exactly ϕ, the difference in performance between the two startups becomes larger following an increase in ϕ. Lastly, the benefit enjoyed by i is increasing in τ because the direct positive impact generated by the larger success probability dominates the reduction in expected return due to the higher likelihood of competition.

2.2. Second-stage Investment Decision

Consider now the the VC's decision to invest in startup 2. At this stage, 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 $(q_1, q_2, \phi, \tau, F, R)$.[26] 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.[27] Formally, I define the selection effect as

[25] The same reasoning applies to an increase in q_j, which reduces startup i's gains.

[26] Lemma A1 shows that, if portfolio management strategies are costless, a passive portfolio management strategy can never arise as an equilibrium outcome when the VC invests at $T = 2$ because not investing would always be preferred. Combining this result with Proposition 2 demonstrates that whenever a VC invests in competing startups, this is part of a strategy that entails an active portfolio management. Hence, when the VC invests in competing startups, the influence effect always exists.

[27] Lemma A2 shows that if q_2 is greater than q_1, the VC invests and engages in symmetric (asymmetric) knowledge sharing for intermediate (high) values of q_2. Otherwise, if q_2 is lower than a threshold, the VC

the difference in the expected probability of success of startup 2 if invested by the VC as compared to if invested by a competing investor.[28]

PROPOSITION 3. *Define*

$$\lambda(q_1, \phi, \tau, F, R) = \begin{cases} \frac{\frac{F}{R}-\tau}{1-2\phi(q_1+\tau)} - \tau, & \textit{if} \quad q_1 < \frac{1}{2\phi} - \frac{F}{R} \\ \\ \frac{\frac{F}{R}}{1-2\phi q_1} - \tau, & \textit{otherwise.} \end{cases} \tag{3}$$

Then the selection effect is $\max\{0, \lambda(q_1, \phi, \tau, F, R)\}$*, and it is strictly positive provided that* $\frac{(F/R)}{2} > \tau$*. Moreover, the selection effect is increasing in the probability of success of startup 1, in startup competition and in the relative investment cost, while it is decreasing in the size of the knowledge transfer.*

To interpret these findings, it is useful to discuss what are the main forces affecting the magnitude of the selection effect. First, selection arises because of the informative advantage of the VC relative to a competing investor. Second, differently from a competing investor, the VC can engage in knowledge sharing, exploiting complementarities and generating grater expected returns as compared to an investor with only one startup. Intuitively, this should reduce selection. Third, the fact that the VC has already invested in startup 1 creates an extra incentive to hedge against startup 1's failure, but also leads to internalizing the cost that a success of both startups generates. To isolate this last effect and determine its net contribution to the selection effect, I fix $\tau = 0$ and compare the actual investment threshold of the VC with that arising if the VC did not have startup 1 in its portfolio but still knew q_1 and q_2. Thus, one can compute this hypothetical threshold as:

$$\mathbb{E}\left[q_1 q_2(1-\phi)R + q_2(1-q_1)R - F\right] \geq 0 \iff q_2 \geq \frac{\frac{F}{R}}{1-\phi q_1}.$$

Therefore, the contribution of the third channel to selection can be expressed as:

$$\lambda(q_1, \phi, \tau = 0, F, R) - \frac{\frac{F}{R}}{1-\phi q_1} = \frac{F}{R}\left[\frac{2\phi q_1}{(1-\phi q_1)(1-2\phi q_1)}\right] > 0,$$

which shows that the competition effect dominates the diversification effect, leading to

does not invest. Conversely, Lemma A3 shows that, if q_2 is lower than q_1, the VC invests an engages in symmetric knowledge sharing for large enough q_2 and does not invest otherwise.

[28]Equation 1 implies that the VC would always invest in startup 2 if startup 1 was not already in its portfolio. In other words, in this case, the value of the VC's investment threshold for q_2 would be zero.

a positive net effect on the magnitude of the selection effect.

In what follows, I ease notation by defining $\sigma(q_1, \phi, \tau, F, R) \equiv \frac{\frac{F}{R}-\tau}{1-2\phi(q_1+\tau)} - \tau$ and $\bar{\sigma}(q_1, \phi, \tau, F, R) \equiv \frac{\frac{F}{R}}{1-2\phi q_1} - \tau$, and I restrict attention to the non-trivial cases in which the selection effect is positive by assuming $0 \leq \tau \leq \frac{(F/R)}{2} < \frac{1}{4}$.[29]

PROPOSITION 4. *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 $q_1 < \frac{1}{2\phi} - \tau$. 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 (below $\frac{1}{2\phi} - \frac{F}{R}$) and transfers large enough (above $\frac{1}{2\phi} - \frac{3}{4}$), 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., $\frac{1}{2\phi} - \frac{F}{R} < q_1 < \frac{1}{2\phi} - \frac{F}{R}\left[\frac{1}{2\phi\left(\frac{3}{4}+\tau\right)}\right]$, then the VC will invest if and only if $q_2 \geq \bar{\sigma}(q_1, \phi, \tau, F, R)$ and they will engage in asymmetric knowledge sharing favoring startup 2.

(iii) If $q_1 > \frac{1}{2\phi} - \frac{F}{R}\left[\frac{1}{2\phi\left(\frac{3}{4}+\tau\right)}\right]$, then the VC never funds startup 2.

(iv) In all the other cases the VC will invest if and only if $q_2 \geq \sigma(q_1, \phi, \tau, F, R)$, and they will engage in symmetric knowledge sharing.

Proposition 4 summarizes the optimal decision of the VC when they have the opportunity to invest knowing q_2. The VC tends to invest in startup 2 when it is better than startup 1, unless the difference in the success probabilities is so small that symmetric knowledge sharing can increase the value of the portfolio or startup 1 is very likely to succeed.[30] Moreover, the quality difference between startups shape the optimal continuation portfolio management strategy. The higher the success probability of startup 2 relative to startup 1, the higher the VC's incentive to asymmetrically share knowledge favoring startup 2. By contrast, the lower this gap, the more likely the VC is to engage in symmetric knowledge sharing.[31]

[29] Note that this is not a restrictive assumption. In effect, I still consider cases in which τ is as high as approximately 0.15, which corresponds to a 40% increase in the probability of success for an average startup—namely a startup with a probability of success of $\frac{3}{8}$.

[30] When q_1 is very high, the VC has a large probability to enjoy R by not investing. Instead, since $q_2 > q_1$, investing is very likely to lead to the competition scenario with a decreased portfolio value.

[31] A natural question is how changes in τ and ϕ affect the VC's investment and continuation portfolio management decisions. Section A.1 in the Appendix offers a discussion of this.

Finally, it is worth highlighting that a direct implication of Proposition 4 is that when the VC knows q_1 and q_2 at the time of the investment decision, the only two possible portfolio management strategies that can be chosen at $T = 3$ are: (i) symmetric knowledge sharing, or (ii) asymmetric knowledge sharing favoring startup 2.

COROLLARY 1. *Conditional on reaching $T = 2$, asymmetric knowledge sharing favoring startup 1 can never arise as an equilibrium outcome.*

2.3. First-stage Investment Decision

The previous analysis has shown how the expertise acquired by the VC through their investment in startup 1 tends to lead to a selection effect in the choice of startup 2. However, in order for this to occur, the VC needs to have the time to learn about startup 2's probability of success. In practice, the VC may be constraint in this ability by the competitive pressure exerted by other investors that are interested in funding startup 2. Therefore, I now analyze VC's incentive to invest into startup 2 right after their investment in startup 1, and hence without knowing q_2. This decision is relevant not only to study the interplay between competition on the capital supply side and the timing of VC's investment, but also to understand the practical importance of the selection effect in this framework. In fact, when the VC invests in startup 2 at T=1, there is no selection effect because they invests without knowing q_2, meaning that any realization in $\left[0, \frac{3}{4}\right]$ is in fact equally likely.

Thus, consider the first-stage investment decision of the VC. This entails choosing whether to invest in startup 2 without knowing q_2, or wait to learn it, running the risk that a competing investor C invests in startup 2. Therefore, the decision to make an early invest 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 $T = 2$ if a competing VC does not invest in the startup. Define $\mathbb{E}[V^{I_t}]$ as the expected continuation value of investing at $T = t$, and p as the probability of not investing at $T = 2$. Then, the VC makes the investment at $T = 1$ if and only if:

$$\mathbb{E}[V^{I_1} - F] \geq (1-\beta)\left[pq_1R + (1-p)\mathbb{E}[V^{I_2} - F]\right] + H(\beta, R, q_1, \phi) \tag{4}$$

where $H(\beta, R, q_1, \phi) = \beta\mathbb{E}[Rq_1q_2(1-\phi) + Rq_1(1-q_2)] = \beta R q_1\left(1 - \frac{3}{8}\phi\right)$ 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 make the investment 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 dominant. This intuition is formalized in thr next proposition.

PROPOSITION 5. *The probability of an early investment in startup 2 at T=1 is increasing in the degree of competition from other investors.*

This result also sheds light on the scope of venture capitalists' market power as a source of the selection effect. To gain intuition into the empirical relevance of the selection effect, consider a scenario with an intermediate level of startup competition, i.e. $\phi = \frac{3}{4}$. In this case, for a VC with an average startup 1 already in the portfolio (i.e., $q_1 = \frac{3}{8}$), given an intermediate level of investor competition ($\beta = 0.5$), a sufficient condition to always prefer not to invest in startup 2 at $T = 1$ is $\tau \leq 0.075$, which correspond to the possibility of increasing the probability of success of an average startup by less than 20%. Moreover, when $\tau = 0$, the VC prefers not to invest at $T = 1$ for any $\beta \leq 0.97$. This suggests that, on average, strategic investments in competitors may be characterized by a significant degree of selection, which, if not accounted for, can lead to upward biased estimates of the effect of this investment behavior on the performance of subsequent startups invested by the same VC in a business area.

Understanding for which values of the parameters the VC makes the investment at $T = 1$ can also shed light on the likelihood that any portfolio management strategy considered arises as an equilibrium outcome. When the VC makes the investment at $T = 2$, the model predicts that startup 1 can never outperform startup 2.[32] Conversely, this can occur in equilibrium if the VC invests at $T = 1$.[33] Thus, I now ask: Given that a pair of competing startups shares the VC, what is the probability that the startup invested first is the only one to benefit?[34]

I find that this rarely happens. To gain the intuition, consider for example the case of $\tau = 0.075$, $\beta = 0.5$ and $\phi = 0.75$. This implies that the VC invests at $T = 1$ anytime q_1 is below the average, i.e. with 50% probability. However, in the monitoring phase, a necessary condition for the VC to favor startup 1 is a q_1 in the top 21% of the unconditional

[32]Corollary 1 states that if the VC does not invest at $T = 1$, then at $T = 2$ it is never optimal to invest when parameters values are such that—conditional on investment—it would be optimal to asymmetrically share knowledge in favor of startup 1.

[33]According to Proposition 1, the VC favors startup 1 if and only if $q_1 > \max\left\{q_2, \frac{1}{2\phi} - \tau\right\}$ and $q_2 \leq \frac{1}{2\phi}$. However, Corollary 1 argues that conditional on reaching T=2, startup 1 never benefits from knowledge sharing.

[34]This is simply the product of the probability of investing at $T = 1$ and the probability of favoring startup 1 conditional on having invested at $T = 1$.

distribution. This implies that under this parametrization, the model never predicts that startup 1 benefits from sharing the VC with startup 2.[35] By contrast, in this same scenario the predicted probability of observing startup 2 being the only one benefiting is more than 20%. Thus, broadly speaking, my model predicts two empirically relevant outcomes: (i) both startups perform better when sharing the VC than what they would have done without sharing them, or; (ii) when sharing the VC, startup 2 performs better than startup 1 and than what it would have done without sharing the VC, while the opposite holds for startup 1.

2.4. Startup Shutdown

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. Moreover, Cunningham, Ederer and Ma (2021) document how incumbent firms may acquire pharma startups solely to discontinue the target's innovation projects and preempt future competition.

Motivated by this evidence, in this section I extend the model to study in which cases the VC can increase the expected returns by discontinuing one of the portfolio startups. This strategy can be optimal since the possibility of divesting one of the startups, even when it is successful, allows the VC to extract more surplus from the remaining one (Fulghieri and Sevilir 2009). An important caveat that is worth emphasizing is that VCs are usually minority share-holders with only partial control, and hence may not always have the ability to shutdown a startup. On the other hand, 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. Moreover, VCs may advice their investees to pivot away from their initial business model, *de facto* killing the startup as it was started.[36] In what follows I abstract from these dynamics and assume that the VC can shutdown portfolio startups at no cost.

Thus, at $T = 3$, a common VC can be passive, share knowledge across portfolio startups but also shutdown one of the two. The next result describes the optimal portfolio management strategy.

PROPOSITION 6. *Conditional on having invested in startup 2, the VC engages in:*

[35] Even if I assume $\beta = 1$, the probability that startup 1 benefits from sharing the VC with startup 2 remains below 19%.

[36] This is an important aspect to consider when thinking about the welfare implications of this portfolio management strategy because this redirection on innovation efforts by VCs may generate important social benefits from reducing duplication of R&D efforts.

(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* $q_i > \frac{q_j+\tau}{2\phi q_j} - \tau$.

Introducing the ability to discontinue startups implies that a passive management approach is never optimal for a common VC. Inspecting the threshold in part (iii) of Proposition 6 illustrates how shutting down startup j can be optimal only in contexts characterized by a high degree of competition between startups, low τ, and by a large enough gap in the probability of success between the best startup and the other. Intuitively, by shutting down a startup, a VC forgoes the benefits generated by a diversified portfolio. Additionally, when startup competition is intense, the VC could asymmetrically share knowledge and maintain a diversified portfolio to hedge against the failure of the ex-ante best project. Therefore, it is clear how to rationalize the extreme decision to discontinue a startup, the VC's ability to share knowledge across startups must be somewhat limited (i.e., τ needs to be low).

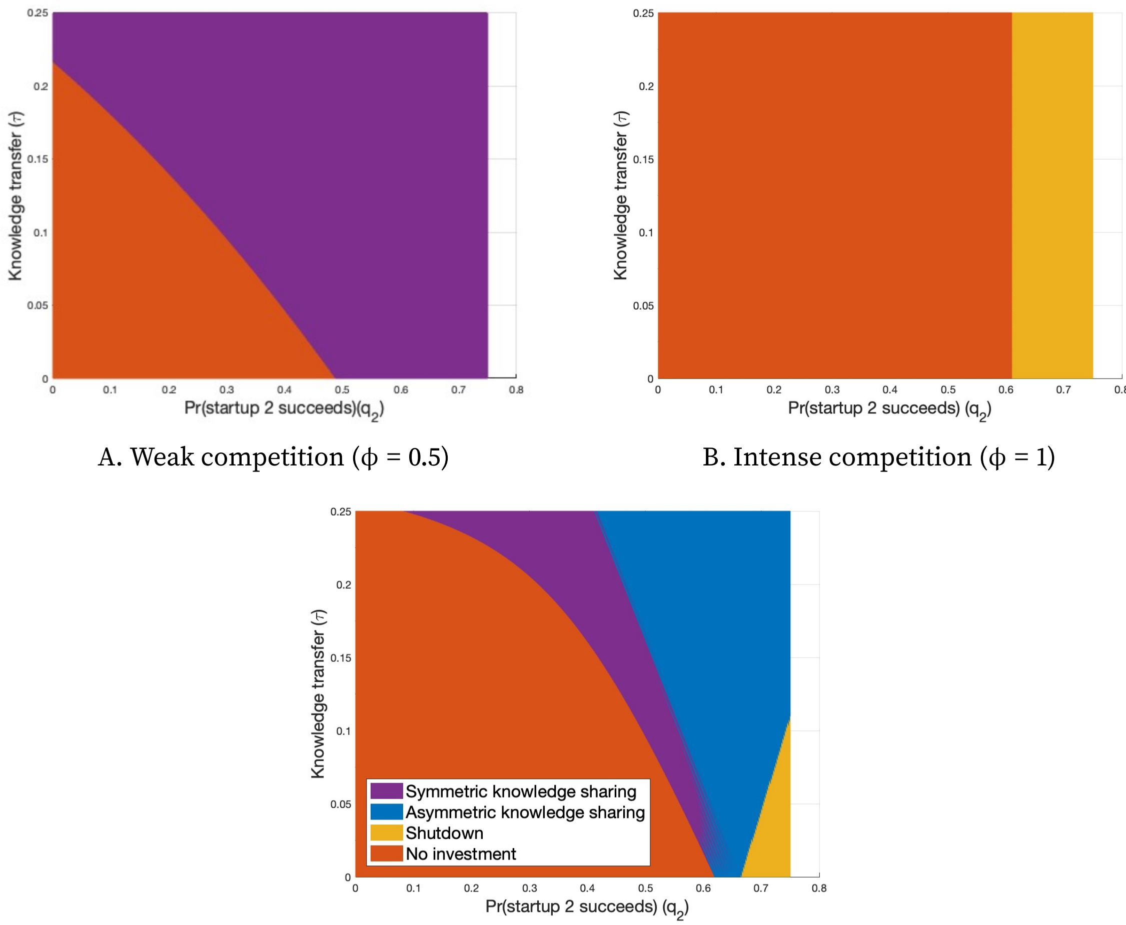
Next, I examine the investment decision of the VC at $T = 2$, when both startups' probability of success are known. It is easy to see that when $q_1 > q_2$ investing in startup 2 to shut it down generates the same value as not investing but requires the VC to bear the investment cost F, and hence is 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 shutdowns startup 1 if and only if,

$$q_2 > \max\left\{q_1 + \frac{F}{R}, \frac{q_1+\tau}{2\phi q_1} - \tau\right\}. \tag{5}$$

To derive the optimal investment strategy, a necessary step is that of computing the continuation value from each decision. To address the non-convexity of this problem, in what follows, I make two further assumptions. First, I consider a discrete set of ϕs, i.e., $\phi \in \left\{\frac{1}{2}, \frac{3}{4}, 1\right\}$. When $\phi = \frac{1}{2}$ ("weak competition"), the two products are differentiated enough that each startup serves half of the market. When $\phi = 1$ ("intense competition"), the two products are homogeneous generating a zero payoff, as if the two startups engaged in Bertrand competition. Finally, I also consider an intermediate case with $\phi = \frac{3}{4}$ ("moderate copetition").[37] Second, I assume that startup 1 is an *average startup*, i.e.

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

$q_1 = \frac{3}{8}$.[38] This assumption allows to focus on the main point of this stage of the model, which is the selection effect on the second startup.



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

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

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

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

Figure 2 illustrates the optimal strategy of the VC as a function of τ and q_2, for different levels of startup competition. The red area represents the areas in which the VC decides not to invest, identifying the selection effect. The selection effect is decreasing in τ and is larger when startup competition is more intense, suggesting that the result shown in Proposition 3 in fact extends to this case where I allow the VC to discontinue portfolio startups. When competition is weak ($\phi = 0.5$ in Figure 2A), a VC with an average portfolio startup will always engage in symmetric knowledge sharing conditional on investing in a new startup. However, the selection effect is still quite

[38]Later in this section I discuss the implications of this assumption in detail and I also show how changes in q_1 affect the decision to invest.

strong, especially for values of τ that are not too large.[39] Conversely, when competition is intense ($\phi = 1$, Figure 2B), having two startups afloat is too costly, so that it is always optimal to discontinue startup 1. Since knowledge sharing is never an equilibrium management strategy, the decision rule is independent on τ. Moreover, investment occurs only for draws of q_2 above the 80^{th} percentile of the distribution, reaffirming that this outcome can only be observed when there is a large enough difference in the success probabilities of startups. Figure 2C illustrates the case of moderate competition ($\phi = 0.75$). 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.

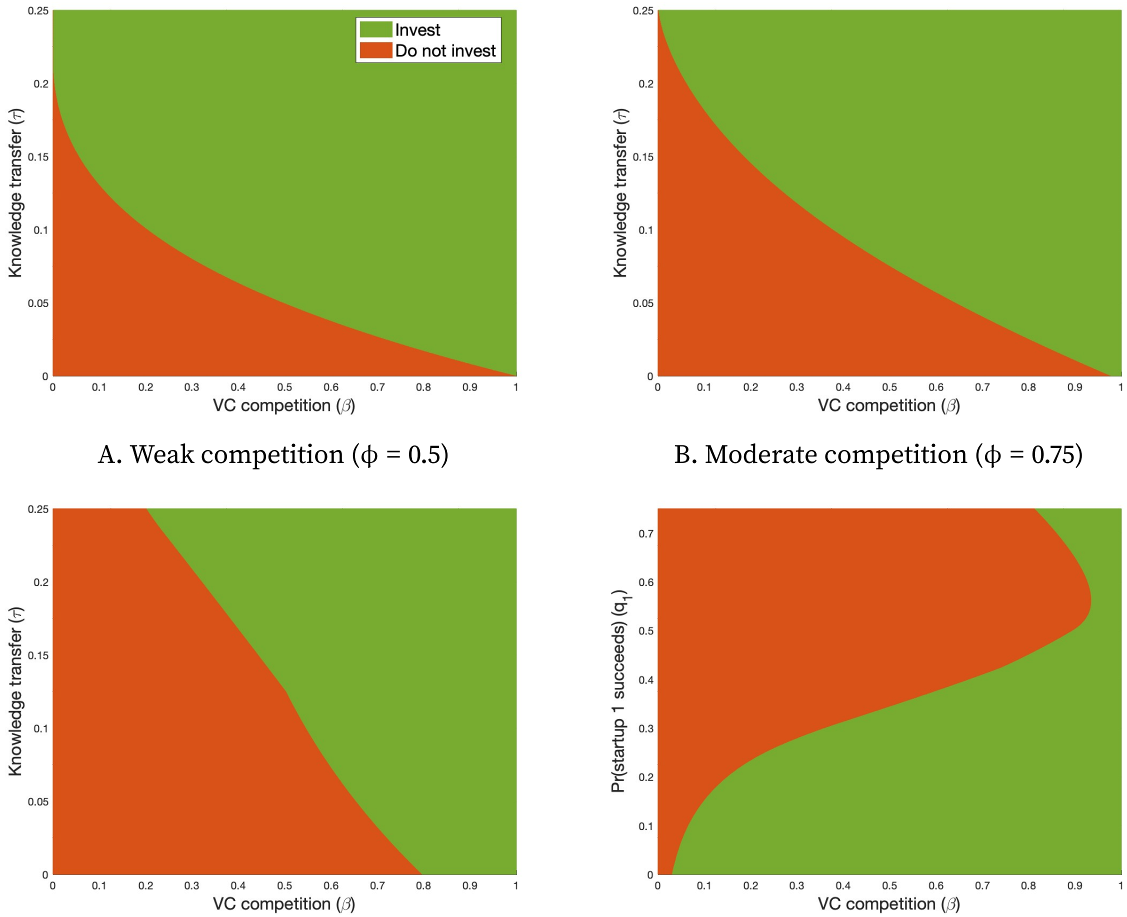
The last step entails illustrating the first-stage investment decision of the VC. Consistently with Proposition 5, all the graphs in Figure 3 display that greater investor competition increases the probability of observing the VC investing at $T = 1$. Note that this implies that selection tends to be less severe in contexts where competition between startups is weak. Figures 3A, 3B and 3C also show that the size of the investment region increases with τ. 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 3C 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 3D 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.[40] (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.[41]

[39] Consider for example $\tau = 0.05$, which still allows the VC to increase an average startup probability of success by more than 13% via knowledge sharing. In this case, in order to invest, the VC needs to encounter a startup that is well-above the average.

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

[41] 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 of startup competition, which lowers the cost of investing F. As suggested by Figure A.1,



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 3. Optimal Investment Strategy at $T = 1$

Hence, similarly to what described by Cunningham, Ederer and Ma (2021) in the context of incumbents' buyouts, 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.

2.5. Discussion and Testable Hypotheses

The main empirical predictions of the model concern the impact of the VC's investment in competing startups on those startups' expected returns (influence effect), and the decision regarding whether to fund potentially competing startups and which specific

the non-monotonicity in the top right corner is explained by τ: with low draws of q_2, the VC can increase its portfolio value by sharing knowledge towards startup 1.

startups to support (selection effect). To ease exposition, I refer to the first of the competing startups invested by the VC as "first startup" (i.e., startup 1 in the model), and to any other startup sharing the VC with a competitor as "subsequent startup" (i.e., startup 2 in the model). Moreover, I refer to any startup not sharing a VC with a competing startups as "solo startup."

Hypothesis 1 (Influence effect). *Subsequent startups perform better than solo startups, which in turn, outperform first startups. Moreover, in some extreme cases, first startups are discontinued by the VC. Under the alternative hypothesis, each startup benefits from sharing the VC with a competitor.* Whether both or only one of the portfolio startups derive benefits from sharing the VC with a competitor depends on the specific values of the parameters, making it an empirical question. However, conditional on having only one startup benefiting, the model clearly predicts that this must be the one invested subsequently. In addition, the model shows that when the quality of this subsequent startup relative to the first one or startup competition is high enough, it can be optimal for a common VC to shutdown the first startup.

Hypothesis 2 (Selection effect). *A VC that has already made an investment in a business niche tends to select higher expected return startups than a VC that has never invested in that niche before.* By investing in a business niche, VCs acquire a better understanding of the market dynamics, potential risks, and opportunities. As a result, they may be more adept at identifying promising startups within that niche, which are more likely to generate higher returns on investment.[42,43]

Additional empirical predictions from the model hinge on the factors that affect the size of the influence effect and the timing of a VC's second investment in the same business niche.

Hypothesis 3 (Influence heterogeneity). *The extent to which a first startup is outperformed by a subsequent startup is increasing in the time lag between investments, in the degree of startup competition and in the size of knowledge transfers.* A key prediction of the model is that the selection effect interacts with the influence effect. Since the VC invests in a subsequent startup only if it has a high enough probability of success, in equilibrium the VC is more likely to engage in asymmetric knowledge sharing favoring it. In the

[42] Investing in a business niche also enables VCs to increase the size of their network of contacts in that niche. This can help them identify high-potential opportunities and avoid potential pitfalls (Hochberg, Ljungqvist and Lu 2007)

[43] The selection effect, as defined in Proposition 3, abstracts from the possibility of selection with respect to q_1. A discussion of this issue of offered in Appendix A.2.

model, selection occurs because the VC can learn the success probability of startup 2 by waiting to invest. In practice, a VC decides if and when to fund a subsequent startup. I assume that the time lag between consecutive investments in different startups in the same business niche captures the VC's probability of learning the quality of the subsequent startup. Therefore, when this lag increases, one should observe a larger selection effect, leading to a greater (positive) difference between the performance of subsequent and first startups. Moreover, conditionally on having two startups in the portfolio, a higher degree of startup competition ϕ or a larger knowledge transfer τ makes it more likely that a VC shares knowledge to favor the subsequent startup invested in the BN. In practice, it is natural to ask what drives τ. First, τ could be viewed as measuring the degree of complementarity across portfolio startups. The challenge is that complementarities are arguably stronger when the business models of the two startups are more similar, making it hard to separately identify the contribution of changes in ϕ and τ. Second, τ may capture the fact that some VCs may be better equipped to realize synergies across portfolio startups or to favor information flows within their portfolio.[44] For example, this could be due to a VC's experience. If this is the case, one should observe that the first startup invested in a business niche is outperformed by the subsequent ones to a greater extent when the VC is more experienced.

Hypothesis 4 (Investment Timing). *The time lag between the first and the second investment in the same business niche is decreasing in investor competition.* When the competition to supply capital is intense, investors may feel the pressure to act swiftly to secure favorable investment opportunities, leading to reduced deliberation time between investments. This, in turn, reduces their access to critical information, having important implications in terms of the quality of the startups' profile chosen.

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.[45] The focus of CB is primarily

[44] Additionally, τ could also be a related to the institutional framework in place, such as the existence of laws regulating investors' conflict of interest.

[45] For recent activity in the academic literature that pertains to this data source, see Hochberg (2016), Kaplan and Lerner (2016), Lerner et al. (2018), Chatterji et al. (2019), Wang (2018) and Jia, Jin and Wagman (2021).

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 of the round, the number and identities of investors, the amount raised, the 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.[46] 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), and level-4 being the narrowest (resembling a market niche, such as "Benefit and Payroll Management" and "Video-On-Demand Servers"). 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 (2023) 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 of more similar businesses as "closer" in its taxonomy.[47]

[46] In total, it covers 41,796 M&A transactions involving 15,323 unique acquirers recorded between 2010 and 2020.

[47] In particular, they show how firms in the same S&P BN tend to have higher cosine similarities—computed using textual business descriptions as common in the literature (e.g., see Hoberg and Phillips (2016))—than firms in the same tech category but different BN, which, in turn, tend to have higher similarities as compared with firms in different tech categories.

3.1. Sample Construction and Summary Statistics

To study the effects of VCs' investment in potentially competing startup on startups' outcomes, a necessary step is defining in which cases a VC is making an investment 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 to each startup a unique investor, namely the lead VC at the first round of venture capital financing. Focusing on the lead VC is a common practice in the entrepreneurial finance literature studying the monitoring effect of VCs (e.g., Bernstein, Giroud and Townsend (2016)) because the lead VC is significantly more likely to be involved in monitoring and to obtain a board seat (Amornsiripanitch, Gompers and Xuan 2019) than any other investor. Moreover, Gompers (1996) defines the lead investor as the one that has invested in the company the longest, a definition which is consistent with the stylized fact that the VC firm originating the investment is usually the one that acquires a board seat first and has the most input into the decisions of the company, even though it might not end up ultimately owning the largest equity stake (Gorman and Sahlman 1989). Under this definition, the lead VC does not change even when new VCs invest in the startup at later stages.[48]

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 afterwards. 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.[49] Most importantly, for each startup in the sample, I need to define the set of competitors. To that extent, I extrapolate the S&P taxonomy to CB data by following the procedure outlined in Section 3.2. In this way, I can attach a BN to every startup in the sample and define any pair of startups belonging to the same BN as potentially "in competition."

These steps enable me to define the set of *"linked"* startups as those that, at some point in time, will share their VC with an active competing startup. I will compare them with the remaining non-linked startups raising their first round of venture capital

[48] Nonetheless, nowadays the notion of lead VC tends to be though of as stage-dependent.

[49] In some cases, VCs may provide capital at earlier stages, such as seed. However, I do not consider these earlier stages to define the lead VC associated to a startup because earlier rounds tend to smaller, and at that stage, startups' business plan is not yet well-developed (see for example: https://www.svb.com/startup-insights/vc-relations/stages-of-startup-capital). This is an important aspect in my analysis as I need to define which are a startup's competitors based on business descriptions. Restricting attention to startups that passed the seed stage also allows me to compare startups with more similar risk profiles.

financing between 2008 and 2019 ("solo startups"). Additionally, I further distinguish linked startups into two groups: (i) "first startups," which represent the first startups invested by a VC in a BN; (ii) "subsequent startups," which are all the other linked startups.[50] For example, Sequoia invested in 2010 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 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 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).[51]

My final sample includes a total of 33,796 startups, and the number of linked startups equals 9,738. Of these, only the 35% is tagged as the first startup, suggesting that is not uncommon for a VC to make more than two investments in the same BN. However, while my sample includes more than 11,000 different investors, only the 13% invests in competitors. Table C.1 suggests that larger and more experienced VCs (as measured by the total number of rounds participated up to the focal one) are more likely to simultaneously hold stakes in active startups that operate in the same BN. Overall, the data suggests it is not uncommon for competing entrepreneurs to raise venture capital from the same VC, but this investment strategy appear to be pursued but only a subset of investors.[52]

Finally, Figure 4 illustrates the funding dynamics of the three groups of startups defined over time, measured as the distance (in years) from the first round of venture

[50] I define an active startup as one that has not yet exited. If a VC invests in a second startup in a BN after the first startup invested has already shut down, it is not considered an investment in competing startups. However, if the same VC makes an investment in a third startup in the same BN, this startup is coded as a subsequent startup, and the second startup invested as a first startup. In some cases, VCs investes 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.

[51] As it is clear from the number of observations (N), some statistics in Table C.1 are at the startup-year level, while others are at the startup level.

[52] In a recent article (available at: https://www.theinformation.com/articles/an-old-vc-taboo-fades-more-firms-invest-in-rivals), Berber Jin argues how in the past investing in competitors was a taboo, due to—for example—reputational concerns. However, this practice has become more and more common among larger funds, reflecting a change in investment norms.

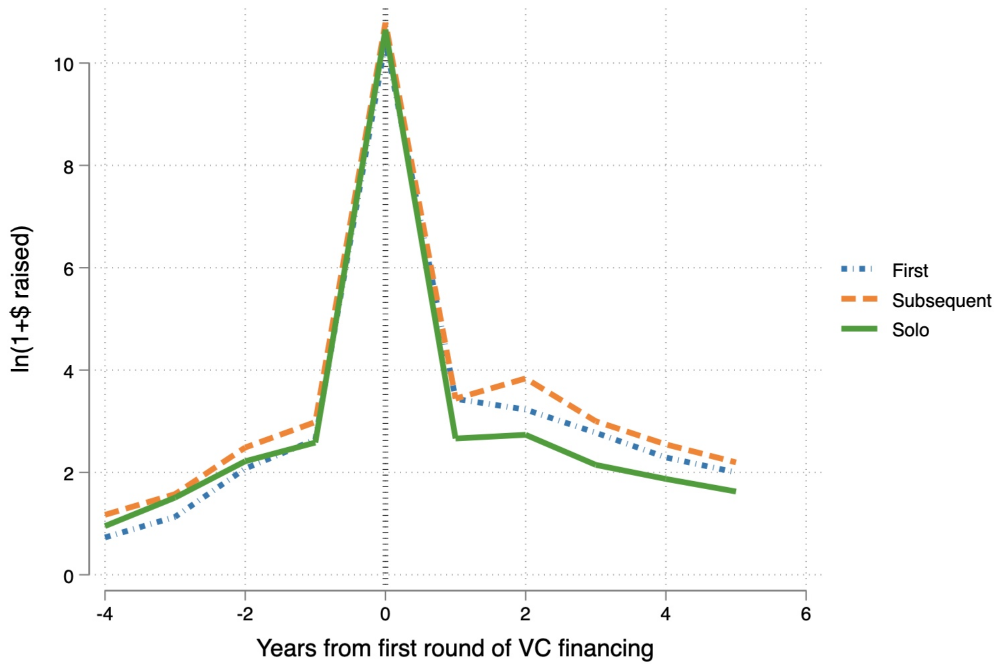


FIGURE 4. Average yearly funds raised by different groups of startups

capital financing (year 0).[53] The graph suggests that each year, subsequent startups are more successful in securing funding over time compared to the other identified groups. This observation is at the core of Hypothesis 1, and will be the focus of the analyses of Section 4.

3.2. Taxonomy Extrapolation

In this section, I describe the procedure used to extrapolate the S&P taxonomy to the investment data. The main idea is that of leveraging 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:

[53]The graph exhibits a significant spike at the zero because in that year by construction all startups in the sample raise a startup round by it may not be the case earlier.

(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.[54] Then, for each startup, I construct and clean a string that includes the startup business description and the CB-assigned keywords.[55]

(2) *Define the training sample.* I identify startups that were acquired, and hence for which BNs are available, by merging CB with S&P.[56] These startups–which are roughly the 5% of the sample—span almost all BNs.[57] 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, and compute the term frequency-inverse document frequency (TF-IDF) values.[58] 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.[59]

(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.[60]

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

[55] 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.

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

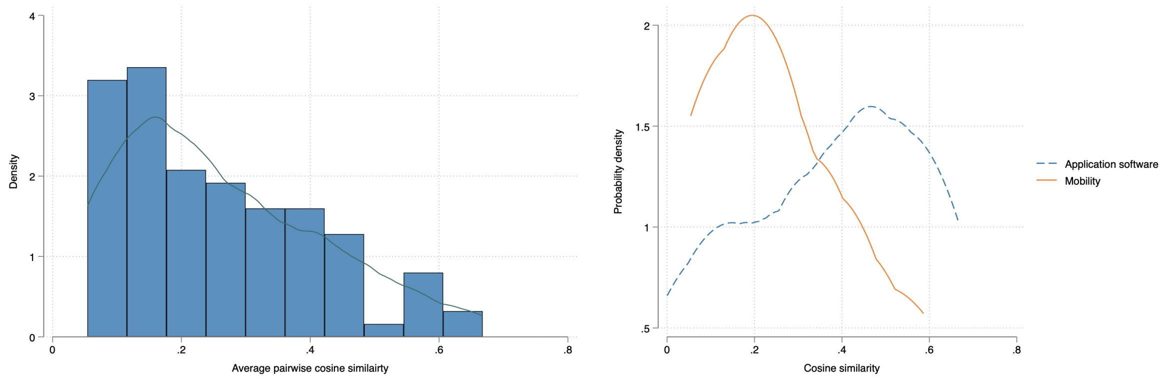
[57] Since some BNs have very few matched startups, I collapse them into other BNs belonging to the same tech category.

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

[59] This is similar to Hoberg and Phillips (2016), although in their algorithm each element is populated by the number one if a firm's string uses the given word, and zero otherwise.

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

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 needs to be set before applying the k-NN algorithm. Therefore, I eventually select the $k \in \{1, \ldots, 50\}$ that maximizes the accuracy of the prediction, i.e. $k = 10$.



A. All BNs

B. BNs in Application software and Mobility

FIGURE 5. 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).

Next, I evaluate the performance of the classifier used. To that end, I compute 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 5A illustrates the distribution of these cosine similarities across all BNs, while Figure 5B 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 5, in Table 2, 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 5 suggests that the algorithm is able to cluster together similar startups.[61]

[61]In Appendix B I perform formal analyses to evaluate the performance of the 10-NN classifier. In

TABLE 2. 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

4. Investment in Competitors: Selection and Influence Effect

In this section, I develop an empirical framework to test Hypotheses 1 and 2, and I present the results of the analyses.

4.1. Empirical Framework

The main contribution of the analytical framework of Section 2 is twofold. First, VCs acquire business niche-specific expertise through previous investments, and this enables them to identify startups with higher expected returns. Then, anticipating what their optimal portfolio management strategy would be if they invested, VCs decide whether to invest or not. This implies that they will invest in a startup in competition with a previous investment only if the new startup is high-quality. Second, if the investment occurs, VCs internalize the competition between the two startups, and may have an incentive to favor the best portfolio startup. However, due to the selection effect, this investment behavior tends to hurt first startups and favor subsequent ones. Therefore, the model provides a mechanism through which investing in competing startups impacts startups' outcomes that hinges upon the interaction of selection and influence effect.

The empirical analyses testing Hypotheses 1 and 2 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 startup i, operating

particular, I illustrate its diagnostic ability using the receiver operating characteristic curve and I compare the 10-NN algorthm with two other commonly used classifiers: XGBoost and Multinomial Naive Bayes.

in BN m in year t, the econometric specification is as follows:

$$Y_{imt} = \alpha_1 \cdot Linked_i + \alpha_2 \cdot First_i + \beta_1 \cdot SharedVC_{it} + \beta_2 \cdot First \times SharedVC_{it} + \\ + \beta_3 \cdot Post_{it} + \beta_4 \cdot (First_i \times Post_{it}) + \boldsymbol{\pi} \cdot \boldsymbol{X_{imt}} + \alpha_{mt} + \varepsilon_{imt}, \tag{6}$$

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 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, $\boldsymbol{X_{imt}}$ is a vector of control variables capturing startup growth, and α_{mt} are BN by year fixed effects. Standard errors clustered at the startup level.[62]

The two key coefficients of interest are β_1 and β_2. The former captures the overall average effect of sharing a VC with a competitor, while $(\beta_1 + \beta_2)$ is the impact on the first portfolio startup invested (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 linked startup that is not the first startup invested in the BN joins the portfolio of the common VC is always the year of the first round of VC financing. Conversely, the startups for which *First* equals one may join the portfolio of the common VC later on in their life-cycle. In this sense, while β_3 controls for the impact on performance 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.

If VCs were randomly matched to competing startups, estimating β_1 and β_2 in Equation 6 (henceforth, the "baseline model") via Ordinary Least Squares (OLS) would provide unbiased estimates of the influence effect. However, in Section 2 I showed how startups that share a VC with a competitor might inherently possess higher quality due to VCs learning from their prior investments. The bias originates in the inability of the econometrician to perfectly observe (and hence control for) all fundamental determinants of a startup's quality (i.e., the success probabilities q_1 and q_2 in the analytical framework). If, as in the analytical model, this underlying source of bias is time-invariant, one can simply augment the baseline model with startups fixed effects (re-

[62] I choose to cluster standard errors at the startup level because this is the unit of assignment to "treatment" (Abadie et al. 2023). If one is concerned that startups outcomes may also be related to what is happening in the BN at the time of the investment, then including $BN \times year$ fixed effects as I do should mitigate the issue. In any case my results are generally robust to other ways of clustering standard errors, such as at the BN level or two-way clustering on startup and BN-year.

ferred to as the "FE model"), and obtain the influence effect by estimating β_1 and β_2 via OLS. Then, the selection effect is identified by the difference between the coefficients of interest estimated with the baseline and the FE model.

In practice, a startup unobserved quality may change over time. For instance, entrepreneurs might acquire managerial skills or recruit highly skilled employees. When such situations arise, the FE model fails to account for the selection effect, resulting in biased estimations of the influence effect. To address this concern and identify the influence effect, I follow an instrumental variable (IV) approach, while still including in the model startup fixed effects (henceforth, "IV model"). In this context, a good instrument needs to possess two key attributes: (i) It should exhibit a correlation with the VC's decision to invest in two startups operating within the same BN. (ii) It should be unrelated to the quality of the startups, thereby satisfying the exclusion restriction. To put it differently, the IV should solely impact the performance of a startup through the VC's choice to invest in competing startups.

To isolate the variation in the VC's decision to invest in competing startups that is orthogonal to the quality of startups, I employ a binary variable indicating whether the VC has previously invested in competing startups within BNs other than the focal one to instrument for whether a startup is linked. Thus, the IV varies for each VC across BNs and over years. This IV satisfies the exclusion restriction because it does not correlate with the underlying source of endogeneity, which is the VC's specialized expertise within the BN where the investment in competitors is taking place. Moreover, because of inertia in resources, capabilities, and internal processes, firms tend to behave consistently over time, so their past actions are considered a credible signal of future behavior (Weigelt and Camerer 1988). Therefore, by capturing investor's past investment strategies, the IV should be highly correlated with the endogenous variable.

These properties of the IV can also be viewed through the analytical model of Section 2 by incorporating a fixed cost D associated with closing a deal (e.g., due diligence costs).[63] This cost influences whether a VC proceeds with a second investment but not its potential returns. The observed heterogeneity in this cost across VCs in the data, driven by factors such as reputation (Hsu 2004) or network (Hochberg, Ljungqvist and Lu 2007), aligns with the variation captured by the proposed IV. It is important to emphasize that this IV exclusively deals with the endogeneity resulting from the selection effect. However, in practice, there are other factors that could potentially constrain my ability to establish causality. For example, VC investing can essentially be viewed as a two-

[63] In Section 2, I simplify the model by setting $D = 0$.

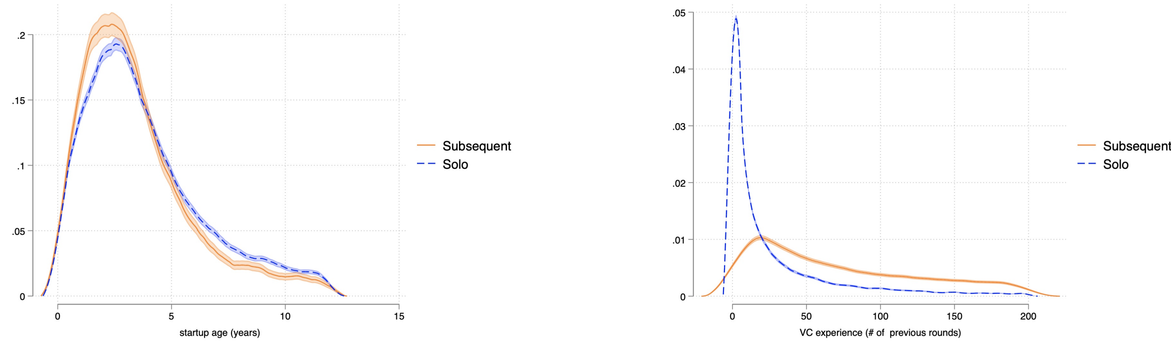
sided matching problem and there may exist unobserved match characteristics that influence the VC's choice to make an offer and the entrepreneur's decision to accept it.

Li, Liu and Taylor (2023) employ the geographic proximity of two startups as an instrument for whether they share a common VC investor, leveraging the premise that venture capital tends to be localized. However, this proposed instrument faces potential challenges in satisfying the exclusion restriction. Firstly, a startup's performance might be influenced by enhanced VC monitoring, driven by lower monitoring costs for closer startups (Bernstein, Giroud and Townsend 2016). Secondly, proximity may impact outcomes due to the shared labor market for valuable employees, like developers and engineers, among the closer startups. Additionally, the instrument might not consistently reflect the underlying mechanism in certain scenarios, such as cases where a VC is positioned between two startups without the startups themselves being close to each other. In contrast, Eldar and Grennan (2023) exploit the staggered adoption of corporate opportunity waivers across eight US states. These waivers shield investors from litigation risks if they appropriate a business opportunity conflicting with a firm's best interest. In addition of its context specificity, this variation might not be entirely exogenous to startup attributes, as it could influence startups' decisions to incorporate in particular states, introducing a selection bias.

4.2. Results

I begin by documenting how startups which eventually find themselves sharing their VC with a competitor are significantly different from—and possibly ex-ante more likely to outperform—solo startups. Figure 6 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 3, 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 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"



A. startup age B. VC experience

FIGURE 6. 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.

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 the 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 3 shows that more experienced investors exhibit a greater inclination towards investing in competing startups, and this trend is particularly pronounced in BNs 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 are more than 40% likelier to replicate such behavior in a distinct BN in the future.[64]

I next formally test Hypothesis 1. According to the hypothesis, investing in startups that are potential competitors of the first startup invested in the BN positively benefits subsequent startups, while hurting first ones. Hence, the estimate of β_1 in Equation 6 is expected to be positive and statistically significant. Conversely, the estimate of β_2 is

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

TABLE 3. 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.

anticipated to be negative, statistically significant and larger in absolute value than β_1.

Columns (1) and (4) of Table 4 present the results for the Baseline model, which I estimate using OLS. The coefficient on *SharedVC* (β_1) is both positive and statistically significant at the 1% level. This indicates that, after they start sharing a VC with a competitor, startups raise approximately 45% more venture capital and exhibit a 2.5% higher likelihood of conducting a funding round each year. However, this effect manifests heterogeneously 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% reduced likelihood of raising an additional funding round compared to a solo startup. Simultaneously, the coefficient associated with *First* $\times$ *Post* underscores 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 secured. Consequently, the comprehensive impact of securing the first round of VC financing from this VC is a reduction by 15% in the amount of future capital raised and by 7% in the likelihood of raising a further funding round. Lastly, together, the coefficients pertaining to *Linked* and *First* imply that subsequent startups yield on average ex-ante superior outcomes relative to solo startups, whereas this does not appear to apply to first startups. This observation offers additional support for Hypothesis 2.

Columns (2) and (5) in Table 4 present the findings yielded by the FE model estimated using OLS. If the source of endogeneity remains constant over time, akin to q_1 and q_2 in the analytical framework of Section 2, the incorporation of startup fixed effects addresses the selection effect. Consequently, 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 via heightened monitoring activities. 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 45.5% (2.5%)—on future capital raised (probability of conducting a funding round), 39.2 (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. Notably, 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.[65]

As highlighted in the previous section, one may argue that startup's unobservable quality evolves over time, indicating that startup fixed effects alone may not suffice to identify the influence effect. Columns (3) and (6) of Table 4 present the results obtained from the IV model, which I estimate through 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 increase 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 Hypothesis 2. However, it is common for IV estimates to be larger than their OLS counterparts (Jiang 2017). In my case, the reason is that the instrument picks up startups funded by VCs that have invested in a competitor in the focal BN and that exhibit a similar investment behavior

[65]Note that adding up the estimates of β_1 and β_2 in the FE model gives a lower value than in the Baseline model. This suggests the existence of a possible negative selection on first startups unobservable quality (q_1). This feature is also consistent with my analytical model, as discussed in Appendix A.2.

TABLE 4. Investment in competitors and startup performance

	ln(1+$ raised)			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	
F statistics Cragg-Donald Wald F statistic			24150.07			24150.07
Kleibergen-Paap Wald rk F statistic			2234.65			2234.65
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 used for *SharedVC* and *First* × *SharedVC* are 0.892 and 0.535, respectively, and both estimates are statistically significant at the the 1% level.

in other BNs. Thus, the IV-compliers are 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 will tend to be larger and more experienced, they will be more able to internalize competition externalities within their portfolios and channel relevant information or resources towards subsequent startups.[66] 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). Additionally, the F-statistics displayed in columns (3) and (6) of Table 4 provide evidence

[66] In general, more experienced VCs tend to outperform those with less experience (Gompers, Kovner and Lerner 2009).

in favor of the strength of the instruments.[67] In terms of the heterogeneous effects for 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.[68] 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).[69] Furthermore, Table 4 demonstrates that $(\hat{\beta}_1 + \hat{\beta}_2)$ is similar in magnitude across the FE and IV models. This suggests that, in accordance with Hypothesis 2, the selection bias primarily affects subsequent startups rather than first ones.

The final part of Hypothesis 1 states that in certain circumstances, the VC might have an incentive to discontinue the first startup invested in the BN. Table 5 furnishes supporting evidence for this conjecture. Column (1) presents the results of the Baseline model, while column (2) and (3) show the results of the FE and IV model. The dependent variable is equal to one if the startup is shutdown 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 significant 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%).[70] Overall, these analyses suggest that both Hypothesis 1 and Hypothesis 2 are empirically validated.

I run several robustness checks. First, I consider a different specification in which I add investor fixed effects to Equation 6 instead of startup fixed effects. This isolates the role played by a VC, regardless of whether they also invested in a competing startup. The estimated coefficients for *SharedVC*—reported in Table C.7—is smaller but still posi-

[67] The first stage coefficients for the instruments reported in the notes of Table 4 provide additional evidence supporting their relevance. Nonetheless, Figure C.2 illustrates that 95% confidence sets for β_1 and β_2 which are robust to weak instruments (in the sense that identification of the coefficients is not assumed), are consistent with the estimates reported in Table 4.

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

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

[70] The analyses in Table C.2 and Table C.3 consider startup exit (via IPO or M&A) and whether the VC provides follow-up financing as possible alternative outcomes, respectively. 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. The results in Table C.2 suggest that overall linked startups tend to remain private and independent longer being less likely to exit via IPO and M&A, although these differences are small in magnitude (less than 0.5%). The positive—although economically small—coefficient on *First* × *Shared* underscores some common VCs' tendency to exit from their first startup invested in the BN after investing in another startup in the same BN.

TABLE 5. 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.

tive and significant. Overall, the results are robust to this alternative specification.[71] 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.9 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.[72] Using the same instrumental variable, I compute the inverse mills ratio and show in Table C.5a that in the second stage these are positive and significant only for linked startups (i.e., subsequent startups). This suggests that VCs that already have made an investment 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 support of Hypothesis 2. Moreover,

[71]In the analysis reported in Table 4 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.8 shows that results are robust when I augment the FE and IV models with VC characteristics interacted with the *Post* dummy.

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

this procedure enables me to run counterfactual analyses comparing the the overall performance post first round of VC financing for linked and solo startups. In particular, Table C.5b shows that a subsequent startup would raise roughly 20% less if it did not share a VC with a competitor. This is qualitative consistent with my previous findings.

Third, I explore an alternative approach, once again excluding first startups from the pool of linked startups. To be more specific, I leverage propensity score matching (PSM) to align the remaining linked and the solo startups based on observable startup characteristics—such as the number of rounds and the amount of funding raised prior to 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 traditional 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 4—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 analytical 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.6, and are consistent with those presented in Table 4.[73]

4.3. 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. While its definition is clear, the intricate mechanisms through which it exerts its impact remain veiled. In the analytical model of Section 2, I motivate the analysis by arguing that a common VC may facilitate information flows across portfolio startups or discontinue a startup. However, in practice, the influence effect may manifests in other forms. For instance, a common VC may unequally allocate time and resources across portfolio startups.

Unfortunately, data limitations prevent me from directly testing the channels whereby the influence effect manifests. However, whatever the mechanism, the influence effect requires some degree of investor activism. In practice, one may argue that, VCs invest

[73]Columns (1), (4) and (7) of Table C.6 show the robustness of the results for the FE model when utilizing tech categories (i.e., S&P level-1s) instead of BNs to define competing startups.

in competitors just as a “diversification strategy,” similar to the *spray and pray* approach described in Ewens, Nanda and Rhodes-Kropf (2018). For example, VCs may be confident about the prospect of a particular BN, but not about which startup is going to be the successful within that space. Countering this argument, the analytical model of Section 2 showed that a passive behavior of the common VC cannot rationalize the better performance of subsequent startups documented in Table 4. Next, I provide direct evidence on the active engagement of common VCs in startup operations.

TABLE 6. 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 for the IV model adding the interaction between *First* × *SharedVC* and three different BN characteristics. The first one (*BN_tightness*) measures how many VCs are active relative to the number of startups seeking financing. The second one (*BN_maturity*) captures the maturity of the BN as measured by the log-transformed number of IPOs had by startups operating in the BN. The third one (*BN_active_VCs*) is is the proxy used throughout the paper to measure VC competition within a BN. Standard errors are reported in parentheses and are clustered at the startup level.

I run six additional regressions using four distinct binary variables as dependent variables, within both the FE and IV models.[74] The first binary variable equals one when a new board member is appointed; the second equals one when a former board member departs the board. The third variable equals one upon the hiring of a new executive, while the fourth signifies a former executive leaving the startup's managerial team.[75]

The findings from these analyses are summarized in Table 6. Column (4) shows that following a startup's integration into a common VC's portfolio, the probability of a director leaving the board is almost 2% higher relative to solo startups. This result does

[74] In all these regression I control for the VC-startup distance, measured by the Harvesine formula (in logs) and also for the interaction term between *First* × *SharedVC* and this distance. This is because the operational impact of a VC may manifests manifest more strongly for startups that are headquartered closer to VC's main office (Bernstein, Giroud and Townsend 2016).

[75] In effect, the recruitment of a non-founder CEO is considered a common monitoring action undertaken by VCs (Lerner 1995; Hellmann and Puri 2002; Ewens and Marx 2018).

not differ across first and subsequent startups. However, there is no notable increase in the likelihood that a new board member is nominated. This outcome aligns with expectations, given that lead VCs—whether common or not—obtain a board seat in 61.5% of cases (Amornsiripanitch, Gompers and Xuan 2019). Additionally, columns (5) to (8) of the table suggests that common VCs are more likely to make changes to the management team by replacing former executives with new ones.

In sum, these analyses collectively highlight the active involvement of VCs who invested in competitors in startup operations. Furthermore, they hint at how VCs might acquire and disseminate sensitive information, offering valuable insights into the practical mechanisms through which common VCs exert influence over startups.

5. Heterogeneous Effect and Timing of Investment in Competitors

In this section, I first study the heterogeneity of the influence effect with respect to the main parameters of the analytical model (Hypotheses 3). Then, I test Hypotheses 4.

5.1. Investment Timing, Knowledge Transfers and Startup Competition

Hypothesis 3 summarizes the main comparative results on the magnitude of the influence effect following a change in the key parameters of the model of Section 2.

To begin, as the temporal gap between consecutive investments in different startups within the same BN increases, the average disparity in performance between first and the subsequent startups becomes more pronounced. The rationale is that an extended time lag provides the VC with a broader window to gather additional information about the BN. Consequently, this augmented information pool bolsters the VC's capacity to discern higher-quality startups, thereby amplifying the selection effect. Consequently, the VC has a stronger incentive to asymmetrically share knowledge favoring subsequent startups.

To study this hypothesis, I construct two different tests, the results of which are summarized in Table 7. 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—according to the analytical model—the VC's incentive to engage in symmetric knowledge sharing. In effect, columns (1) and (3) show that both startups—symmetrically as $First \times SharedVC$ is not significant at 5%—register improved perfor-

TABLE 7. 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 were either the first or the second investment in the BN and 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*). For these regressions, linked startups are those that were either the first or the second startup invested in the BN. Standard errors are reported in parentheses and are clustered at the startup level.

mance when sharing the VC, raising more funds and being more likely to raise a round in the following years. The second test mirrors the approach used in the previous analyses. Specifically, I interact *First* × *SharedVC* with the time lag between investments. The model predicts a negative coefficient for the funding raised and the probability of a successful round, along with a positive coefficient for startup discontinuation. Notably, 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*× *VC_experience* are not significant at the 5% level for the probability of raising a round and the probability of startup shutdown.

A key parameter of the analytical model is τ, which I refer to as the *size* of the knowledge transfer. In practice, however, it is not trivial to construct a proxy for τ and test whether a larger τ increases the performance of subsequent startups relative to first ones. In Section 2.5 I argued that τ could be viewed as a VC's ability to favor information flows within the portfolio. A natural assumption in this setting is that more experienced VCs are better equipped to share knowledge across portfolio startups. If this is the case, then one should observe that first startups are outperformed by

TABLE 8. Heterogeneous effects: VC experience

	ln(1+$ raised)		𝟙{round raised}	
	(1)	(2)	(3)	(4)
	(OLS)	(IV)	(OLS)	(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*. 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.

subsequent startups to a greater extent when the VC is more experienced. Therefore, I test this part of Hypothesis 3 by introducing the interaction between *First* × *SharedVC* and *VC_experience* in the FE and IV models. According to Hypothesis 3, this interaction term should negatively impact startup performance. Table 8 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 significant at the 5% level.

The last part of Hypothesis 3 that remains to be tested is the one concerning the relationship between the influence effect and startup competition.[76]

I begin by interacting *First* × *SharedVC* with two potential measures of the degree of competition among portfolio startups. According to Hypothesis 3 the interaction term should be negative for the dollar raised and the probability of raising an additional

[76]Table C.4 displays the heterogeneous effects across some BN characteristics. These analyses are not directly tied to any of the hypotheses developed through the model of Section 2. Specifically, I interact *First* × *SharedVC* with VC competition, BN tightness—computed as the ratio between the number of active VCs and startup in a BN—and BN maturity—measured by the number of past IPOs in the BN. Although the results are not always significant at 5%, Table C.4 suggests that a VC's incentive to play favorites may be lower when they invest in startups operating in a BN in which there is a higher relative supply of venture capital and that is more mature.

TABLE 9. Heterogeneous effects: BN competition

a. IV model with interaction terms

	ln(1+$ raised)		𝟙{round raised}		𝟙{Shutdown}	
	(1)	(2)	(3)	(4)	(5)	(6)
SharedVC	0.926***	0.986***	0.042***	0.052***	0.000	0.001
	(0.086)	(0.095)	(0.006)	(0.007)	(0.001)	(0.001)
First × *SharedVC*	-2.411***	-1.494**	-0.175***	-0.159***	0.009***	0.018**
	(0.267)	(0.720)	(0.018)	(0.050)	(0.003)	(0.007)
First × *SharedVC* × *pairwise_cosine*	3.259***		0.237***		0.004	
	(0.939)		(0.065)		(0.009)	
First × *SharedVC*× *BN_competition_index*		-0.301		0.131		-0.006
		(1.262)		(0.087)		(0.012)
Observations	286,192	286,192	286,192	286,192	286,192	286,192
BN × Year FE	✓	✓	✓	✓	✓	✓
Startup FE	✓	✓	✓	✓	✓	✓

b. OLS model accounting for same tech category investments

	ln(1+$ raised)		𝟙{round raised}		𝟙{Shutdown}	
	(1)	(2)	(3)	(4)	(5)	(6)
SharedVC_L1	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 × *SharedVC_L1*	-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
Level-1 × Year FE	✓		✓		✓	
BN × Year FE		✓		✓		✓
Startup FE	✓	✓	✓	✓	✓	✓

Notes: *** p<0.01, ** p<0.05, * p<0.1. The top panel shows the results of the IV model adding the interaction between *First* × *SharedVC* and two measures of startup competition, i.e. the pairwise cosine similarity with teh closest competitor in the portfolio (*pairwise_cosine*) and the average competition within the BN (*BN_competition_index*). The bottom panel reports the results of the model of Equation 7, 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 any year before the first round of VC financing. Standard errors are reported in parentheses and are clustered at the startup level.

round, and positive for startup shutdown. The first measure I use is the pairwise cosine similarity between each startup and its closest competitor within the same VC portfolio. The third row of Table 9a rejects the hypothesis. In particular, while the first startup is generally hurt by sharing a VC with a competitor, this is not as much the case for startups that are more similar, and hence more in competition with the following investment of the VC. Since this measure does not account for the average competitiveness of the BN, I next consider *BN_competition_index*, already defined in Section 4.2. The results obtained using this alternative measure are reported in the fourth row of Table 9a. While they differ from what previously obtained using the first measure, they again appear to reject Hypothesis 3.

Recognizing the substantial reliance of these results on the variable used to approximate ϕ, I adopt an alternative approach to examine the impact of changes in ϕ on the performance of portfolio startups. This approach capitalizes on the hierarchical structure of the S&P taxonomy, wherein each tech category encompasses multiple BNs. Hence, I exploit the variation stemming from startups that share a common VC with a startup operating within the same tech category but in distinct BNs. The underlying assumption is that startups within the same tech category yet different BNs exhibit a comparatively lesser degree of competition than those operating within the same BN.[77] This test necessitates the introduction of two additional variables to Equation 6, namely *SharedVC_L*1 and *First_L*1. These variables are conceptually identical to their BN counterparts but are grounded in 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:

$$\begin{aligned} Y_{inmt} = {} & \alpha_i + \alpha_{nt} + \beta_1 \cdot SharedVC_{it} + \beta_2 \cdot First_i \times SharedVC_{it} + \beta_3 \cdot Post_{it} + \\ & \beta_4 \cdot (First_i \times Post_{it}) + \gamma_1 \cdot SharedVC\_L1_{it} + \gamma_2 \cdot First \times SharedVC\_L1_{it} \\ & + \gamma_3 \cdot (First\_L1_i \times Post_{it}) + \boldsymbol{\pi} \cdot \boldsymbol{X_{imt}} + \varepsilon_{inmt}. \end{aligned} \tag{7}$$

In particular, if β_2 in Equation 7 takes on a negative and statistically significant value, it implies that when startups are not only within the same tech category but also share the same BN, the performance differential between subsequent and first startups becomes larger. This can be viewed as a discrete shift in startup competition.

Table 9b reports the results of the model of Equation 7 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

[77] This assumption is empirically validated by the results in Jin, Leccese and Wagman (2023) discussed in footnote 47.

tech category by year (α_{nt}) or BN by year (α_{mt}) fixed effects. In all specifications β_1 is not statistically significant at the 5%, which suggests that sharing the VC with a startup within the same BN does not generate any additional benefit via the VC's influence relative to sharing them with a startup operating only within the same tech category.[78] In contrast, the first startup invested is hurt significantly more when it is the first in the BN and not only in the tech category in terms of venture capital and rounds raised, but not in terms of the probability of being discontinued. Specifically, a startup that is the first invested in a BN raises roughly 85% (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 product market competition among startups in the portfolio of the same VC shapes the VC's influence effect, and hence the relative performance dynamics between portfolio startups.

5.2. Timing of Investment in Competitors

This subsection examines Hypothesis 4, which posits that the temporal gap between first and subsequent investments within the same BN is inversely related to the level of competition among VCs. In the analytical model, after having invested in a first startup in the BN, the VC learns its quality q_1. Acquiring the expertise to exactly understand the quality realization (i.e., q_2) of a new startup to fund in the same BN takes time, and hence the VC is not able to do it right after its investment in the first startup. In the model, VC competition (β) is the primary driver leading VCs to invest in the second startup prior to learning the realization of q_2. Therefore, in this section I study how the pace at which VCs who have already invested in a BN opt to invest in a new startup within the same BN responds to changes in the degree of VC competition.

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 have made investments within the BN over the past two years.[79] I begin by categorizing BNs based on high and low VC competition, determined by the median value of

[78] Nevertheless the coefficient is positive suggesting that there may be some additional positive influence effect for subsequent startups when startup competition increases.

[79] 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 (e.g., see 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.

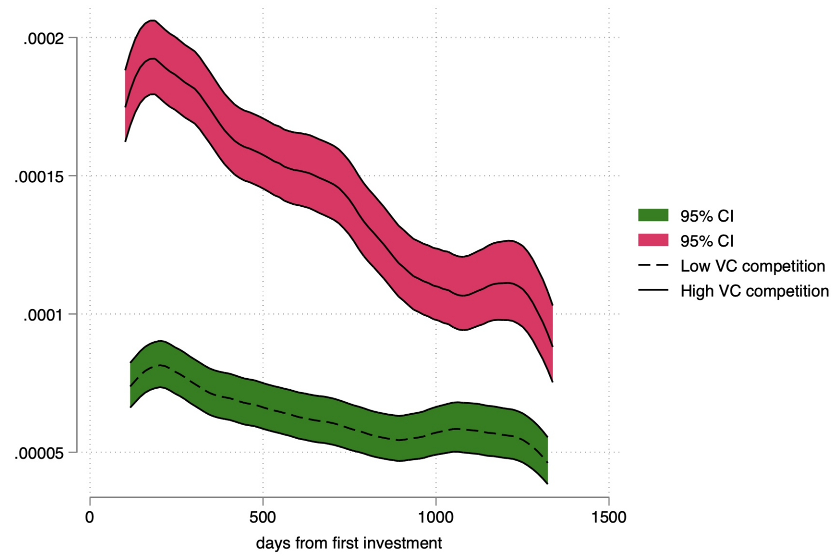


FIGURE 7. Hazard of the second investment in the same BN

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.

BN_active_VCs. In Figure 7, I illustrate the smoothed hazard estimates for each category. Here, "failure" corresponds to a VC making a second investment in a BN it has already invested in. It is important to clarify that this depiction arises 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. For each VC-BN pair, the days until the next investment are computed.[80] Evidently, Figure 7 aligns with Hypothesis 4, depicting a notably higher conditional probability of an investment in a second startup immediately after having invested in the first startup within BNs characterized by high VC competition, and a substantially lower probability within BNs with lower VC competition.

Next, I develop two additional formal tests of Hypothesis 4, the outcomes of which are summarized in Table 10. Firstly, Columns (3) and (4) of Table 10 display the regression outcomes stemming from the semi-parametric Cox duration model, and consistently affirm the hypothesis. Column (3) underscores that a marginal increase in VC competition yields an 18% increase in the likelihood of investing in a new startup within

[80]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.

the same BN.[81] Column (4) suggests that the observed results are primarily driven by persistent differences across BNs.

TABLE 10. Determinants of the timing investment in competitors

DEP. VAR.	(1)	(2)	(3)	(4)
	ln(investment lag) (OLS)		$\mathbb{1}$\{second investment\} (Duration model)	
BN_competition_index	-0.355	0.0147	0.0206***	-0.00868***
	(0.323)	(0.413)	(0.00205)	(0.00251)
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 invested 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 they have already invested in. The sample also include solo startups. Robust standard errors are reported in parentheses.

Columns (1) and (2) of Table 10 narrow the focus to the subset of investor-BN pairs where the investment in the subsequent startup eventually materialized. For this subset it is possible to compute the temporal lag—measured in days (log-transformed)—until the occurrence of the investment in the subsequent startup. Then, I use this variable as a dependent variable in a specification including *BN_active_VCs* as the key regressor of interest. As postulated by Hypothesis 4, the coefficient associated with *BN_active_VCs* should assume a negative value, given that heightened VC competition tends to expedite the VC's decision to invest in a further startup within the same BN, thereby shortening the temporal lag. The outcomes align with this expectation, effectively reinforcing the validity of the hypothesis. In all these regressions I control for the degree of competition in the BN, as measured by *BN_competition_index*, and I include fixed effects for the year in which the first round of VC financing occurred.[82]

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

[82]The analytical framework does not directly explore the relationship between ϕ and the investment lag. Nevertheless, model simulations, such as those presented in Figure 3, suggest a negative correlation. The estimate for the coefficient on *BN_competition_index* in Table 10 deviate from this prediction, except for Column (4) of Table 10.

6. Conclusion

This paper investigates, both theoretically and empirically, how strategic investments made by VCs in competing startups impact those startups' outcomes. The analytical model demonstrates that when VCs acquire expertise in a specific business niche from prior investments, the subsequent startups they invest in within the same business niche tend to exhibit higher quality in equilibrium. The strength of this selection effect, along with the level of product market competition among portfolio startups, serve as the primary drivers of the 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 through a machine learning method. Employing both a fixed effects model and an instrumental variable approach, I find that the first startups invested in a particular business niche, following their VC's investment in a competing startup, exhibit poorer performance compared to startups that do not share a common VC with a potential competitor. In contrast, subsequent startups invested in the same business niche outperform solo startups. 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. Nonetheless, this positive influence is channeled by common VCs towards subsequent startups, while first startups are negatively affected.

These findings reconcile contrasting evidence in the literature (Li, Liu and Taylor 2023; Eldar and Grennan 2023) by emphasizing the importance of the selection effect and the intensity of competition among startups in shaping the portfolio management activities of common VCs. Moreover, they have practical implications not only for VCs in terms of optimizing screening and portfolio management strategies for startups operating 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 regulatory and policy considerations related to competition and VC investments.

To formulate effective regulations in this context, a clear understanding of the welfare implications of VCs' strategic investments in competitors is essential. Given the significant role of technology startups in driving innovation and economic growth, and the pivotal role played by VCs in their development and likelihood of success, conducting analyses that quantify the social costs and benefits stemming from such strategic investments is a natural direction for future research.

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Appendix A. Proofs and Additional Theoretical Results

Proof of Proposition 1.

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:

(A1)
$$q_i \leq \min\left\{\frac{1}{2\phi}-\tau, \frac{1}{\phi}-q_j-\tau\right\} = \begin{cases} \frac{1}{2\phi}-\tau, & \text{if } q_j \leq \frac{1}{2\phi} \\ \frac{1}{\phi}-q_j-\tau, & \text{else.} \end{cases}$$

Therefore, suppose first that $q_j \leq \frac{1}{2\phi}$. Then, by A1 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 A1 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 2.

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:

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

$\square$

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 1, $q_i \geq q_j \geq \frac{1}{2\phi}$. 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:*

$$q_2 \geq \frac{\frac{F}{R} - \tau}{1 - 2\phi(q_1 + \tau)} - \tau \equiv \sigma(q_1, \phi, \tau, F, R) \tag{A2}$$

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:*

$$q_2 \geq \frac{\frac{F}{R}}{1 - 2\phi q_1} - \tau \equiv \bar{\sigma}(q_1, \phi, \tau, F, R) > \sigma(q_1, \phi, \tau, F, R) \tag{A3}$$

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*:

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

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

□

Note that, since $\phi \geq \frac{1}{2}$, the assumption in 1 directly implies $\frac{F}{R} > \tau$, so that $q_1 < \frac{1}{2\phi}$ is a necessary condition for asymmetric knowledge sharing in favor of startup 2 to occur. Intuitively, when q_1 is large, the VC's incentive to diversify is low, and they can simply preempt startup 2's competition by not investing.

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 1 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 3.

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 this exactly identifies the selection effect.

By definition, selection is: $\mathbb{E}\left[q_2 | q_2 > \lambda(q_1, \phi, \tau, F, R)\right] - \mathbb{E}\left[q_2\right]$. Since q_2 is distributed as a uniform over $\left[0, \frac{3}{4}\right]$, selection can be written as:

$$\begin{aligned}&\int_{\lambda}^{3/4} \frac{1}{\frac{3}{4}-\lambda} x dx - \int_{0}^{3/4} \frac{4}{3} x dx \\ &= \frac{1}{2}\left(\frac{3}{4} + \lambda(q_1, \phi, \tau, F, R)\right) - \frac{3}{8} \\ &= \lambda(q_1, \phi, \tau, F, R).\end{aligned}$$

Thus, it is easy to that $\lambda(q_1, \phi, \tau, F, R)$ is increasing in $\frac{F}{R}$, ϕ and q_1. As for τ, when $q_1 > \frac{1}{2\phi} - \frac{F}{R}$ it is easy to see that selection is always decreasing in τ. When $q_1 < \frac{1}{2\phi} - \frac{F}{R}$, selection is decreasing in τ *iff*:

$$\begin{aligned}\frac{\partial \lambda(q_1, \phi, \tau, F, R)}{\partial \tau} = \frac{-1 + 2\phi(q_1 + \tau) + 2\phi\left(\frac{F}{R} - \tau\right)}{\left[1 - 2\phi(q_1 + \tau)\right]^2} - 1 \leq 0 \iff \\ \left[1 - 2\phi(q_1 + \tau)\right]^2 \geq 2\phi\left(q_1 + \frac{F}{R}\right) - 1 \iff \\ q_1 \leq \frac{1 + \left[1 - 2\phi(q_1 + \tau)\right]^2}{2\phi} - \frac{F}{R},\end{aligned}$$

which always holds because $\frac{1}{2\phi} < \frac{1 + \left[1 - 2\phi(q_1 + \tau)\right]^2}{2\phi}$. □

Proof of Proposition 4.

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 $q_2 \geq \sigma$.

Consider now the case in which $q_2 \geq q_1$. Since I focus on cases where selection is always present, there are two other thresholds to consider. First, one needs to find the condition under which the VC invests and engages in asymmetric knowledge sharing. 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:

- $q_2 > \frac{1}{2\phi} - \tau$ 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 $\frac{3}{4}$. This is the case whenever:

- $\tau \geq \frac{1}{2\phi} - \frac{3}{4}$ if the relevant threshold is $q_2 > \frac{1}{2\phi} - \tau$. Note that a sufficient condition for this to hold is that startup competition is not too low, i.e. $\phi \geq \frac{2}{3}$.

- $q_1 < \frac{1}{2\phi} - \frac{F}{R}\left[\frac{1}{2\phi\left(\frac{3}{4}+\tau\right)}\right]$ if the relevant threshold is $\frac{F/R}{1-2\phi q_1} - \tau$.

Furthermore, I check that:

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

which is the case whenever $q_1 < \frac{1}{2\phi} - \frac{F}{R}$. This shows that when q_1 increases above $\frac{1}{2\phi} - \frac{F}{R}$, the selection effect becomes bigger and the thereshold to invest increases from σ to $\bar{\sigma}$. Lastly, noting that:

$$\frac{1}{2\phi} - \frac{F}{R} < \frac{1}{2\phi} - \frac{F}{R}\left[\frac{1}{2\phi\left(\frac{3}{4}+\tau\right)}\right],$$

and combining all the thresholds derived leads to the result. $\square$

Proof of Proposition 5.

PROOF. Using inequality 4, it is enough to show that the derivative of the right hand side with respect to β is decreasing, i.e.:

$$Rq_1\left(1-\frac{3}{8}\phi\right) - \left[pq_1R + (1-p)\mathbb{E}[V^{I_2} - F]\right] \leq 0.$$

This is always the case because:

$$\begin{aligned} pq_1R + (1-p)\mathbb{E}[V^{I_1} - F] &\geq Rq_1 \\ &\geq Rq_1\left(1-\frac{3}{8}\phi\right), \end{aligned}$$

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 for any $\phi \in \left[\frac{1}{2}, 1\right]$, $\left(1-\frac{3}{8}\phi\right) < 1$. $\square$

Proof of Proposition 6.

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 1 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 $q_i \geq q_j$. □

A.1. Second-stage Investment Decision: Discussion of Comparative Statics

Proposition 4 sheds light on how the investment decision depends on the success probability of startup 1 given τ and ϕ. An increase in ϕ shrinks the region in which investment and knowledge sharing occurs, and makes it more likely that the VC avoids to invest in startup 2.[83] Conversely, the effect of a change in τ is less straightforward. If q_2 is smaller than q_1, then an increase in the size of the knowledge transfer shrinks the range of values of q_1 such that investment in startup 2 occurs, ceteris paribus. However, this is not enough to conclude that investment becomes less likely because this effect is potentially offset by the selection on q_2, as shown by Proposition 3.

To get the intuition consider a scenario in which the VC has in its portfolio a startup with average probability of success. Furthermore, suppose that $\tau = 0$ and $\phi = \frac{3}{4}$. This parametrization fits the scenario presented by part (i) of Proposition 4. In this case, the VC will invest in any new startup with probability of success above 0.62, and they will favor the second investment when its success probability is above 0.67. Now suppose, one increases the size of the knowledge transfer to $\tau = 0.1$. This significantly reduces

[83] This can be see by replacing Equation 1 into the derived thresholds and by taking derivatives with respect to ϕ. It is easy to see how all the thresholds for q_1 are decreasing. However, $\frac{F}{R}\left[\frac{1}{2\phi(\frac{3}{4}+\tau)}\right]$ decreases more than $\frac{1}{2\phi} - \frac{F}{R}$.

selection as the VC will invest in any startup with probability of success above 0.29. Intuitively, increasing τ when q_1 is not too large, provides the VC with a strong incentive to help the growth of both startups. In this case asymmetric knowledge sharing favoring startup 2 happens for $q_2 > 0.57$. Next, consider a last case where $\tau = 0$ but startup competition ϕ increases up to one. Intuitively, this increases selection, and in particular fits the scenario in part (iii) of Proposition 4: the VC is not willing to fund any startup because competition is too intense and the expected return offered by the first startup if alone in the market is large enough.

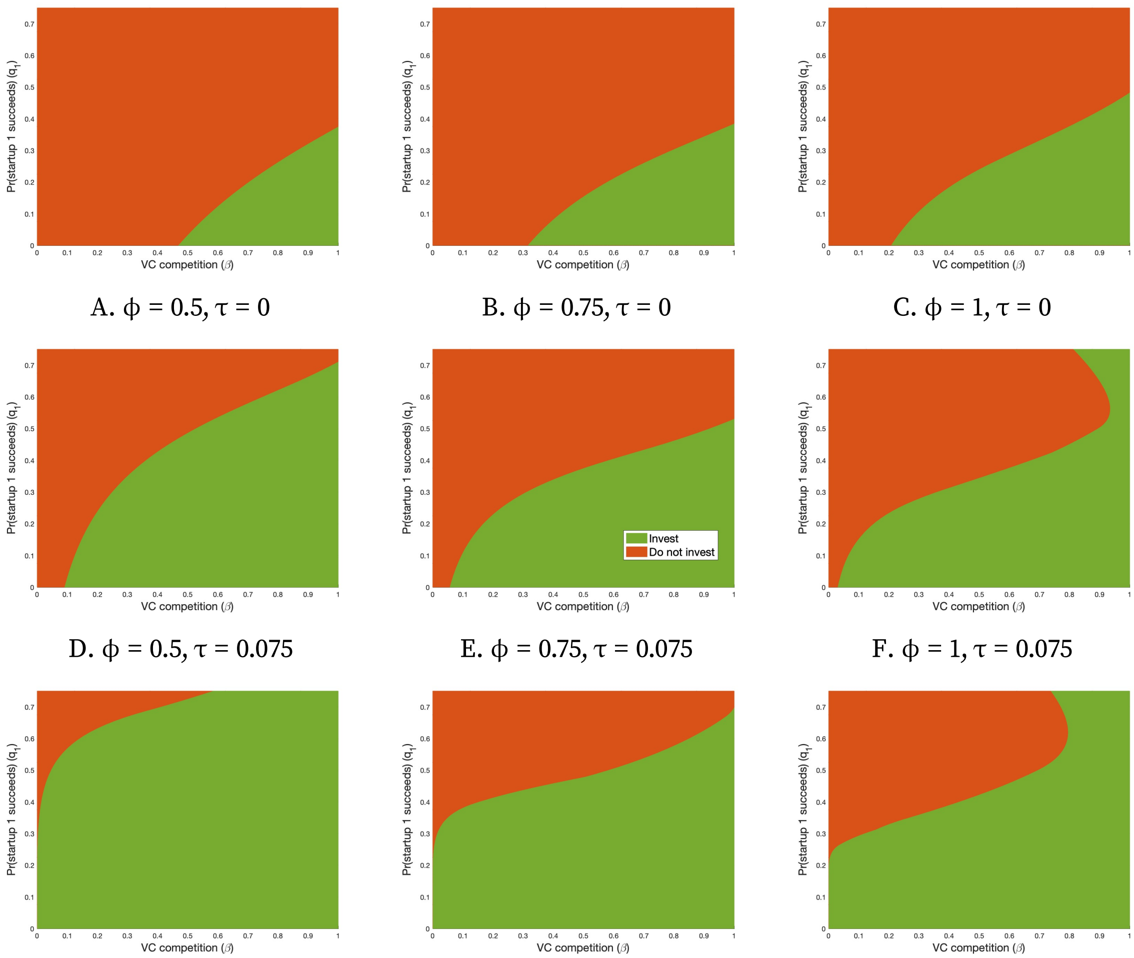
A.2. First-stage Investment and the Relative Quality of Subsequent Startups

Proposition 3 defines the selection effect as the probability of success of startup 2 when invested by the VC relative to the probability of success of startup 2 when invested 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.1 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 $\tau \in \{0, 0.075, 0.19\}$ and $\phi \in \{0.5, 0.75, 1\}$. Beside allowing for several comparative statics exercise, 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.2, 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 in fact be high–quality. In other words, there may be a subset of solo startups, which are not those invested by the competing investor, that have average quality similar or even greater than that of subsequent



A. $\phi = 0.5, \tau = 0$ B. $\phi = 0.75, \tau = 0$ C. $\phi = 1, \tau = 0$

D. $\phi = 0.5, \tau = 0.075$ E. $\phi = 0.75, \tau = 0.075$ F. $\phi = 1, \tau = 0.075$

G. $\phi = 0.5, \tau = 0.19$ H. $\phi = 0.75, \tau = 0.19$ I. $\phi = 1, \tau = 0.19$

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

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. In practice, however, I show in Section 4 that this is rejected in the data, and results are consistent with Hypothesis 2.

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:

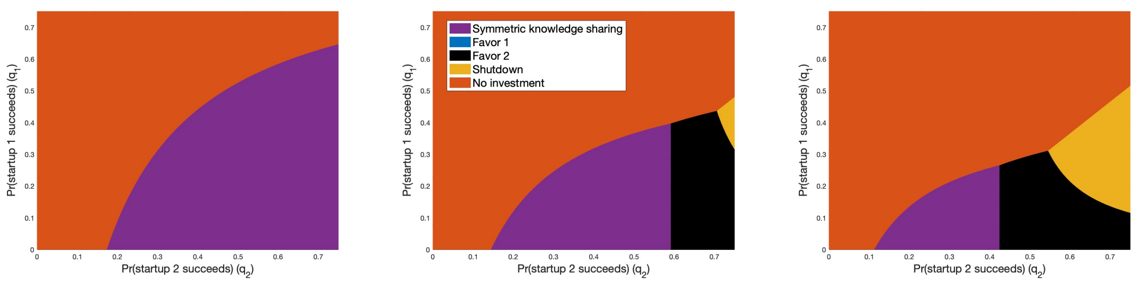
- If the VC invests at $T = 1$, then the first startup (startup 1) and the subsequent startup (startup 2) are of similar quality, on average, given that the investment in startup 2 occurs before learning the realization of q_2.

- 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, consistently with Hypothesis 2, 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.2. Optimal Investment Strategy at $T = 2$ varying q_1

Appendix B. Performance of K-NN Classifier

A formal—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 more than two-hundreds BNs. Hence, to plot the ROC curve, I focus on tech categories (level-1s) and I treat each tech category as a separate binary classification problem. Figure B.1 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.1, although the graph also suggest the presence of some heterogeneity in the quality of prediction across level-1s.

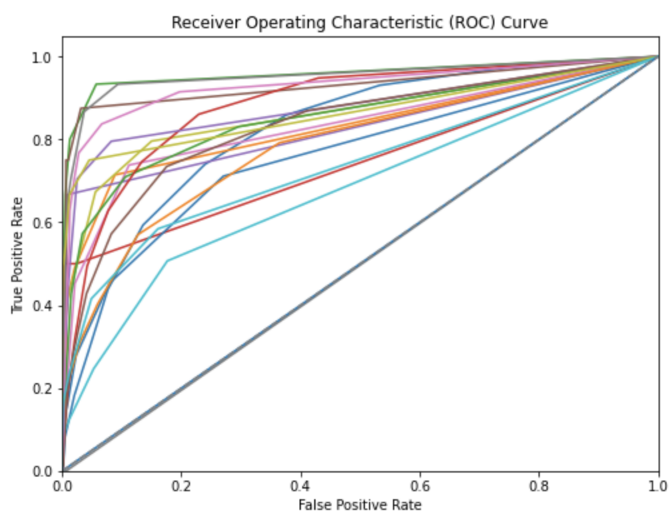


FIGURE B.1. Validation of the extrapolation procedure: ROC Curve

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.

To provide further evidence in favor of the goodness of the 10-NN classifier chosen to perform taxonomy extrapolation, in Table B.1, 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. Afterwards, the algorithms 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 classifier is an implementation of the eXtreme Gradient Boosting (XGBoost) algorithm for classification tasks. XGBoost is a powerful and widely used machine learning algorithm known for its efficiency, scalability, and excellent predictive performance in various real-world applications and machine learning competitions. In short, XGBoost is an ensemble learning algorithm that combines the predictions of multiple decision trees while iteratively improving and correcting its mistakes. It focuses on difficult cases, adjusts its predictions, and ultimately creates a powerful predictive model capable of handling complex relationships in the data. 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.1. 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:[84]

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

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.1 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%.

[84]The F1-score is especially useful in my setting because some classes have significantly more instances than the 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
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
$\mathbb{1}${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
$\mathbb{1}${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).

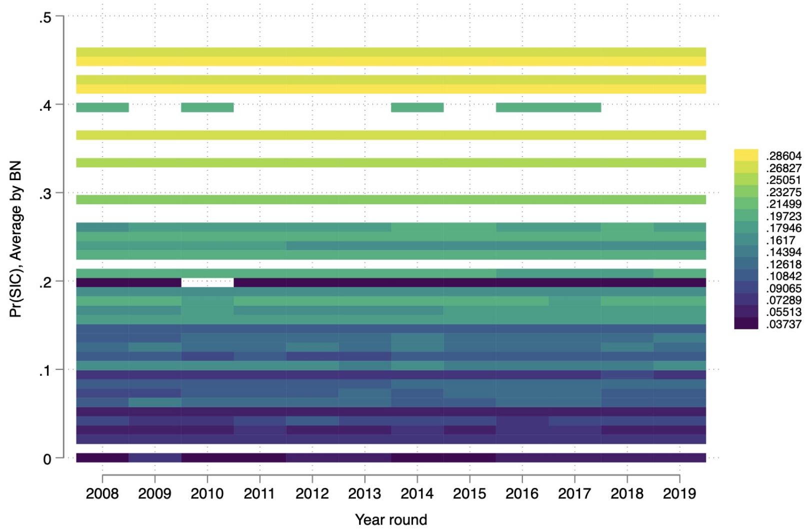


FIGURE C.1. Correlation between being linked and the instrument

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 IV over time. Darker colors indicate a lower correlation.

TABLE C.2. Effect of investing in competitors on startup exit

	𝟙{IPO}			𝟙{M&A}		
	(1)	(2)	(3)	(4)	(5)	(6)
	(OLS)	(OLS)	(IV)	(OLS)	(OLS)	(IV)
Linked	0.000**			-0.000*		
	(0.000)			(0.000)		
First	-0.000			0.000*		
	(0.000)			(0.000)		
Post	0.003***	0.001	0.001	0.015***	0.002***	0.002**
	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
First × *Post*	-0.005***	-0.007***	-0.006**	-0.018***	-0.016***	-0.008*
	(0.000)	(0.001)	(0.003)	(0.001)	(0.002)	(0.005)
SharedVC	-0.001**	-0.004***	-0.005***	-0.002**	-0.003**	-0.005**
	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
First × *SharedVC*	0.005***	0.006***	0.006*	0.020***	0.016***	0.007
	(0.001)	(0.001)	(0.003)	(0.001)	(0.002)	(0.006)
Observations	286,321	286,192	286,192	286,321	286,192	286,192
R-sq	0.010	0.067		0.009	0.080	
BN × Year FE	✓	✓	✓	✓	✓	✓
Startup 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 for the Baseline, FE and IV models using startup exit (M&A or IPO) as dependent variables.

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.

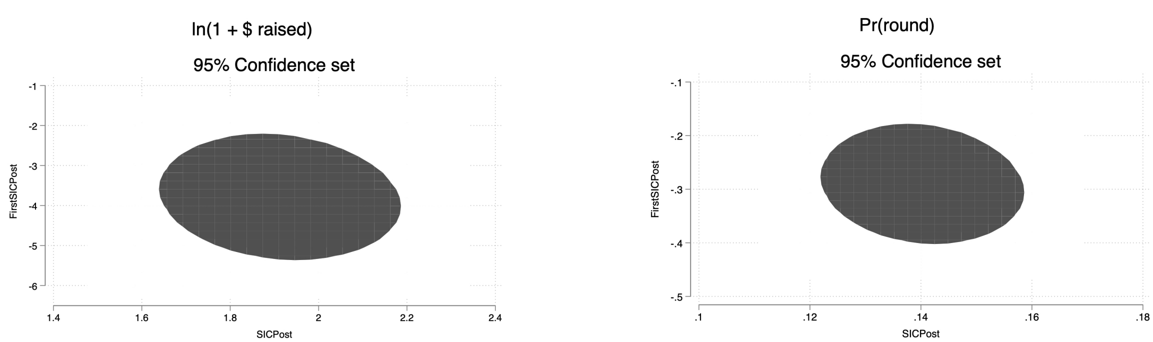


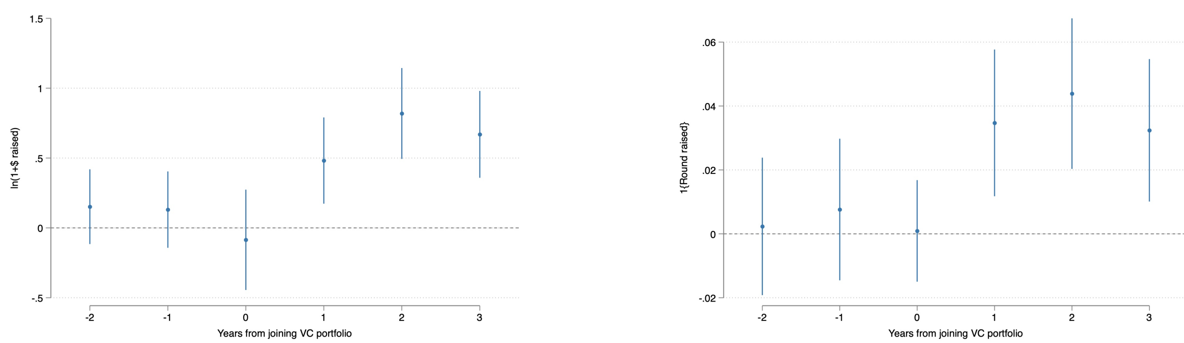
FIGURE C.2. Robustness check: Weak-IV robust confidence intervals

Notes: The figure illustrates 95% confidence set for the estimates of β_1 and β_2 in the IV model that are robust to the case in which the instruments are weak. Thus, the shaded area represents the range of he estimates of β_1 and β_2 such that the rejection probability (i.e., $1-$ *pval ue*) is below 95%.

TABLE C.4. Heterogeneous effects: venture capital supply and BN maturity

	ln(1+$ raised)			$\mathbb{1}$\{round raised\}			$\mathbb{1}$\{Shutdown\}		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	(IV)	(IV)	(IV)	(IV)	(IV)	(IV)	(IV)	(IV)	(IV)
SharedVC	0.452***	1.029***	0.988***	-0.014**	0.053***	0.054***	-0.000	0.001	0.002
	(0.083)	(0.097)	(0.112)	(0.006)	(0.007)	(0.008)	(0.001)	(0.001)	(0.001)
First × *SharedVC*	-3.549***	-2.294***	-0.406	-0.424***	-0.200***	-0.025	-0.008	0.017**	0.022*
	(0.881)	(0.712)	(1.220)	(0.063)	(0.049)	(0.084)	(0.008)	(0.007)	(0.012)
First × *SharedVC*× *BN_tightness*	0.137			0.040***			0.004**		
	(0.155)			(0.011)			(0.001)		
First × *SharedVC*× *BN_maturity*		0.127			0.021*			0.000	
		(0.162)			(0.011)			(0.002)	
First × *SharedVC*× *BN_active_VCs*			-0.134			0.004			0.001
			(0.190)			(0.013)			(0.002)
Observations	320,077	285,592	286,192	320,077	285,592	286,192	320,077	285,592	286,192
BN × year FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
Startup FE	✓	✓	✓	✓	✓	✓	✓	✓	✓

Notes: *** p<0.01, ** p<0.05, * p<0.1. The table shows the results of the IV model adding the interaction between *First* × *SharedVC* and three different BN characteristics. The first one (*BN_tightness*) measures how many VCs are active relative to the number of startups seeking financing. The second one (*BN_maturity*) captures the maturity of the BN as measured by the log-transformed number of IPOs had by startups operating in the BN. The third one (*BN_active_VCs*) is the proxy used throughout the paper to measure VC competition within a BN. Standard errors are reported in parentheses and are clustered at the startup level.



A. ln(1+$ raised)

B. $\mathbb{1}$\{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 traditional 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 prior to the first round of venture capital financing, as well as the year of this round.

Table C.5. 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 include 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 post first round of venture capital financing scenario. 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 t–test of mean difference.

TABLE C.6. Robustness check: Tech categories and subsample with first two investments only

	ln(1+$ raised)			𝟙{round raised}			𝟙{Shutdown}		
	(1) (OLS)	(2) (OLS)	(3) (IV)	(4) (OLS)	(5) (OLS)	(6) (IV)	(7) (OLS)	(8) (OLS)	(9) (IV)
SharedVC	0.374***	0.209**	0.936***	0.018***	0.011**	0.037***	-0.001	-0.001	-0.000
	(0.053)	(0.080)	(0.124)	(0.004)	(0.006)	(0.009)	(0.001)	(0.001)	(0.001)
First × *SharedVC*	-1.499***	-1.209***	-2.073***	-0.167***	-0.126***	-0.145***	0.005***	0.003**	0.010***
	(0.101)	(0.121)	(0.269)	(0.007)	(0.008)	(0.019)	(0.001)	(0.001)	(0.003)
Observations	286,259	263,804	263,928	286,259	263,804	263,928	286,259	263,804	263,928
Adj. R-sq	0.349	0.348		0.382	0.382		0.122	0.118	
Startup FE	✓	✓		✓	✓		✓	✓	
BN × Year FE		✓	✓		✓	✓		✓	✓
Level-1 × Year FE	✓			✓			✓		

Notes: *** $p<0.01$, ** $p<0.05$, * $p<0.1$. Standard errors are reported in parentheses and are clustered at the startup level. Columns (1), (4) and (7) show the results for the FE model using tech categories instead of BNs to define competing startups. The other columns show the results of the FE and IV models excluding from the sample linked startups that were the third or later startup invested by the VC in the same BN.

TABLE C.7. Robustness Check: Investor Fixed Effects

OLS MODEL	(1) ln(1+$ raised)	(2) 𝟙{round raised}	(3) 𝟙{Shutdown}	(4) 𝟙{IPO}	(5) 𝟙{M&A}
Linked	0.204***	0.025***	-0.000	0.002***	-0.000
	(0.068)	(0.005)	(0.000)	(0.000)	(0.000)
First	-0.297***	-0.024***	0.000	0.000	0.000
	(0.085)	(0.007)	(0.000)	(0.000)	(0.001)
Post	4.004***	0.370***	0.003***	0.004***	0.015***
	(0.049)	(0.003)	(0.000)	(0.000)	(0.001)
First × *Post*	1.917***	0.161***	-0.004***	-0.007***	-0.019***
	(0.139)	(0.009)	(0.000)	(0.000)	(0.001)
SharedVC	0.254***	0.008	-0.001*	-0.003***	-0.004***
	(0.075)	(0.005)	(0.000)	(0.001)	(0.001)
First × *SharedVC*	-2.840***	-0.239***	0.005***	0.007***	0.021***
	(0.144)	(0.009)	(0.001)	(0.001)	(0.002)
Observations	286,294	286,294	286,294	286,294	286,294
Adj. R-sq	0.177	0.206	0.031	0.033	0.015
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.8. 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.9. 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.

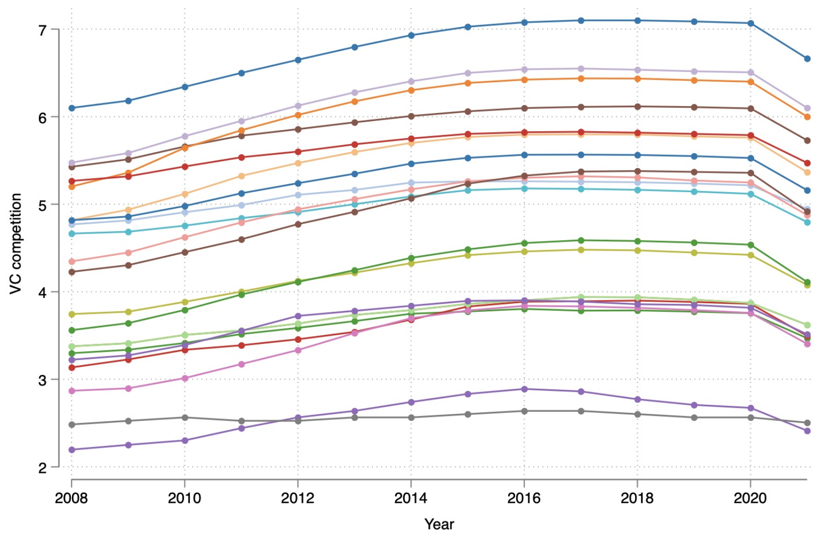


FIGURE C.4. Average VC competition over time across tech categories

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