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The Lifecycle of Venture Capital Funds

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Abstract

We analyze the lifecycle dynamics of venture capital (VC) funds and find that the outcomes of portfolio companies vary over a fund's lifespan. Investments made earlier in a fund's life are more likely to achieve successful exits through IPOs and M&As. We attribute this pattern to three key channels: the financing channel, which reflects the deeper in-the-money option for follow-on investments available in younger funds; the monitoring channel, which captures the extended non-financial support these funds provide; and the selection channel, which suggests that higher-quality entrepreneurs prefer younger funds due to the added value of financing and monitoring. First, we present empirical evidence to establish these channels. Next, we develop a theoretical model to formalize the underlying mechanisms and validate founder preferences through a survey of investors and entrepreneurs.

Keywords: Fund Age, Fund Lifecycle, Entrepreneurial Selection, Startup-VC Matching, Financial Frictions, Exits, M&As, IPOs, Board, Serial Entrepreneurs

מחזור החיים של קרנות הון סיכון

מאיה הרן רוזן, אסנת זהר, יונתן זנדברג ואלכסנדר מונטג

תקציר

אנו מנתחים את מחזור החיים של קרנות הון סיכון (VC) ומוצאים כי תוצאות ההשקעה של הקרנות בחברות הזנק משתנות לאורך חיי הקרן. השקעות שמתבצעות בשלבים מוקדמים יותר של חיי הקרן מובילות בהסתברות גבוהה יותר לאקזיטים מוצלחים דרך הנפקות ציבוריות (IPO) או מיזוגים ורכישות (M&A). המחקר מזהה שלושה מנגנונים מרכזיים שמובילים לדינמיקה הזו: ערוץ המימון, המשקף את האפשרות להשקעות המשך שמציעות קרנות צעירות; ערוץ החונכות, המדגיש את התמיכה הלא-פיננסית המתמשכת שקרנות אלו מספקות; וערוץ ההתאמה, המצביע על כך שיזמים איכותיים מעדיפים קרנות צעירות בזכות הערך המוסף שהן מספקות במימון וחונכות. ראשית, אנו מציגים עדויות אמפיריות לקיומם של מנגנונים אלו. לאחר מכן אנו מפתחים מודל תיאורטי המנתח את המנגנונים הללו ומתקפים את העדפות היזמים באמצעות סקר בקרב משקיעים ויזמים.

The Lifecycle of Venture Capital Funds

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Abstract

We analyze the lifecycle dynamics of venture capital (VC) funds and find that the outcomes of portfolio companies vary over a fund's lifespan. Investments made earlier in a fund's life are more likely to achieve successful exits through IPOs and M&As. We attribute this pattern to three key channels: the financing channel, which reflects the deeper in-the-money option for follow-on investments available in younger funds; the monitoring channel, which captures the extended non-financial support these funds provide; and the selection channel, which suggests that higher-quality entrepreneurs prefer younger funds due to the added value of financing and monitoring. We first provide empirical evidence supporting these channels by examining patterns in follow-on investments, industry financial intensity, board representation, sector specialization, serial entrepreneurship, and general market conditions. We then develop a theoretical model to formalize these mechanisms and finally validate founder preferences through a survey of investors and entrepreneurs.

Keywords: Venture Capital, Fund Age, Fund Lifecycle, Entrepreneurial Selection, Startup-VC Matching, Financial Frictions, Exits, M&As, IPOs, Board, Serial Entrepreneurs

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1 Introduction

Venture capital (VC) funds play a pivotal role in financing high-growth startups, which disproportionately contribute to innovation (Kortum and Lerner, 2000) and consequently drive economic growth (Aghion and Howitt, 1992; Romer, 1990). The matching of high-potential startups with VC funds is crucial for value creation, as entrepreneurs seek capital from the most beneficial funds and VC firms aim to invest in the most promising ventures (Sorensen, 2007; Gompers et al., 2020; Ewens et al., 2022; Sannino, 2024). We introduce a previously undocumented factor influencing this sorting process and the resulting investment outcomes: the age of the VC fund. Specifically, we find that investments made earlier in a fund's lifecycle are significantly more likely to achieve successful exits through mergers and acquisitions (M&As) or initial public offerings (IPOs).

VC fund managers (general partners, GPs) and their investors (limited partners, LPs) face significant agency problems and incentive misalignments (Gompers and Lerner, 2004). To mitigate these concerns, VC funds typically adopt a limited partnership structure with finite lifespans, usually around ten years (Metrick and Yasuda, 2010; Kandel et al., 2011; Barrot, 2017), incentivizing GPs to prioritize the timely development and successful exits of their portfolio companies. Two critical frictions make this limited lifespan particularly important. First, the substantial costs associated with raising new funds constrain VC firms' access to additional capital, limiting their ability to provide continued financing support. Second, the scarcity of high-quality GPs restricts their capacity for sustained and effective monitoring. Together, these frictions imply that fund age plays a crucial role in shaping the value proposition VC firms offer to startups. In this paper, we examine how the finite lifespan of VC funds affects the matching between startups and VCs, as well as subsequent investment outcomes.

Our hypothesis that fund age influences the VC-startup sorting process is grounded in the fundamental characteristics of the VC industry. VC investments involve three key components: (1) the supply of capital, (2) the option for follow-on investments (Hsu, 2010), and (3) the provision of professional guidance through active monitoring (Kaplan and Strömberg, 2001; Hellmann and Puri, 2002; Bernstein et al., 2016; Gompers et al., 2020; Gornall and Strebulaev, 2022; Fu, 2024). Given the finite lifespan of VC funds, startups that secure investments earlier in a fund's lifecycle benefit from a longer commitment to professional guidance and an increased likelihood of receiving follow-on investments. Consequently, we propose that startups funded earlier in a fund's lifecycle are more likely to achieve successful exits due to three key mechanisms: (1) the financing channel, where younger funds have greater flexibility to provide follow-on investments; (2) the monitoring channel, where startups receiving early-stage investments benefit from extended oversight and strategic guidance; and (3) the selection channel, where higher-quality startups preferentially match with younger funds that offer longer-term support.

Importantly, in a frictionless world, VCs could raise new funds and hire additional GPs whenever they identify a strong investment opportunity, rendering fund age irrelevant to the matching process. Our finding that fund age plays a significant role in investment outcomes suggests that raising and structuring new funds is, indeed, subject to friction. To the best of our knowledge, this paper is the first to systematically examine how these three channels interact with fund age to shape startup outcomes.

We analyze the temporal dynamics of VC funds using a comprehensive dataset of Israeli VC-backed startups. The dataset encompasses the near-universe of Israeli VC-backed startups for the last 35 years and includes detailed information on which VC fund invests in each startup. Unlike commonly used databases like PitchBook or Crunchbase, which typically link investments to VC firms rather than individual funds, our dataset allows for an in-depth fund-level analysis. This granularity is essential for comparing the outcomes of investments made by the same fund at different stages of its lifecycle and is particularly useful for our analysis of the various underlying mechanisms.

Our primary empirical finding is that each additional year in the fund's age reduces the probability of an exit by as much as 5pp, amounting to 21.5% compared to the sample's unconditional mean of 23.5% exits. To ensure the robustness of this result and rule out alternative explanations, we impose stringent sample restrictions and controls. Specifically, we focus exclusively on 1,043 first-time, seed-stage, single-VC-investor investments. This focus on seed-stage startups mitigates potential confounding effects from the tendency of mature funds to invest in more established companies (Barrot, 2017). Furthermore, we include fund fixed effects to account for unobserved differences in fund manager quality, which are known to influence startup sorting into funds (Sorensen, 2007). We use various additional controls and fixed effects, which together with the sample restrictions, enable us to isolate and analyze the age-dependent mechanism independently of previously documented sorting dynamics.

After establishing a negative correlation between fund age and startup performance, we analyze the financing channel. First, we examine the number of follow-on investments each startup receives from the same fund. Our findings indicate that investments made later in a fund's lifecycle are less likely to receive follow-on investments. Specifically, each additional year in a fund's life is associated with a 27% decrease in the number of follow-on investments, compared to the sample's unconditional mean of 1.04 follow-on investments per startup. This result supports our hypothesis that investments made earlier in a fund's lifecycle are more likely to lead to follow-on investments by the same fund.

To identify the time-dependent financing channel and address potential endogeneity in a fund's decision to provide follow-on investments, we examine how fund age affects industries with varying levels of financial intensity. We find that the marginal benefit of each additional year spent with a fund is proportionate to a startup's industry-specific financial needs. Specifically, a one-standard-deviation increase in the startup's industry financial intensity is associated with a 5% increase in the probability of a successful exit for each additional year with the fund. Put differently, startups in capital-intensive industries are more likely to achieve successful exits when they receive initial investments from younger funds. If financing had no temporal effect, performance should not vary with financial intensity when holding fund age constant.

Next, we examine the monitoring channel and start by studying VCs' representation in startups' boards of directors. Having a VC represented on the board allows the fund to engage more closely with the company's operations, thereby enabling more intense monitoring. VCs ask for a board seat as it offers oversight and serves as a platform to enhance the value of the startup. Entrepreneurs, on the other hand, may either prefer to limit board involvement to retain autonomy or welcome a VC board member if they bring strategic guidance, credibility, or access to resources critical for scaling. Ultimately, the decision for board representation is mutual and is set in the investment contract between the VC and the entrepreneur, balancing their incentives and usually set separately from cash flow and control rights (Kaplan and Strömberg, 2003). VCs are generally inflexible regarding board control (Gompers et al., 2020), and gain more board representation as the startup matures and their capital contribution increases (Kaplan and Strömberg, 2003; Ewens and Malenko, 2024), and when risks and uncertainties are higher (Kaplan and Strömberg, 2004).

Utilizing unique administrative data on board members from the Israeli Company Registrar, we explore the correlation between fund age and board representation. We find that each additional year in the fund's age is associated with a 10% decline relative to the unconditional probability of 73% for board representation. This negative correlation can be interpreted in two ways. First, VCs may be more likely to assign a director when the fund is young due to capacity constraints, leading to a decline in monitoring intensity as the fund ages. Alternatively, the correlation may stem from the selection channel: if VCs prioritize board representation for their most promising portfolio companies to maximize their chances of success, and if higher-quality startups tend to match with younger funds, this could create an observed positive correlation between fund age and board representation. To distinguish between these explanations, we include proxies for the perceived ex-ante quality of the startup and the fund's attractiveness at the time of funding in our regressions. The negative correlation remains robust, suggesting that capacity constraints play a role in this equilibrium.

To identify the temporal aspects of monitoring, we compare specialist and generalist funds. Specialists have historically outperformed generalists (Gompers et al., 2009) by selecting better investments, adding value through monitoring, or both. We exploit this difference to determine whether specialist VCs' active involvement contributes significantly to their startups' success and how this impact varies with the time spent together. If monitoring does not add value to the startup, time should not have a differential effect on the investment outcome depending on the type of investor. However, if VCs add value through monitoring, specialists should see greater improvements over time compared to generalists. Indeed, we find that each additional year increases the probability of a successful exit by 27% for specialists compared to the sample's unconditional mean, suggesting that monitoring plays a role in the fund's intertemporal value proposition.

The third mechanism through which fund age influences investment outcomes is the selection channel, which captures how high-quality founders select among available VC funds. All else equal, entrepreneurs who recognize the value of time prefer younger funds, as these funds offer a longer runway for follow-on investments and extended monitoring. We provide empirical evidence supporting this sorting mechanism through three distinct strategies. First, using our unique data from the Israeli Company Registrar, we identify serial entrepreneurs and demonstrate that they are more likely to match with younger funds. Serial entrepreneurs tend to be more productive (Shaw and Sørensen, 2019) and have higher success rates than first-time entrepreneurs (Gompers et al., 2006). These advantages give them greater bargaining power and more influence over their choice of VC. Since both young and mature funds prefer entrepreneurs with higher expected success rates, they are more likely to favor serial entrepreneurs. As a result, the equilibrium outcome in which serial entrepreneurs match with younger funds is primarily driven by the entrepreneurs' preferences. We find that each additional year in a fund's age reduces the probability that a founder is a serial entrepreneur by 26% relative to the unconditional probability of a founder being a serial entrepreneur of 31.9%, pointing to older funds' difficulty in attracting serial entrepreneurs. To support the assumption that VCs indeed favor serial entrepreneurs, we show that these entrepreneurs receive, on average, 20.8% larger investment amounts and are 13.3% more likely to receive follow-on investments. Interestingly, once controlling for the amount invested, we do not find a statistically significant correlation between being a serial entrepreneur and achieving a successful exit.

In our second strategy, we exploit cross-sectional variation in fund age to assess how startup performance differs based on relative market conditions. We flag all funds older than the average active fund in a given year and test whether investments made by these older funds are less likely to result in successful exits even after controlling for the funds' age. We find that investments made by older-than-mean funds are 27.9% less likely to experience a successful exit compared to the unconditional exit probability. This suggests that higher-quality startups systematically match with the youngest available funds.

In our third strategy, we adopt an instrumental variable (IV) approach to strengthen the causal interpretation of these results. Following Nanda and Rhodes-Kropf (2013), we instrument the older-than-mean variable with lagged US buyout fundraising, leveraging the fact that LPs allocate capital to private equity as a broad asset class, leading to correlated fundraising trends across VC and buyout markets. The first-stage results confirm that lagged buyout fundraising is a strong predictor of whether a fund is older than the market average. The second-stage results indicate that a one-standard-deviation increase in lagged buyout fundraising is associated with a 7.6% decrease in a startup's likelihood of a successful exit relative to the unconditional probability of an exit. These findings provide further evidence that entrepreneurs systematically select younger funds, reinforcing the role of fund age in shaping investment outcomes. We illustrate the VC fund lifecycle and summarize the three channels with their relevant empirical tests in Figure 1.

Lastly, we address four potential concerns relating to our empirical findings: window dressing, cross-investments, strategic fund initiations, and external validity. First, we address the possibility that fund managers engage in 'window dressing' by allocating their most promising investments to new funds to showcase strong performance and attract investors for raising subsequent funds (Lakonishok et al., 1991). To mitigate this concern, we restrict our sample to standalone funds that cannot reallocate investments to a newer fund. Our results remain robust, with fund age negatively correlated with both the likelihood of exits and the number of follow-on rounds.

Second, we test whether cross-investments, where portfolio firms receive financing from multiple funds managed by the same VC firm, invalidate our limited time horizon assumption. Although cross-investments are rare in our sample (only 1.5% of startups received funding from two different funds of the same VC firm), we address this concern by restricting the analysis to VC firms managing more than one, two, or three active funds in Israel, where cross-investments could theoretically occur. If cross-investments constitute a significant value proposition, their effect should weaken the observed relationship between fund age and outcomes as the number of active funds increases. However, our results remain robust, supporting the validity of our baseline findings.

Third, we mitigate the potential selection bias from VC firms timing the initiation of new funds based on attractive new investment opportunities by excluding each fund's first investment. We find results consistent with our baseline findings, implying that strategic timing of fund initiations cannot fully explain our results.

Fourth, we test the external validity of our findings and assess whether the effect of fund age might be unique to the Israeli market by replicating our analysis in a sample of VC-backed startups in the United States using data from PitchBook. The PitchBook data, however, have some significant limitations, including incomplete coverage and missing fund IDs, which are essential for the identification of the mechanisms we analyze. Nonetheless, the PitchBook data allow us to replicate our baseline analysis on a subsample of deals. We find negative correlations between a fund's age and both the startup's likelihood of exit and the number of follow-on investments by that fund, implying that our baseline results are not unique to the Israeli market.

To formalize the mechanisms underlying our empirical results, we develop a theoretical model examining the value VC funds provide throughout their limited lifespan and how this shapes their matching with entrepreneurs. We model an environment with overlapping generations of VC funds, each period featuring funds of equal quality but at different stages: young, mature, and liquidated. Simultaneously, new entrepreneurs enter the market, establishing startups with either high or low potential. The match between a fund and an entrepreneur influences the startup's valuation through both monitoring and financing accumulated until liquidation. Young funds offer extended periods of monitoring and the potential for follow-on investments, while mature funds nearing liquidation provide limited monitoring and no option for additional funding. Recognizing the value of prolonged support and the embedded option of follow-on investments, entrepreneurs prefer to partner with younger funds. VC funds, on their part, prefer investing in higher-quality startups to maximize expected returns. These preferences result in a stable matching (Gale and Shapley, 1962) where higher-quality startups partner with younger VC funds. The theoretical analysis shows that this matching is primarily driven by the preferences of high-quality entrepreneurs, whose scarcity allows them to shape outcomes.

To complement our empirical analysis and theoretical framework, we conducted a survey to explore how entrepreneurs and investors evaluate VC fund characteristics in the startup-VC matching process. The survey asks participants to rank key fund attributes, including fund age, available capital for follow-on investments, industry specialization, and mentoring capabilities, and to make funding decisions in hypothetical investment scenarios. These scenarios contrast fund age, capital availability, and sector expertise to assess how respondents weigh the trade-offs between financing and monitoring. The survey was distributed through targeted outreach to founders, both with and without VC-backed experience, and to VC investors. In total, 101 participants completed the survey, providing a reasonably large and diverse dataset consisting of both investors and founders.

The survey results reinforce our findings on the importance of fund age and financing. When choosing between a younger and an older fund with no additional information provided, respondents are indifferent between a startup with minimal capital needs but strongly prefer the younger fund for a capital-intensive venture. Similarly, when presented with a choice between a fund with $8M and one with $30M in available capital, most respondents prioritize the larger fund, particularly for capital-intensive startups. These findings suggest that financing plays a dominant role in fund selection, while the importance of mentoring varies by startup type. Further supporting this conclusion, respondents exhibit a preference for sector-specialist funds over generalist funds, indicating that while mentoring may be of second-order importance, it is overall a valuable component of the VC value proposition. Together, these results highlight how entrepreneurs internalize the value of time and capital when selecting VC investors, further supporting our hypothesis that fund age influences the startup-VC matching process.

Overall, our survey results and theoretical predictions support our empirical findings and illustrate how the financing, monitoring, and sorting channels influence equilibrium outcomes. Startups matched with younger VC funds exhibit better performance due to deeper in-the-money options for follow-on investments, monitoring, and sorting driven by entrepreneurs' understanding of the associated temporal value creation.

Our paper contributes to the literature on the finite horizon of VC funds. Barrot (2017) shows that VC funds invest in older, more mature startups as the remaining fund life diminishes. Yao and O'Neill (2022) examines how venture capitalists' exit pressure due to finite fund lifecycles influences the likelihood of various venture exit outcomes through its impact on board cooperation and coordination. Kandel et al. (2011) model the conflict of interest between limited and general partners in the decision to continue projects, stemming from the fund's limited lifespan and general partners' informational advantage. Chakraborty and Ewens (2018) and Crain (2018) analyze how raising a new fund impacts the investment decisions at a VC investor's current fund. More generally, Da Rin et al. (2013) provides a comprehensive survey of the VC literature. Our paper complements these studies by showing that higher-quality startups sort with younger VC funds. Importantly, by focusing on seed rounds only, we hold the maturity of startups constant, which implies that our sorting mechanism is different from that in Barrot (2017).

We also contribute to the theoretical literature on VC-entrepreneur matching. Sorensen (2007) develops a two-sided matching model to analyze the relative importance of quality-based matching between funds and entrepreneurs. Ewens et al. (2022) develops a search-and-matching model with negotiated contracts between VC funds and entrepreneurs. Sannino (2024) develops a sorting model, explicitly distinguishing between low- and high-value-add

VCs. Additionally, empirical studies highlight the role of external factors such as the legal system (Bottazzi et al., 2009), trust (Bottazzi et al., 2016), and investor activism (Bottazzi et al., 2008; Li et al., 2024) in influencing the sorting of VC investors and startups. The contribution of our theoretical model is the focus on matching based on the age of a VC fund.

Furthermore, our paper contributes to the literature on the Israeli VC ecosystem. Conti (2018) uses a regulatory shock in Israel to show that relaxation of a subsidy's restrictions increases the likelihood of startups applying for that subsidy. Conti and Guzman (2023) studies the migration of Israeli startups to the United States. Falik et al. (2016) interview 144 Israeli entrepreneurs to study the relationship between entrepreneurs' experience and the relative importance they attach to a deal's valuation versus contractual terms and Brav et al. (2023) analyze the industry's performance. We complement these studies by assembling and analyzing, to the best of our knowledge, the most comprehensive Israeli VC fund-startup matched dataset.

The remainder of the paper is organized as follows. In Section 2 we present our empirical analysis, in Section 3, we present our theoretical model, and in Section 4 we present our analysis of the Survey. Section 5 concludes.

2 Empirical Analysis

We begin by outlining our data construction process and summarizing key statistics. We then introduce our hypotheses and empirical approach before presenting our findings and examining how they align with our predictions.

2.1 Data

We draw our sample from a dataset compiled by the IVC Research Center, which covers the near-universe of VC-backed startups in Israel. We match this dataset to proprietary records from the Israeli Company Registrar to obtain information on founders, startup ownership, and board seats. To ensure a complete mapping of VC firms and funds, we cross-reference IVC data with PitchBook and Crunchbase. When an investment record only lists a fund name (e.g., Vision Fund), we use these sources to identify the corresponding VC firm (e.g., SoftBank). This yields what we believe is the most comprehensive mapping of the Israeli startup-VC investor universe.

The full dataset includes 72,513 investments in 10,861 startups by 14,147 investors between 1990 and 2024. These investors include VC funds (31.2%), Angels (17.4%), corporate venture capital (4.5%), private equity funds (1.5%), and government agencies (1.2%). Investments span all funding stages, from 24,788 seed-round investments to 2,072 IPOs and M&As, with a maximum of 15 funding rounds recorded.

We focus on first-time investments by VC firms from funds that have invested in at least two startups between 2003 and 2023. Funds with a single investment are excluded as the fund fixed effects would absorb them. Our sample starts in 2003, as exit data (M&As and IPOs) only become available from this year onward. After applying these filters, we obtain 3,618 first-time investments in 2,263 startups by 413 VC funds, spanning from seed to ninth-round funding. Among these startups, 62 have an IPO, 472 have an M&A, and 9 experience both. We define the first of these two events as the exit and refer to this dataset as the "*investment-level dataset*."

To examine how the timing of investments within a fund's lifecycle impacts startup performance, we further refine our sample. Since our dependent variable, a dummy indicating whether a startup has a successful exit, is time-invariant, our empirical analysis should include only one observation per startup. We, therefore, focus on seed-round investments made by a single VC fund, resulting in 1,043 startups backed by 202 VC funds. Each observation represents a startup raising its first institutional capital, ensuring that all startups are in the earliest stage of their lifecycle. Among these, 17 have an IPO and 232 have an M&A. We refer to this dataset as the "*startup-level dataset*."

Using only single-VC investments allows us to isolate the effect of fund age without the confounding influence of multiple investors entering at different stages, providing a cleaner setting to identify our economic mechanisms. As shown in Table 1, the average fund invests in 8.76 Israeli startups, with an average check size of $11.96 million across all rounds and $3.94 million for single-VC seed rounds.

To track board representation, we leverage the Israeli Company Registrar, which provides detailed director data for registered firms. Of the 1,043 startups in our "*startup-level dataset*," we are able to get a definitive match for 942, out of which 917 contain detailed director data. Among these, we identify directors affiliated with VC firms using multiple sources, including LinkedIn, the IVC website, and VC firm websites. A director is classified as representing the fund if they are a partner at the VC firm at the time of investment.

After identifying 942 registered startups from our 1,043 "*startup-level dataset*," we manually match 5,296 board members to 917 of these startups. A startup is flagged as having VC board representation if at least one board member is affiliated with the fund and as not having VC representation if all board members can be ruled out as fund-affiliated. Among the 917 registered startups, we definitively determine board representation for 832, with 73% having a VC partner on the board. To account for uncertainty in the remaining 85 cases, we calculate lower and upper bounds for this estimate, finding that VC board representation ranges from 67% (if none of the excluded firms have VC representation) to 75% (if all do), indicating strong VC involvement in single-VC seed investments.

Finally, we drop 28 additional companies because their respective funds made only a single investment within the sample of 832 companies, meaning they would be absorbed by the fund fixed effects. Our final board representation dataset consists of 804 startup-level observations.

To identify startups founded by serial entrepreneurs, we begin with a list of 2,559 founders from the IVC database and check whether they held ownership or a board seat in other startups within the previous five years using the Registrar data. A startup is classified as having a serial entrepreneur if at least one founder has prior ownership or a board seat in another startup, whereas it is classified as non-serial only if all founders are identified, and none have previous ownership or a board position. This results in the definitive classification of 1,927 founders of 699 startups, with 223 led by serial entrepreneurs and 476 by first-time founders. All results remain robust when using a three- or four-year window. We use a window to mitigate a truncation problem, as the further back we go in the data, the fewer prior years are covered by the Registrar.

A potential concern with the focus on single-VC seed rounds is the representativeness of seed rounds more generally. We, therefore, conclude our descriptive statistics by performing two-tailed t-tests to compare our startup-level dataset with seed-stage investments involving more than one VC investor. As shown in Table 2, the majority of seed rounds have only a single VC investor (73%). Table 2 also shows that the average deal amount for single-VC seed rounds ($3.9M) is lower than that for syndicated seed rounds ($7.5M), consistent with VC syndicates providing seed funding to startups with higher capital requirements or of higher quality. However, when we normalize this measure by dividing the total deal amount by the number of VCs in that round, the average decreases to $4.4M, which is close to, and not statistically different from, the $3.9M for single-investor rounds. When examining startup trajectories, we find no significant differences in the number of follow-on investments and exit rates. When examining fund characteristics, we find that funds involved in syndicated rounds have, on average, 1.3 fewer portfolio companies compared to funds that invest alone. This is consistent with smaller funds seeking risk-sharing by syndicating early-stage investments (Lockett and Wright, 2001; Hopp and Rieder, 2011).

Overall, single- and multiple-VC investor seed rounds look reasonably similar. Even though syndicated rounds have higher absolute deal amounts, investments on a per-investor basis are almost identical. Startups in single-investor and syndicated rounds have similar trajectories in terms of follow-on rounds and exit rates. Taken together, this implies that the benefit of a tighter identification of our single-investor seed round sample restriction comes at relatively low losses of representativeness relative to VC-backed seed rounds more generally.

2.2 Empirical Strategy

2.2.1 Performance and Fund Age

Our main specification uses the "*startup-level dataset*" to assess the association between startup quality and VC fund age. As detailed in the data section, this dataset consists of startups receiving seed-stage investments from a single VC fund that invested in at least two different startups. More specifically, we regress:

$$\begin{aligned}\mathbb{I}\{Exit_s\} &= \beta_1 FundAge_s + \beta_2 Ln(DealAmount)_s + \beta_3 PortfolioSize_s \\ &\quad + FundFE + DealYearFE + Inv.CountryFE + IndustryFE + \epsilon_s\end{aligned} \tag{1}$$

where s indexes startups. $\mathbb{I}\{Exit_s\}$ represents our performance measure, a dummy variable indicating if a startup has an exit through an M&A or an IPO.[1] In our main specification, illustrated in Figure 2, we examine the number of years since a fund's inception, calculated as the difference between the time of investment and the time of the fund's first-ever investment.

Our controls include the logarithmic transformation of the total deal amount, that is, the total dollar amount invested in that round, to allow for comparisons between investments of similar scale. We also control for the total number of startups in the fund's portfolio at the time of investment to isolate the effect of investment timing, rather than conflating it with the increasing number of startups in the fund's portfolio over time.

In our "*startup-level dataset*," we do not control for startups' age because all firms in this sample are raising their first seed investment, resulting in minimal variability in this measure. To account for unobserved heterogeneity and capture time trends, country-specific, and industry-specific effects, we include industry, time, and investor-country fixed effects. Arguably, more importantly, we incorporate fund fixed effects to control for potential differences in fund quality. Including VC fund fixed effects allows us to compare startups receiving investments from the same investors within the lifecycle of a single fund. Standard errors are clustered at the deal-year and investor-country levels.

[1] Amor and Kooli (2020) examines the relationship between VC firm reputation and exit types (M&A versus IPO). Exit outcomes are commonly used as proxies for fund performance (see, for example, Hochberg et al. (2007)), and they correlate positively with actual fund performance (Phalippou and Gottschalg, 2009).

2.2.2 The Financing Channel

In our second empirical setting, we examine the temporal dynamics of the financing channel and examine whether younger funds are more likely to provide follow-on investments. We first find that VC investments are sticky. The conditional probability of a follow-on investment being made by an investor who has previously invested in the startup is 65% [95% CI: 0.639–0.664]. This result suggests that follow-on investments for seed-stage startups are most likely made by the same fund.

We replace our dependent variable, $Exits_s$, in our baseline empirical setting described in Equation 1, with a counter that tracks the number of follow-on investments each startup receives from the same fund.

Because the number of follow-on investments changes over time for a given startup, we can also use the "*investment-level dataset*" to assess the impact of a fund's age on the number of follow-on investments. Specifically, we regress:

$$\begin{aligned} FollowOns_{s,v,r} = {} & \beta_1 \mathit{FundAge}_{s,v,r} + \beta_2 \mathit{Ln(DealAmount)}_{s,r} + \beta_3 \mathit{StartupAge}_{s,r} \\ & + \beta_4 \mathit{PortfolioSize}_{v,r} + \mathit{RoundFE} + \mathit{FundFE} + \mathit{DealYearFE} \\ & + \mathit{Inv.CountryFE} + \mathit{IndustryFE} + \epsilon_{s,v,r} \end{aligned} \tag{2}$$

where s indexes startups, v VC funds, and r rounds of funding. $FollowOns_{s,v,r}$ measures the number of future additional rounds of funding a startup raises from the same fund, and $\mathit{StartupAge}_{s,r}$ is a startup's age at the time of investment. In contrast to the "*startup-level dataset*," startup age varies in the "*investment-level dataset*" because it includes all funding rounds. We, therefore, include startup age in this regression to control for potential selection bias, which may be driven by a fund's preference for more mature startups later in the fund lifecycle (Barrot, 2017). We also include round fixed effects to ensure we compare startups at the same funding stage as we now include all rounds of funding and not only seed.

In an alternative approach to this analysis, we include startup fixed effects to examine the funds' lifecycle impact while controlling for startup quality. In this specification, our fixed effects limit our analysis to funds investing in at least two different startups and startups receiving investments from at least two different VC funds.

Next, we analyze the marginal impact of a time-dependent financing channel. We hypothesize that startups in capital-intensive industries benefit more from this channel, making fund age more central to their success. If the financing channel were not central to the value creation of startups, both capital-intensive and non-capital-intensive startups would derive the same benefit from the fund's age. To test this, we interact fund age with an industry-level exit-multiple index. To evaluate this exit-multiple index, we aggregate data at the industry level and compute the ratio of the total exit value to the total capital raised across all portfolio firms that received seed funding before 2015. We use this restriction to include only portfolio companies with sufficient time to evolve. After creating this industry-level exit-multiple measure, we take its inverse to assess the industry's financial intensity, apply it to the entire sample, and interact it with fund age in our "*startup-level dataset.*" Specifically, we regress:

$$\begin{aligned}\mathbb{I}\{Exit_s\} = {} & \beta_1 \mathit{FundAge}_s + \beta_2 \mathit{Ln(DealAmount)}_s + \beta_3 \mathit{PortfolioSize}_s \\ & + \beta_4 \mathit{FundAge}_s \times \mathit{Fin.Intensity}_j \\ & + \mathit{FundFE} + \mathit{DealYearFE} + \mathit{Inv.CountryFE} + \mathit{IndustryFE} + \epsilon_{s,j}\end{aligned} \tag{3}$$

where $Fin.Intensity_j$ measures our industry-level financial intensity index value for an industry to which startup s belongs. The marginal effect of each additional year is measured by the coefficient of the interaction term $\mathit{FundAge} \times Fin.Intensity$, β_4. The industry fixed effects absorb the standalone $Fin.Intensity_j$ variable.

2.2.3 The Monitoring Channel

We first analyze the temporal dynamics of the monitoring channel, focusing on VC-controlled board seats. Amornsiripanitch et al. (2019) find that VC board membership is correlated with VC characteristics, such as the VC's track record and the size of its network, as well as deal-specific characteristics, such as the VC's lead investor status, VC-founder prior relationship, and geographical proximity. In our analysis, we control for most of these factors and study the additional role of fund age in determining board representation. We first modify our baseline regression in Equation 1 by replacing fund age with a dummy that equals one if a startup has a VC partner on its board of directors. A positive coefficient on this dummy indicates a within-fund positive correlation between board representation and exit probability, controlling for investment amount, portfolio size, time, industry, and investor country. We then rerun our baseline regression, this time using the board seat dummy as the dependent variable. A negative correlation between fund age and board seats suggests that funds later in their lifecycle are less likely to take board seats in the startups they invest in, potentially limiting their ability to provide hands-on monitoring and oversight.

To evaluate the time-dependent monitoring channel, we compare the effects of fund age on performance between generalist and specialist funds. We classify funds investing in at least three different industries as generalists, and funds investing in at most two different industries as specialists. Our analysis relies on the hypothesis that the monitoring channel is more significant among specialists, given the added value derived from the expertise of a specialist VC fund compared to a generalist fund (Gompers et al., 2009). Specifically, we regress:

$$\begin{aligned}\mathbb{I}\{Exit_s\} = {} & \beta_1 FundAge_s + \beta_2 Ln(DealAmount)_s + \beta_3 PortfolioSize_s \\ & + \beta_4 FundAge_s \times \mathbb{I}\{Specialist_v\} \\ & + FundFE + DealYearFE + Inv.CountryFE + IndustryFE + \epsilon_s\end{aligned} \tag{4}$$

where $\mathbb{I}\{Specialist_v\}$ is a dummy variable that equals one if a VC fund invests in two or fewer industries. The marginal effect of an additional year of fund age for specialist funds is captured by the coefficient of the interaction $FundAge \times \mathbb{I}\{Specialist\}$, β_4. The presence of a time-dependent monitoring channel implies that each additional year with a specialist fund is associated with better startup performance. If the superior performance of specialist funds were solely driven by selection, it would imply that β_4 is statistically insignificant. The fund fixed effects absorb the standalone $\mathbb{I}\{Specialist_v\}$ variable.

2.2.4 Startup Selection Preferences

We examine the selection channel by analyzing startups' preferences for matching with younger funds using three empirical strategies.

First, we test whether serial entrepreneurs are more likely to match with younger funds than first-time founders. To test this equilibrium result, we rerun our baseline analysis with the dependent variable replaced by a dummy that equals one if at least one founder is a serial entrepreneur. A negative coefficient on fund age indicates that serial entrepreneurs are more likely to match with younger funds.

In our second empirical test, we use a cross-sectional lifecycle measure. As illustrated in Figure 3, we use our more extensive "*investment-level dataset*" to estimate market conditions by examining the age of all active funds in a given year and flagging those older than the average active fund for that year. By flagging the ones that are older than the mean, we address the competitiveness of the venture capital market in that year and a startup's preferential matching with respect to fund age. We regress our performance measure against this dummy variable while controlling for a fund's age in our more restrictive "*startup-level dataset*:"

$$\begin{aligned}\mathbb{I}\{Exit_s\} = {} & \beta_1 \mathbb{I}\{OlderThanMean_{s,t}\} + \beta_2 FundAge_s \\ & + \beta_3 Ln(DealAmount)_s + \beta_4 PortfolioSize \\ & + FundFE + DealYearFE + Inv.CountryFE + IndustryFE + \epsilon_s\end{aligned} \tag{5}$$

A negative correlation between the *OlderThanMean* dummy and exits, even after controlling for the fund age, constitutes evidence consistent with the existence of an age based selection channel. Entrepreneurs, aware of the added value generated by a younger fund, prefer the younger ones available when raising capital. A negative correlation is suggestive evidence of an equilibrium where higher-quality startups choose younger available funds, and lower-quality startups end-up matching with older ones.

In our third empirical strategy addressing the selection channel, we adopt the instrumental variables (IV) strategy in Nanda and Rhodes-Kropf (2013), which exploits plausibly exogenous variation in the supply of new VC funds. This IV approach leverages two distinctive characteristics of the VC industry. First, limited partners typically allocate capital to private equity as a broad asset class despite the fundamental differences between various types of private equity funds, each facing distinct investment opportunities. VC funds finance innovation by providing risk capital to high-growth startups, whereas buyout funds operate in the market for corporate control by acquiring majority stakes in large private or public companies. Second, limited partners' asset allocation decisions are often based on backward-looking measures, such as past private equity firm returns, and are frequently rebalanced in response to returns in other asset classes (Samila and Sorenson, 2011).

To account for these dynamics, we re-estimate Equation 5 using a two-stage least squares (2SLS) approach, instrumenting the *OlderThanMean* variable with total buyout fundraising in the US twelve months preceding the focal single-investor seed-stage investment. Since our baseline sample begins in 2003, we collect buyout fundraising data from VentureXpert, which provides better coverage than PitchBook before 2010.

The intuition behind this IV strategy is as follows. Because limited partners typically use historical private equity firm returns to allocate capital across private equity subcategories, VC and buyout fundraising tend to be highly correlated. However, decisions to invest in buyout funds are primarily based on past returns of buyout firms and are arguably unrelated to the future success of VC-backed startups. We use US buyout fundraising as an instrument for two reasons. First, the US buyout market is the largest globally, and its fundraising is strongly correlated with fundraising in other regions. Specifically, the correlation between US and rest-of-world quarterly buyout fundraising in the full VentureXpert dataset is 0.75. Second, and more importantly, lagged US buyout fundraising is less likely to be directly associated with the eventual outcomes of Israeli VC-backed startups than Israeli buyout fundraising, thereby strengthening the exclusion restriction of our approach.

The instrumented *OlderThanMean* variable captures variation in a given VC fund's competitiveness based on shifts in the average age of other active VC funds due to capital inflows or outflows from the VC industry that are unrelated to the future success of high-growth startups currently seeking funding. If limited partners allocate more capital to buyout funds, VC fundraising will also increase because private equity is treated as a single asset class. This, in turn, reduces the average age of active VC funds as new funds emerge. All else equal, increased capital inflows into the VC industry make fundraising easier, leading to the formation of more newly raised VC funds. If entrepreneurs prefer younger VC funds, an exogenous increase in the supply of younger funds should reduce the likelihood of incumbent VC funds matching with high-quality startups.

We use lagged buyout fundraising as an instrument because, between 2014 and 2024, the median VC fund took 12 months to complete fundraising (NVCA, 2024). When re-estimating Equation 5, we retain all control variables, including fund age, since our objective is to exploit plausibly exogenous variation in a VC fund's likelihood of being older than the average active VC fund, while controlling for the focal fund's age. Because these regressions include deal-year fixed effects, identification in the IV regression relies on variation across funds investing in different months within the same calendar year.

2.3 Empirical Results

We examine the empirical evidence supporting our hypotheses on how fund age influences investment outcomes. We begin by establishing the relationship between fund age and startup success before exploring the underlying financing, monitoring, and selection channels. We then assess the robustness of our findings by addressing potential alternative explanations.

2.3.1 Performance and Fund Age

Our baseline empirical result, presented in Table 3, Column 1, shows a within-fund negative correlation between fund age and a startup's exit probability after controlling for the number of portfolio companies, invested amount, deal year, investor country, and industry. The likelihood of a startup having an exit decreases by 5.06pp for each additional year that a particular VC fund invests after its inception. This represents approximately 21.5% of the unconditional probability of 23.5% for a startup to have an exit in this subsample.

We conduct a series of robustness tests to validate this finding. In the first set of tests, we rerun our baseline analysis by adding various controls and fixed effects sequentially, as reported in Table A.3 in the Appendix. Notably, our results hold even when excluding fund fixed effects. While the direction of the correlation remains negative and statistically significant, the reduction in the coefficient's magnitude underscores the importance of fund quality in the startup-fund matching process. Nevertheless, the fact that the effect remains negative and significant after dropping the fund fixed effects, indicates that fund age is important even after accounting for selection based on fund quality.

In the second set of robustness tests, reported in Table A.4, we replicate the setting of our baseline regressions in logit regressions, given that our dependent variable is binary. The findings, although attenuated, are robust across these alternative empirical specifications. All three approaches yield consistent results, supporting an equilibrium in which higher-quality startups are more likely to sort with younger funds.

2.3.2 The Financing Channel

To assess the impact of a fund's age on the financing channel, we first investigate whether investments made earlier in the fund's lifecycle result in more follow-on investments by the same fund. As shown in Table 3 Column 2, we find that each additional year in a fund's age is associated with a 0.277 decrease in the number of follow-on investments, equivalent to a 27% decrease relative to the 1,043 startup-level observations' unconditional mean of 1.04 follow-ons.[2] This result suggests that the age of a fund at the time of investment is negatively correlated with the number of follow-on investments it can potentially offer.

One advantage of using the follow-on variable instead of the exits variable is that it allows us to exploit the richness of the data by analyzing the "*investment-level dataset*." We can examine multiple investments made by different funds in the same startup, as the number of follow-ons varies by VC fund and funding round. As reported in Table 4 Column 2, our investment-level regressions yield results similar to those at the startup level. A key difference between the two datasets is that startups in the investment-level dataset are at various stages and, consequently, at different ages.

Although the decision to invest is clearly endogenous to a startup's maturity, we find that the relationship between fund age and follow-on investments holds true even after accounting for the startup's age at the time of investment as proposed by Barrot (2017), and including financing round fixed effects. By incorporating round fixed effects, startup age, and the total amount invested, we can compare startups receiving similar financing rounds at comparable stages of development. The identifying variation then comes from differences in VC fund age at the time of investment.

In an alternative approach, reported in Table 4 Column 3, we include startup fixed effects to account for both startup and investor quality. In this setting, we compare two or more initial investments from different VC funds in the same company, with the only distinguishing factor being the fund's age. We find that the negative correlation between fund age and follow-on investments persists even when comparing investments in the same company by

[2]The 1,043 startups in our "startup-level dataset" received a total of 1,088 follow-on investments. Specifically, 293 startups received one follow-on investment; 144 received two; 87 received three; 31 received four; 18 received five; 4 received six; and 1 startup received eight. 465 startups received no follow-on investment.

funds of different ages. In other words, when the same startup receives investments from two different funds at different stages of their lifecycle, it is more likely to receive a follow-on investment from the younger fund. These results are consistent in magnitude with our previous findings, which do not include startup fixed effects.

To assess the financing channel's intensive margin and to address potential identification concerns in this setting, we regress the interaction between our industry-level financial intensity index and the fund's age as shown in Equation 3. As presented in Table 3 Column 3, we find that a one standard deviation increase in the financial intensity index (std. dev. = 0.584) reduces the probability of an exit by 2.11pp for every additional year in a fund's age, which represents a decrease of 5.2% relative to the sample's unconditional mean (= coefficient $\times$ std. dev. / unconditional prob. of exit = 0.0211 $\times$ 0.584 / 0.235). This result suggests that the available time horizon of funds is more valuable in industries with higher financial intensity. If the observed correlations between fund age and exit probability were solely driven by channels other than the financing channel, we would not expect to see differences based on the industry's financial intensity. Therefore, when holding the VC fund age constant, there should be no difference in exit probabilities between capital-intensive and non-capital-intensive industries. The fact that we do observe such differences indicates that the financing channel contributes to the correlation between VC fund age and exits.

2.3.3 The Monitoring Channel

To assess the impact of fund age on the monitoring channel, we first examine whether investments made earlier in a fund's lifecycle increase the likelihood of the fund securing a board seat in the startups it invests in. As shown in Table 3 Column 4, each additional year in a fund's age is associated with a 7.34pp decrease in the probability of obtaining a board seat, equivalent to a 10% decline relative to the unconditional probability of 73%.

This negative correlation may reflect capacity constraints that lead VCs to assign directors when the fund is young or a sorting effect in which VCs prioritize board seats for higher-quality startups, which in turn prefer younger funds. To distinguish between these explanations, we introduce measures correlated with perceived startup quality. Specifically, we include a dummy variable for whether the fund is older than the average active fund (*OlderThanMean*) and a dummy variable indicating whether at least one of the founders is a serial entrepreneur. As reported in Table A.5 in the Appendix, and consistent with the sorting hypothesis, we find that older-than-mean funds are less likely to be represented on the board, while startups with a serial entrepreneur in the founding team are more likely to have VC board representation. Nonetheless, the negative correlation between board representation and fund age persists, suggesting that capacity constraints play a role in the fund's lifecycle. We conclude that startups receiving seed investments from younger funds are more likely to experience intensive monitoring through VC board representation.

Finally, we regress our exit dummy on board representation and, as reported in Table A.6, find a strong positive correlation between the two. This result supports the hypothesis that board representation is closely associated with successful exits, either due to selection effects, value added through monitoring, or both.

We identify the monitoring channel by evaluating the marginal value of specialist funds relative to generalist funds, using a similar approach to our analysis of the financing channel. We hypothesize that an additional year of monitoring is more beneficial to a startup when the investment comes from a specialist fund rather than a generalist fund. Specialist funds focus on a specific industry or sector, whereas generalist funds invest across multiple sectors and may be less effective in providing targeted value through monitoring. We interact fund age with a dummy variable that equals one for specialist funds, as described in Equation 4. Our findings, presented in Table 3 Column 5, show that each additional year with a specialist fund decreases the probability of a successful exit by 6.24pp, representing 26.6% of the sample's unconditional mean. This result suggests that additional time spent with VC funds is valuable for startups, which benefit from monitoring and mentoring by VC partners. This added value translates into a higher probability of a successful exit. If mentoring had no impact, we would not expect to see a significant difference in the performance of generalist and specialist VCs when holding fund age constant.

One might argue that the superior performance of specialist funds is driven solely by their ability to select high-potential startups. If that were the case, only the coefficient on the standalone *Specialist* variable (which is absorbed by the fund fixed effect in our setting) would load significantly. However, the negative coefficient on the interaction of the *Specialist* dummy with time indicates that the additional value of a specialist fund accumulates over time, likely due to its enhanced capacity to monitor and mentor portfolio companies.

2.3.4 Startup Selection Preferences

We define a third channel as the preferential selection channel of startups. This channel suggests that all else equal, entrepreneurs who recognize the added value of time prefer younger funds. Thus, younger funds attract higher-quality ventures, amplifying the economic effects of the financing and monitoring channels. We begin by demonstrating that serial entrepreneurs, who have greater bargaining power than first-time founders, tend to match with funds earlier in their lifecycle. As shown in Table 3 Column 6, each additional year in a fund's age reduces the probability that a founder is a serial entrepreneur by 8.29pp, equivalent to a 26% decrease relative to the unconditional probability of 31.9%.

We strengthen the validity of the assumption that serial entrepreneurs are highly sought after with two additional tests, reported in Table A.7 in the Appendix. Column 1 shows that serial entrepreneurs receive, on average, 20.8% larger investment amounts, while Column 2 shows they are likely to receive 13.3% more follow-on investments than the average. Interestingly, after controlling for the amount invested, we do not find a statistically significant correlation between being a serial entrepreneur and achieving a successful exit, as reported in Column 3.

While we lack a clear empirical method to quantify the relative magnitude of each of the three channels, we can demonstrate that our results hold in the cross-section. This implies that investments should be more successful when made during periods in which a fund is younger than the average active fund. This argument supports a sorting narrative in which higher-quality startups benefit from choosing funds of equal quality that are younger than their competitors at the time of investment. Our hypothesis is that time together plays an important role in a VC fund's value proposition.

In our empirical test, shown in Table 3 Column 7, we assess the impact of competition on our equilibrium result and attempt to isolate the startup's preferential sorting channel. To evaluate market conditions at the time of investment, we flag all funds older than the average age of all active funds each year. Our null hypothesis is that there should be no difference in a startup's performance when the investment is made by a fund that is older than the other active funds in that year after we control for a fund's age. We find that investments made by funds older than the average active fund in that year are 6.55pp less likely to experience a successful exit, equivalent to a 27.9% decrease compared to the unconditional probability of an exit.

In the final test for the sorting mechanism, we use an IV approach. Table 5 presents the results for 2SLS estimation of Equation 5.[3] Column 1 shows a negative correlation between lagged buyout fundraising and *OlderThanMean*, with an F-statistic above the commonly used threshold of 10, suggesting that the instrument is relevant. Column 2 shows a negative effect of the instrumented *OlderThanMean* variable on a startup's likelihood to exit successfully. A one standard deviation increase in lagged US buyout fundraising corresponds to a decrease of 1.78pp (= std. dev. $\times$ instrument coeff. $\times$ instrumented coeff. = $12.587 \times 0.0026 \times -0.545$) in a startup's likelihood to exit successfully or 7.6% compared to the unconditional probability for an exit. Overall, these results provide further evidence for the existence of an entrepreneur selection channel.

[3]We partial out the logarithm of the total deal amount and the number of portfolio companies in the fund at the time of investment controls to ensure a full-rank covariance matrix. Importantly, the Frisch-Waugh-Lovell theorem states that the coefficients of the remaining regressors, including *Fund Older than Mean*, are unaffected by the partialling out in IV estimation.

2.4 Extensions

In our final set of empirical analyses, we address four alternative explanations for our baseline assumptions and results. The first is that funds may engage in 'window dressing' by allocating their most successful startups to younger funds to showcase strong performance to potential investors in subsequent funds. The second is that our assumption of a limited time horizon becomes invalid when cross-investments are possible, namely, when VC firms can offer additional support through subsequent funds. The third alternative explanation is that our results are driven by the VC firm's choice of when to open a new fund. The fourth explanation is that the economic mechanisms underlying our results may be unique to the Israeli market.

2.4.1 'Window Dressing'

The first alternative explanation for our results is that fund managers engage in 'window dressing' (Lakonishok et al., 1991) to make their funds look appealing to potential limited partners (LPs). Many VC firms aim to raise new capital from LPs and open a new fund as they approach the end of the investment period of their current fund. This 'window dressing' behavior incentivizes fund managers to allocate promising investments to young funds, enabling them to present appealing performance to potential investors they hope to attract to the new fund.

Indeed, Gompers (1996) and Chakraborty and Ewens (2018) show that fundraising incentives impact investment decisions at the VC firm and fund levels, respectively. Specifically, Gompers (1996) documents that investments made by younger VC firms are more likely to go public. An important distinction between our study and Gompers (1996) lies in the definition of age: we refer to the age of the fund, whereas Gompers' study refers to the age of the VC firm. Our phenomenon occurs at the fund level, while Gompers' findings pertain to the VC firm level. In Gompers (1996), younger VC firms face greater information asymmetries regarding their quality and use early exits as a signal of quality to build a reputation. In contrast, in our study, younger VC funds have a longer remaining fund life and can, therefore, provide more monitoring and a higher likelihood of follow-on funding to startups. Notably, even an experienced, established VC firm starting a new fund will have that fund's age reset to zero in our setting.

Chakraborty and Ewens (2018) shows that VC firms delay write-offs of and reinvestments in lower-quality portfolio companies at existing funds until after the new fund is raised. In contrast to Chakraborty and Ewens (2018), we analyze exits and follow-on funding of portfolio companies during the entire life of VC funds, and not just around fundraising periods.

This is important because delaying negative information about startups while fundraising should not change the overall likelihood of a startup exiting successfully or raising follow-on funding.

However, such behavior is more likely among young VC funds and less likely among reputable VCs who maintain ongoing relationships with LPs. VCs who engage in 'window dressing' might lose their investors' trust and severely damage their brand as they have a fiduciary duty to maximize their investors' returns, and such behavior would jeopardize their practice.

Nevertheless, we test this possibility by limiting our sample to standalone funds. VC firms that manage only a single fund cannot allocate good opportunities found late in the fund's lifecycle into a new and younger fund. Fund age remains negatively correlated with the likelihood of exiting and the number of follow-on rounds, with coefficient estimates similar in magnitude to those in our baseline regressions (Columns 1 and 2 of Table 6).

2.4.2 Cross-Investments

A second concern is around the validity of our limited time horizon assumption. VC firms with multiple active funds may offer cross-investments to extend their financing and monitoring channels. Among the 1,043 startups in our sample, cross-investments are rare, occurring in only 24 instances across all funding rounds, with 16 (1.5% of all cases) involving VC firms investing in a startup's seed round with one fund and providing additional financing in later rounds with another. Despite the scarcity of cross-investments in the data, it is theoretically possible that the mere option of cross-investments weakens the effect of fund age on startup outcomes.

To address this concern, we limit our sample to VC firms running multiple funds. Coefficients on fund age regressed against exits, and the number of follow-ons from the same fund remain similar in magnitude and statistical significance whether we look at VC firms with more than one fund (Columns 3 and 4 of Table 6), or more than two or three funds (Table A.8 in the Appendix).

2.4.3 Timing of Fund Initiation

A third possible explanation for our results lies in the funds' endogenous decision to initiate new funds. While VC firms likely time the initiation of a new fund based on the availability of an attractive investment opportunity, they cannot alter a fund's age once it begins investing. Therefore, it is possible that the first investment opportunity is what drives our results but not the ones that follow. To address this potential selection bias, we exclude the first investment made by each fund and rerun our analysis. The aim of this approach is to eliminate the effect of the VC firm's decision to start a new fund in response to a specific investment opportunity. Our results remain robust when excluding funds' first investments, implying that endogenous fund initiation timing cannot fully explain our baseline results (Columns 5 and 6 of Table 6).

2.4.4 External Validity

A fourth possible alternative explanation relates to the uniqueness of the Israeli market. The effect of fund age might be unique to Israeli startups due to unknown and unobserved factors. To address this possibility and to test the external validity of our results, we re-run our baseline tests on a sample of VC-backed startups from the United States that we constructed using data from PitchBook. While data from PitchBook are commonly used by papers studying the VC industry (Gompers et al., 2021; Lerner and Nanda, 2023; Yimfor and Garfinkel, 2023, to name a few), these data have several limitations for the context of our study. First, PitchBook does not have the entire universe of VC deals in the US. In contrast, the IVC data contains the near-universe of VC-backed startups in Israel. This is especially important for our mechanism tests. Specifically, having the population of active VC funds and startup exits allows us to precisely define the "*OlderThanMean*" and variable and the industry financial intensity index. Second, we lose 62% of investments by VCs in US startups in the PitchBook data because of missing fund IDs. However, our analysis crucially depends on being able to link investments to VC funds, and not just VC firms, because our identifying variation comes from changes in fund age.

Although the PitchBook data has these limitations in the context of our study, it still allows us to construct the variables needed for our baseline regressions—namely, fund age, exits, and follow-on investments. We follow the same sample construction steps used for the IVC data. The "*PitchBook investment-level dataset*" includes 69,434 investments in 26,411 startups by 6,479 VC funds, and the "PitchBook startup-level dataset" includes 10,849 single-investor seed round investments by 2,729 VC funds, with 33% of startups achieving a successful exit. We find negative and statistically significant correlations between fund age at the time of the initial investment and both the likelihood of exit and follow-on investments, suggesting that our baseline results are not unique to the Israeli market (Columns 7 and 8 of Table 6).

Taken together, these additional analyses reinforce the robustness of our findings, indicating that the negative relationship between fund age and both exit likelihood and follow-on investments is consistent across different contexts and neither driven by potential biases nor unique characteristics of the Israeli market.

3 Model

Our empirical findings point to differences in portfolio company outcomes based on the timing of investment within a VC fund's lifecycle. To formalize the underlying mechanisms, we develop a theoretical model that captures the key channels driving these patterns: the financing channel, the monitoring channel, and the selection channel. The model describes an environment of overlapping generations of VC funds of uniform quality alongside startups that vary in quality. Within this framework, we analyze how younger funds, which can offer more follow-on financing and provide extended monitoring, attract higher-quality startups that anticipate these benefits. The equilibrium sorting emerges as a result of founders' preferences for funds that can offer both financial and non-financial support over a longer horizon.

3.1 Setting

Time is discrete with an infinite horizon. There are two sorts of agents: VC funds and entrepreneurs.

VC Funds

A new VC fund is created in each period. This fund makes active investments over two periods and must liquidate all its positions in the third period. As a result, at any given time, there are three active VC funds: one in its initial investment phase (young), one in its late investment phase (mature), and one in its liquidation phase (liquid).

During the investment phases, the fund operates under a periodic, non-divisible budget constraint of x. This structure reflects staged financing, which, as demonstrated by Kerr et al. (2014), can increase the initiative's expected NPV through the incorporation of a termination option. In addition to financial infusion, the fund creates value by actively monitoring its portfolio of startups. All funds have the same quality and thus provide monitoring of similar value. The model abstracts away from variations in VC fund quality to focus on matching based on fund age, as quality-based matching has been studied previously (Sorensen, 2007; Ewens et al., 2022) and we control it in our empirical setting using fund fixed effects. The fund aims to maximize returns by selling its portfolio companies during the liquidation phase.

Entrepreneurs

In each period, two entrepreneurs launch a startup, one of high quality (type H) and one of low quality (type L). Figure 4 illustrates the stock of startups and funds in each period. Table A.1 in the Appendix summarizes the notation used in the model. Let θ_0 denote the startup's quality when it is launched, where $\theta_0 \in \{\theta_0^H, \theta_0^L\}$ and $\theta_0^H > \theta_0^L$.

Assumption 1. *Once an entrepreneur has matched with a fund, she cannot receive funding from a different fund. If a startup has not matched with a fund, it will not survive to the next period.*

Assumption 1 is motivated by empirical evidence on the persistence of VC investments, as discussed in Section 2.2.2. It implies that a startup can receive up to two monitoring periods and two funding units, depending on when the matching occurred in the fund's lifecycle. Financing and monitoring are expected to increase the value of the startup.

Let $t \in \{0, 1, 2\}$ denote the number of periods since the startup first matched with a fund, and let $\mathbb{I}_t^f$ equal one if the startup receives financing in period t and zero otherwise. We assume that first-time investment always entails financing, namely $\mathbb{I}_0^f = 1$, but follow-on investments will take place only if both agents accept the terms of the contract, namely, $\mathbb{I}_1^f \in \{0, 1\}$. We assume that monitoring is provided in both investment periods $t \in \{0, 1\}$. Specifically, a monitoring unit will be added in the second period, regardless of the agents' decision on whether to pursue a follow-on investment.

Monitoring and financing affect the startup's quality in the following period. Specifically, monitoring or financing provided in period $t-1$ contributes a random component ϵ_t^m or ϵ_t^f, respectively, where $\epsilon_t^m \sim N(\mu^m, \sigma_m^2)$ and $\epsilon_t^f \sim N(\mu^f, \sigma_f^2)$ are independent. The quality of the startup in period t is therefore:

$$\theta_t = \theta_0 + \sum_{i=1}^{t} \left[\epsilon_i^m + \mathbb{I}_{i-1}^f \epsilon_i^f\right] = \theta_{t-1} + \epsilon_t^m + \mathbb{I}_{t-1}^f \epsilon_t^f$$

Assumption 2. *The value of a startup with quality θ_t is $V_t = \exp(\theta_t)$.*

We will denote the initial startup value by $V_0^i = \exp(\theta_0^i)$. Assumption 2 implies that the value of the startup in period $t \geq 1$ can be written as:

$$V_t = V_{t-1} \exp(\epsilon_t^m + \mathbb{I}_{t-1}^f \epsilon_t^f).$$

Thus, given V_{t-1}, the t-period value has a Log-Normal distribution:

$$\ln V_t \sim N\left(\ln V_{t-1} + \mu^m + \mathbb{I}_{t-1}^f \mu^f \,,\, \sigma_m^2 + \mathbb{I}_{t-1}^f \sigma_f^2\right).$$

Namely, Assumption 2 implies that post-investment valuations have a Log-Normal distribution, matching the empirical nature of VC-backed ventures, as documented by Cochrane (2005).

Denote the expected benefits from monitoring and financing by $b^m = E[\exp(\epsilon_t^m)] = \exp(\mu^m + \frac{1}{2}\sigma_m^2)$ and $b^f = E[\exp(\epsilon_t^f)] = \exp(\mu^f + \frac{1}{2}\sigma_f^2)$, respectively. The conditional expected startup value can be written as follows:

$$E\left(V_t \middle| V_{t-1}, \mathbb{I}_{t-1}^f\right) = \begin{cases} V_{t-1} b^m b^f & \text{if there was financing in } t-1 \, (\mathbb{I}_{t-1}^f = 1) \\ V_{t-1} b^m & \text{otherwise } (\mathbb{I}_{t-1}^f = 0). \end{cases}$$

Namely, each period of monitoring is expected to increase the startup's value by a factor of b^m, and each unit of financing is expected to increase the value by a factor of b^f. This implies that the value upon liquidation is affected by whether the entrepreneur and the fund sign their initial contract when the fund is young or mature and on their mutual decision to pursue a follow-on investment.

It is important to note the potential trade-off between the benefit of extending the fund's activity by an additional period and the cost of delaying an exit. In this paper, we focus on the timing constraints imposed by the contractual agreements between VC funds and their limited partners. Consequently, we assume that the added value generated is substantial enough to offset the cost of delaying the exit by one period:

Assumption 3. *Let $R \geq 1$ denote the gross risk-free rate then $b^m, b^f \geq R$.*

For simplicity, we will assume that $R = 1$ from this point onward.

In an extension of the baseline model that incorporates experimentation, which more accurately reflects the dynamics of the VC-entrepreneur relationship (Kerr et al., 2014; Kerr and Nanda, 2015; Manso, 2016), we assume that financing and monitoring enable both the entrepreneur and the fund to better assess the true value of the startup. As in the baseline model, financing and monitoring contribute to the expected value of the startup; however, the added value diminishes over time. Nonetheless, these insights do not alter the main results of the model. For more details, see Appendix B.

Investment Contracts

Entrepreneurs and VC funds may establish three types of contracts; each includes x units of funding: (1) an initial investment contract between a young fund and its matched startup, (2) a follow-on investment contract, and (3) an investment contract between a mature fund and a second startup. We assume that all contracts adhere to a similar structure, consistent with simplified common practices in real-world venture capital agreements. Specifically, we assume an all common-share ownership with no liquidation preferences, so the fund's ownership share is determined by the ratio of the investment amount to the startup's post-money valuation.

The most common contract between entrepreneurs and VCs in practice is of convertible preferred equity. The literature (see Da Rin et al. (2013) for a survey) demonstrates the benefits of these contracts in addressing agency problems like double moral hazard (Casamatta, 2003; Schmidt, 2003; Hellmann, 2006) and incentive mismatches in continuation decisions (Cornelli and Yosha, 2003; Dessi, 2005). In our model, we use a simplified version of contracts, specifically common shares, because our primary focus is not on agency problems or incentive mismatches. Instead, our analysis centers on temporal aspects of the entrepreneur-VC relationship.

Assumption 4. *Given a startup's value at the time of investment, V, an investment contract stipulates that the fund receives a share λ of the startup in exchange for an investment amount x, where $\lambda(V) = \frac{x}{V+x}$.*

The following assumption guarantees that first-time investments are viable, thereby eliminating uninteresting cases:

Assumption 5. *A new startup of type $i \in \{H, L\}$ has an expected positive NPV, even if it is expected to receive only one round of funding and monitoring, namely:*
$E[V_1|V_0^i] - V_0^i - x = V_0^i b^m b^f - V_0^i - x > 0.$

The combination of Assumptions 4 and 5 guarantees that both the fund and the entrepreneur find the first investment beneficial. Namely, the fund prefers to invest in the startup rather than retain x as $\lambda(V_0)E\left[V_1|V_0^i\right] = \frac{xV_0^i b^m b^f}{V_0^i+x} > x$. Additionally, the entrepreneur prefers to forfeit a share $\lambda(V_0)$ of the startup in exchange for an expected increase in its value rather than maintaining full ownership at the startup's initial value $[1-\lambda(V_0)]E\left[V_1|V_0^i\right] = \frac{(V_0^i)^2 b^m b^f}{V_0^i+x} > V_0^i$.

Equilibrium Concept

We study stable matches in this setting by following Gale and Shapley (1962). In our setting, there are four elements that characterize this solution:

1. Strategies of entrepreneurs and funds for deciding when to accept a follow-on investment contract.
2. Entrepreneurs' preferences regarding the age of the fund when establishing the initial investment contract.
3. Funds' preferences regarding the type of startup.

4. Stable matching (Gale and Shapley, 1962) between funds and startups in each period.

We now turn to analyzing each of these elements and show that there is a unique stable match in this model.

3.2 Follow-on Investments

Suppose that when the fund was young, it matched with a startup of type i, and after the first investment, the startup's value is $V_1 = V_0^i \exp\left(\epsilon_1^m + \epsilon_1^f\right)$. Both parties are now contemplating a follow-on investment that will grant the fund an additional ownership share of $\lambda(V_1)$.

The VC fund has two outside options to consider if it decides against a follow-on investment: (1) retain the amount x without making any investment, or (2) reenter the market to match with a new startup of type j for a single period of investment and monitoring before having to liquidate. Given Assumption 5, investing in a new company is always more profitable than not investing. Thus, the fund's outside option is to match with startup j for one period of monitoring and financing, while providing the incumbent startup of type i another period of monitoring. The expected value of the fund's portfolio if it chooses the outside option is thus $\lambda(V_0^i)V_1 b^m + \lambda(V_0^j)V_0^j b^m b^f$. The fund will agree to the follow-on contract if it is expected to yield a higher profit than the outside option, namely if:

$$\left[\lambda(V_0^i) + \lambda(V_1)\right] V_1 b^m b^f > \lambda(V_0^i)V_1 b^m + \lambda(V_0^j)V_0^j b^m b^f. \tag{6}$$

The entrepreneur's alternative to accepting a follow-on contract is to proceed to liquidation with one more period of monitoring and no dilution. The entrepreneur will prefer to take the follow-on investment and relinquish a share $\lambda(V_1)$ of the startup if she expects to derive benefit from additional funding despite the dilution, namely if:

$$\left[1 - \lambda(V_0^i) - \lambda(V_1)\right] V_1 b^m b^f > \left[1 - \lambda(V_0^i)\right] V_1 b^m. \tag{7}$$

The following proposition shows that the entrepreneur and the fund will agree to the follow-on contract only if the current startup value is high enough. Specifically, this occurs when V_1 exceeds a certain threshold determined by the initial stake granted to the fund, $\lambda(V_0^i)$, and the fund's outside option. If rejecting the follow-on investment will allow the fund to match with a new startup of type H, it will require the incumbent startup to have a higher expected quality to pursue a follow-on investment than if the fund's outside option were a type-L startup.

Proposition 1. *Suppose a fund matched with a startup of type $i \in \{H, L\}$ when it was young. In addition, suppose that when it is mature, the fund's outside option is investing in a startup of type $j \in \{H, L\}$. There is a threshold $T^{i,j} \in \mathbb{R}_+$, such that a follow-on investment is profitable for the entrepreneur of startup i and the fund if and only if $V_1 > T^{i,j}$. Furthermore, $T^{i,j}$ is increasing in V_0^j.*

Proof. See Section A.1 in the Appendix.

3.3 Entrepreneurs' Preferences

Recall that entrepreneurs are only matched with a fund once, at the startup's foundation. Therefore, we focus on the entrepreneurs' preferences during this initial stage. If an entrepreneur is matched with a mature fund, she will receive one round of financing and monitoring, with neither an option for a follow-on investment nor an additional monitoring period. Conversely, if an entrepreneur is matched with a young fund, she will benefit from extended monitoring for an additional period and an option for follow-on investment. Both of these additional activities are expected to increase the value of the entrepreneur's share in the startup. Thus, she would prefer to match with a young fund:

Proposition 2. *An entrepreneur prefers to be matched with a young fund rather than a mature one.*

Proof. See Section A.2 in the Appendix.

3.4 Funds' Preferences

The following proposition shows that young funds prefer to be matched with high-value startups. At first glance, this might seem trivial, as higher-value startups are generally expected to yield better returns than lower-valued ones. However, the intertemporal decision-making process for young funds is more nuanced. Young funds must consider the probability of securing a follow-on investment and the expected gains if it is secured. These factors do not necessarily increase with the startup's initial value. For example, if a young fund invests in a higher-type startup, it starts its mature phase holding a smaller share of the company than it would have gotten if it had invested in a lower-value startup ($\lambda(V_0)$ is decreasing in V_0). Thus, it has a smaller incentive to put more resources into that company. It might be the case that the young fund would prefer to invest in the low type to get a bigger share of the company, anticipating higher returns in the follow-on phase. However, in our setting, such a scenario does not occur, and young funds ultimately prefer higher-value startups, due in part to the overall expected gains from follow-on investments:

Proposition 3. *A young fund prefers to be matched with a startup of type H rather than one of type L, irrespective of its outside option in the second investment period.*

Proof. See Section A.3 in the Appendix.

3.5 Stable Matching and Startup Performance in Equilibrium

The following proposition characterizes the unique stable matching in this setting.

Proposition 4. *There is a unique stable matching where the young fund is paired with the high-type startup, and the mature fund, if it seeks a new investment, is paired with the low-type startup.*

Proof. Proposition 2 states that entrepreneurs prefer young funds over mature ones. Proposition 3 shows that young funds prefer high-type startups over low-type ones. Consider the two possible deferred acceptance algorithms (Gale and Shapley, 1962): "entrepreneur proposing" and "fund proposing." In the "entrepreneur proposing" version, both entrepreneurs initially approach their first priority, which is the young fund. The young fund rejects L, so the stable matching is H-young, L-mature. In the "fund proposing" version, the young fund initially approaches H. If the mature fund also approaches H, it is rejected, and in any case, the resulting matching is H-young, L-mature. Since both versions yield the same matching, it is the unique stable matching. □

We now analyze the model's equilibrium outcomes and their interaction with the empirical findings. Specifically, we use the model to illustrate how a fund's age at the time of the initial contract with an entrepreneur influences the startup's performance upon liquidation.

In equilibrium, a startup matched with a mature fund is of a low type and will get one round of funding and monitoring. Thus, the average valuation of such startups upon liquidation is:

$$E[V|\text{matched with mature}] = E[V_1|V_0^L] = V_0^L b^m b^f \tag{8}$$

However, a startup matched with a young fund is of a high type. It will get two monitoring periods and one or two rounds of funding. The average valuation of such startups upon liquidation is:

$$
\begin{aligned}
E[V|\text{matched with young}] = E[V_2|V_0^L] = \\
\Pr(V_1 \leq T^{H,L}|V_0^H)E\left[V_1 b^m \middle| V_1 \leq T^{H,L}, V_0^H\right] + \\
\Pr(V_1 > T^{H,L}|V_0^H)E\left[V_1 b^m b^f \middle| V_1 > T^{H,L}, V_0^H\right] = \\
E\left[V_1 b^m \middle| V_0^H\right] + \Pr\left(V_1 > T^{H,L} \middle| V_0^H\right) E\left(V_1 \middle| V_1 > T^{H,L}, V_0^H\right) b^m \left[b^f - 1\right] = \\
V_0^H (b^m)^2 b^f + \Pr\left(V_1 > T^{H,L} \middle| V_0^H\right) E\left(V_1 \middle| V_1 > T^{H,L}, V_0^H\right) b^m \left[b^f - 1\right] \quad (9)
\end{aligned}
$$

The following proposition formalizes the relationship between fund age and startup performance:

Proposition 5. *$E[V|\text{matched with young}] > E[V|\text{matched with mature}]$*

To prove Proposition 5, note that the difference between (9) and (8) can be decomposed into three components – sorting, monitoring and the option for additional financing:

$$
\begin{aligned}
E[V|\text{matched with young}] - E[V|\text{matched with mature}] = \\
\underbrace{\left[V_0^H - V_0^L\right] b^m b^f}_{Sorting} + \underbrace{V_0^H b^m b^f \left[b^m - 1\right]}_{Monitoring} + \\
\underbrace{\Pr\left(V_1 > T^{H,L} \middle| V_0^H\right) E\left(V_1 \middle| V_1 > T^{H,L}, V_0^H\right) b^m [b^f - 1]}_{Financing} \quad (10)
\end{aligned}
$$

Each of the components in Equation (10) is positive as $b^m > 1$ and $b^f > 1$ (Assumption 3). To achieve this decomposition suppose we take a startup matched with a mature fund and change its type from L to H, but leave it with only one unit of monitoring and financing. The added value from this change is attributed to sorting. Next, we give this hypothetical startup an additional unit of monitoring. The added value from this step is attributed to monitoring. Finally, we provide this hypothetical startup with an option for follow-on investment. The added value from this step is attributed to additional financing. Together, these hypothetical steps add up to the total gap between a startup matched with a young fund and one matched with a mature fund. However, this decomposition is not unique. Since the model is not linear, the order in which sorting, monitoring, and financing are added changes their attributed contributions. The following proposition shows that the contribution of each channel is positive, regardless of the decomposition order.

Proposition 6. *The contribution of each channel–sorting, monitoring, and financing–to the total value difference between a startup matched with a young fund and one matched with a mature fund is positive, regardless of the order in which these channels are added.*

Proof. See Section A.4 in the Appendix.

In conclusion, the model illustrates the underlying forces driving our main empirical findings. Specifically, it shows that fund age is positively correlated with startup performance, with startups matched with younger funds more likely to achieve successful exits. This relationship is driven by three key channels. The financing channel captures the greater flexibility of younger funds in providing follow-on financing, thereby increasing the likelihood of success. The monitoring channel reflects the extended non-financial support that younger funds can offer, improving operational outcomes for startups. Finally, the selection channel emphasizes how higher-quality entrepreneurs are more likely to seek out younger funds, recognizing the value of both financial and non-financial support. Together, these channels explain why investments made earlier in a fund's lifecycle are more likely to lead to better startup performance upon liquidation.

4 Survey

To complement our empirical findings and theoretical framework, we conducted a survey designed to explore how entrepreneurs and investors evaluate the matching process. The survey aims to capture founders' and investors' preferences regarding key fund characteristics such as fund age, available capital for follow-on investments, industry specialization, and mentoring capabilities.

4.1 Survey design and distribution

The survey is structured into three main components:

(a) Ranking of VC Fund Attributes – Participants rank the importance of various VC fund traits, including fund age, capital availability, mentorship, and track record of successful exits.

(b) Scenario-Based Fund Selection – Respondents are presented with hypothetical investment scenarios where they must choose between two VC funds with different attributes (e.g., fund age, capital availability, mentoring quality). The goal is to determine which factors entrepreneurs prioritize when selecting an investor.

(c) Demographics and Experience – Participants provide information on their entrepreneurial background, the number of companies they have founded, and the total amount of VC funding they have raised. This allows us to segment responses based on founder experience and funding history.

The survey was distributed through targeted outreach to founders, both with and without experience in VC-backed startups, as well as to investors working in VC funds. Invitations were initially sent to the authors' personal networks of founders and investors. To ensure a diverse pool of respondents, we expanded our outreach by using social media to solicit participation. The survey was hosted on Qualtrics and took approximately five to ten minutes to complete. Participation was voluntary and anonymous, with responses de-identified. The complete questionnaire can be found in Section C in the Appendix, and summary statistics of the respondents' characteristics can be found in Section D.

4.2 Survey results

Our survey analysis examines responses to hypothetical funding scenarios, where participants prioritize different VC funds when considering a funding round for two types of startups: an online marketing startup expected to become self-sustaining within three years and a quantum computing startup with significant capital requirements. The scenarios aims to assess whether respondents value the embedded option for follow-on investments and long-term monitoring.

In the first scenario (Figure 5), respondents choose between a 1-year-old fund and a 4-year-old fund. Out of a total of 101 participants who completed the survey, the majority are indifferent for the marketing startup (68 selected "Both funds are equally attractive"), but a strong preference emerges for the younger fund in the quantum computing case (69 selected "A 1-year-old fund"). This suggests that while fund age matters, its relevance is primarily driven by the financing channel. When no additional information is provided, respondents show no clear preference for startups with minimal capital needs but strongly associate younger funds with follow-on investment opportunities, supporting our hypothesis that the embedded call option for future funding is more relevant in capital-intensive industries.

In the second scenario (Figure 6), respondents choose between a fund with \$8M in dry powder and one with \$30M. As expected, most participants prioritize the \$30M fund for the quantum computing startup (91 selected "A fund with \$30M in dry powder"), while a majority is indifferent for the marketing startup (54 selected "Both funds are equally attractive").

The third scenario (Figure 7) examines fund age preferences when both funds have limited capital (\$8M in dry powder each). The goal is to assess the value of time when capital is constrained and to provide suggestive evidence for the monitoring channel. While we expect a general preference for the younger fund, this is only observed in the quantum computing case (55 selected "A 1-year-old fund with \$8M in dry powder"). In contrast, most respondents are indifferent when selecting a fund for the marketing startup (69 chose “Both funds are equally attractive”). This suggests that the monitoring channel plays a lesser role when a startup is expected to reach self-sufficiency within a few years.

The fourth scenario (Figure 8) tests revealed preferences when choosing between stronger financing with limited monitoring versus stronger monitoring with limited financing. The results show a clear preference for the financing channel in the quantum computing case (69 selected “A 4-year-old fund with $30M in dry powder”) and a weaker preference in the marketing startup (51 selected “Both funds are equally attractive,” 39 selected “A 4-year-old fund with $30M in dry powder,” and only 11 selected “A 1-year-old fund with $8M in dry powder”). These findings further emphasize the dominant role of the financing channel compared to the monitoring channel.

In the fifth scenario (Figure 9), we move beyond the lifecycle framework to assess the monitoring channel by comparing specialist and generalist funds, regardless of fund size and age. Respondents prefer specialist funds across both startup types, with 41 selecting a specialist fund for the marketing startup and 88 for the quantum startup. This suggests that while monitoring is secondary to financing, it plays a meaningful role in the matching process and is perceived as a valuable proposition offered by VC funds and preferred by entrepreneurs.

The final scenario (Figure 10) explores whether portfolio size influences the matching process. Most respondents are indifferent between a fund with 2 startups and one with 9 in its portfolio (60 for marketing and 47 for quantum selected “Both funds are equally attractive”). A weak preference for larger portfolios emerges in both cases (31 preferred 9 portfolio firms vs. 10 who preferred 2 firms in marketing, and 29 preferred 9 firms vs. 25 who preferred 2 firms in quantum computing). The reasons behind this preference remain unclear, but we hypothesize that either network effects or accumulated experience associated with a larger portfolio outweigh the benefits of intensive mentoring and the option for follow-on investments. Further exploration of this potential mechanism is left for future research.

We conclude the survey by asking respondents to rank five key characteristics of VC funds. As reported in Table A.10, (1) industry specialization, (2) the presence of a reputable investor as a board member, and (3) the VC’s track record of successful exits ranked first and second (tie). This suggests that when explicitly asked, founders and investors prioritize high-quality monitoring over financing, with the amount of available capital ranking only fourth.

Taken together, the survey results highlight the complex trade-offs founders and investors consider when matching. The hypothetical funding scenarios consistently show that financing availability is the dominant factor in fund selection, particularly for capital-intensive startups. Entrepreneurs strongly associate younger funds with greater flexibility for follow-on investments, reinforcing our hypothesis that fund age matters primarily through the financing channel. However, when explicitly ranking VC fund characteristics, respondents prioritize industry specialization, board representation, and track record of successful exits over financing, suggesting that high-quality monitoring is also a key consideration. Our findings suggest that while entrepreneurs prioritize capital when facing direct trade-offs, they still recognize the long-term value of strong industry expertise and governance, particularly when selecting between funds of similar financial strength. These results provide further evidence that both financing and monitoring shape the startup-VC matching process, with their relative importance varying based on the specific decision context.

5 Conclusion

This paper reveals a strong negative correlation between VC fund age at the time of investment and eventual portfolio company outcomes. We attribute this finding to three primary channels: monitoring, financing, and selection. Startups funded earlier in a fund's lifecycle benefit from more sustained mentorship and a greater likelihood of follow-on investments. Consequently, founders of higher-quality startups favor younger funds, resulting in higher-quality ventures getting funded earlier in a fund's lifecycle. These results highlight the importance of fund age in shaping VC investment dynamics and suggest that fund lifecycle constraints materially impact the value proposition offered by VC funds.

Our analysis also underscores the existence of frictions that prevent VC firms from achieving an optimal allocation of resources across their funds' lifecycles. In a frictionless world, VCs could seamlessly hire additional partners and raise capital whenever promising investment opportunities arise. However, our empirical findings indicate that these processes are constrained and thus bear an effect on fund performance over time. Several key frictions contribute to this phenomenon.

First, agency problems and incentive mismatches between LPs and GPs lead to structuring VC funds with a limited lifespan and fixed size. A defined lifespan ensures GPs deploy and return capital within a predictable timeframe, preventing indefinite fee collection and aligning incentives for strong performance. It also helps LPs manage cash flows and mitigate asymmetric information risks by requiring GPs to demonstrate returns within the fund's duration.

Second, VCs face capital-raising constraints that limit their ability to continuously replenish investment pools. Raising a new fund is a lengthy and uncertain process, often requiring strong historical performance, established relationships with LPs, and favorable macroeconomic conditions. As a result, VCs cannot always access new capital when attractive investment opportunities arise. This constraint directly impacts their ability to provide follow-on funding to startups funded later in a fund's life.

Third, human capital constraints hinder VCs' ability to scale their monitoring capacity. While venture firms may expand by hiring additional partners, doing so requires time, effort, and the availability of experienced professionals. Since monitoring and strategic guidance are crucial components of VC value-add, a fund's ability to effectively support its portfolio companies diminishes as existing partners' bandwidth becomes increasingly constrained over time. Our findings that later-stage investments receive less board representation support this explanation, suggesting that monitoring capacity is a scarce resource that cannot be easily expanded.

Overall, our findings demonstrate that VC fund lifecycle constraints significantly shape investment dynamics and outcomes. Frictions related to agency conflicts, capital-raising limitations, and human capital constraints prevent VCs from optimally allocating resources across a fund's lifespan. These limitations affect the matching between funds and entrepreneurs and contribute to the observed decline in investment outcomes over time.

The study indicates that companies which received investment in the later stages of the fund's life received less financial support and mentorship, and therefore may not have realized their full potential. This insight highlights gaps that emerge in the private market and can help focus the efforts of organizations aimed at supporting the development of high-tech companies where private funding and mentorship may be lacking.

Future research could examine how the temporal channels we identify interact, particularly whether financing and monitoring function as substitutes or complements. For instance, additional capital might compensate for less intensive professional monitoring, prompting funds that cannot generate value through monitoring to invest in fewer companies or make larger investments in individual startups. Additionally, understanding how variations in fund quality interact with fund age in the matching process may reveal significant differences in value creation among VC funds.

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Figures

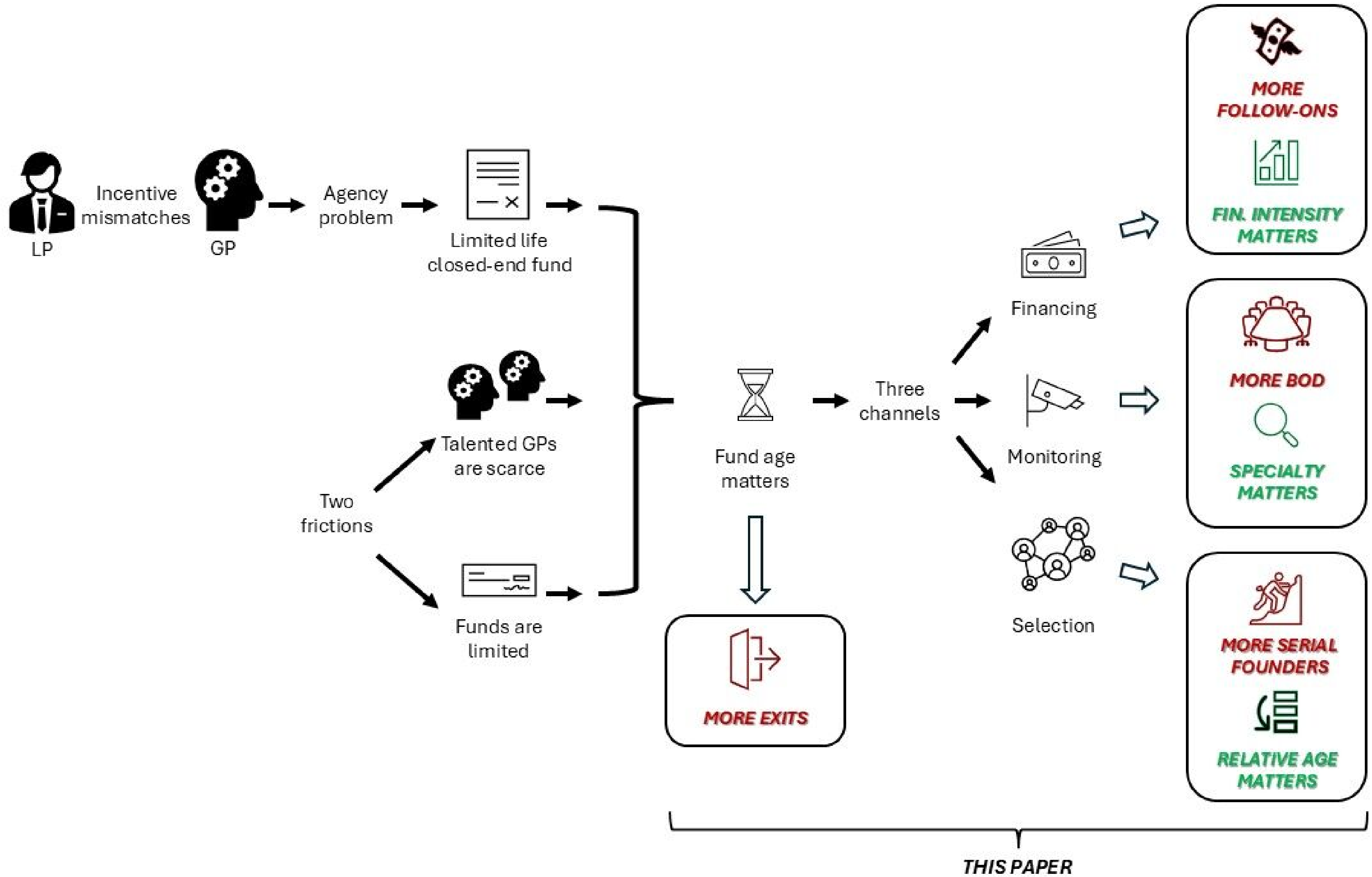

Figure 1. Summary of the mechanisms analyzed in our study. Incentive mismatches generate an agency problem between LPs and GPs. To mitigate this problem, funds adopt a limited-life, closed-end structure, which amplifies two frictions: constrained access to additional capital and high-quality GPs. These frictions make fund age a significant determinant of startup outcomes. Specifically, younger funds provide greater value through three channels: (1) a financing channel, enabling more frequent follow-on investments, identified using the financial intensity index; (2) a monitoring channel, characterized by increased board representation, identified by specialized funds; and (3) a selection channel, where younger funds disproportionately attract serial entrepreneurs, particularly when younger relative to their peers. Collectively, these mechanisms explain why investments made early in a fund's lifecycle are associated with higher probability of successful exits.

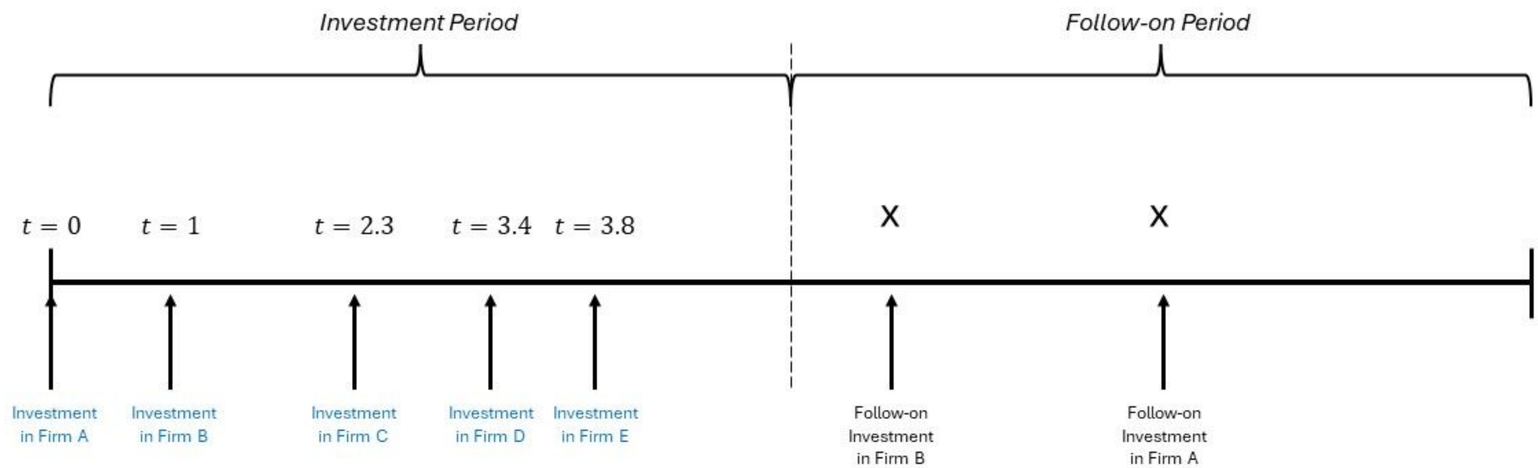

Figure 2. Fund Age. The variable '*Fund Age*' marks the initial investment of each fund as time zero and measures the number of days between that investment and every subsequent investment made by the same fund. These days are then converted into years for analysis, with any follow-on investments excluded from the calculation.

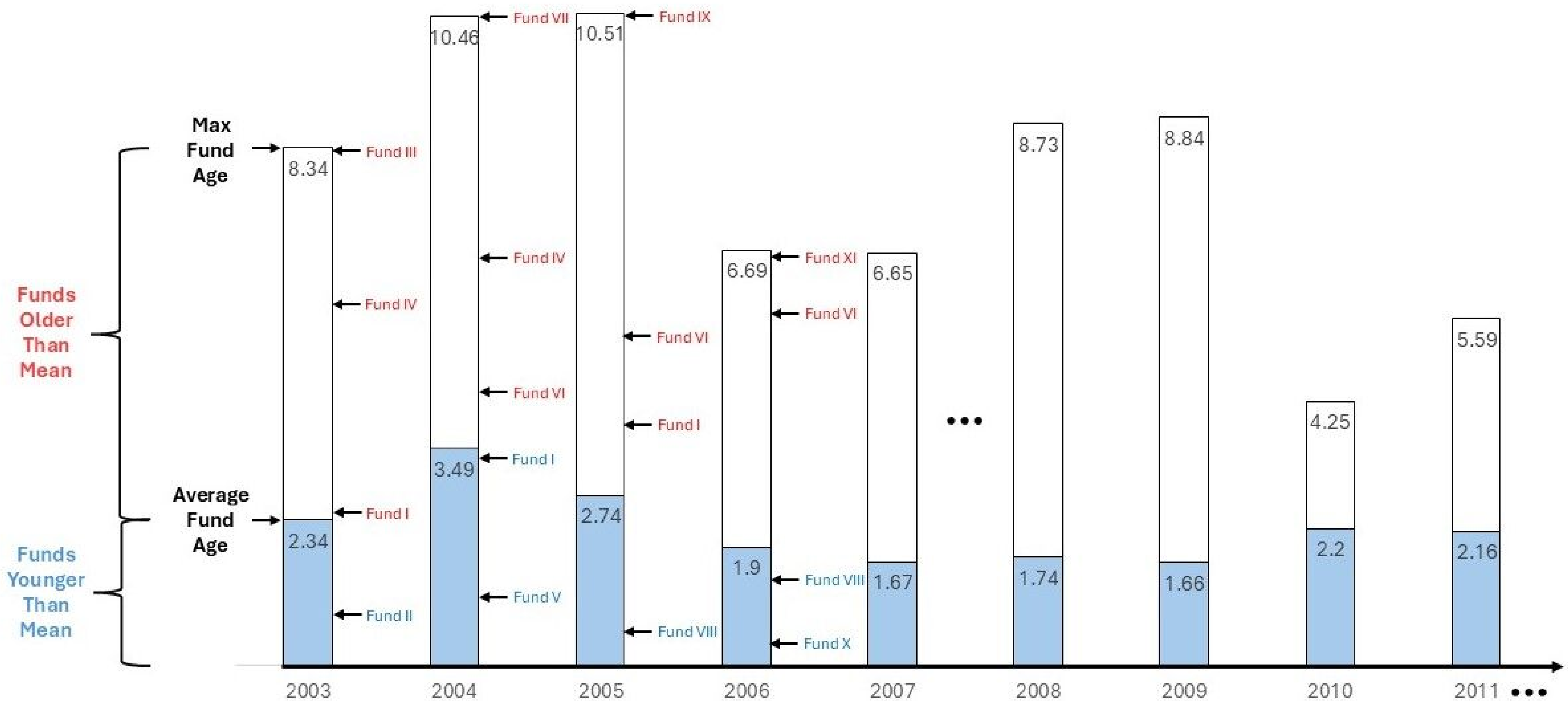

Figure 3. Older than Mean. The variable '*Fund Older than Mean*' is a dummy that flags funds older than the average age of all active funds in a given year. For each year, we identify all active funds, calculate their average age, and classify funds as "old" if they exceed this average. All follow-on investments are excluded from this analysis.

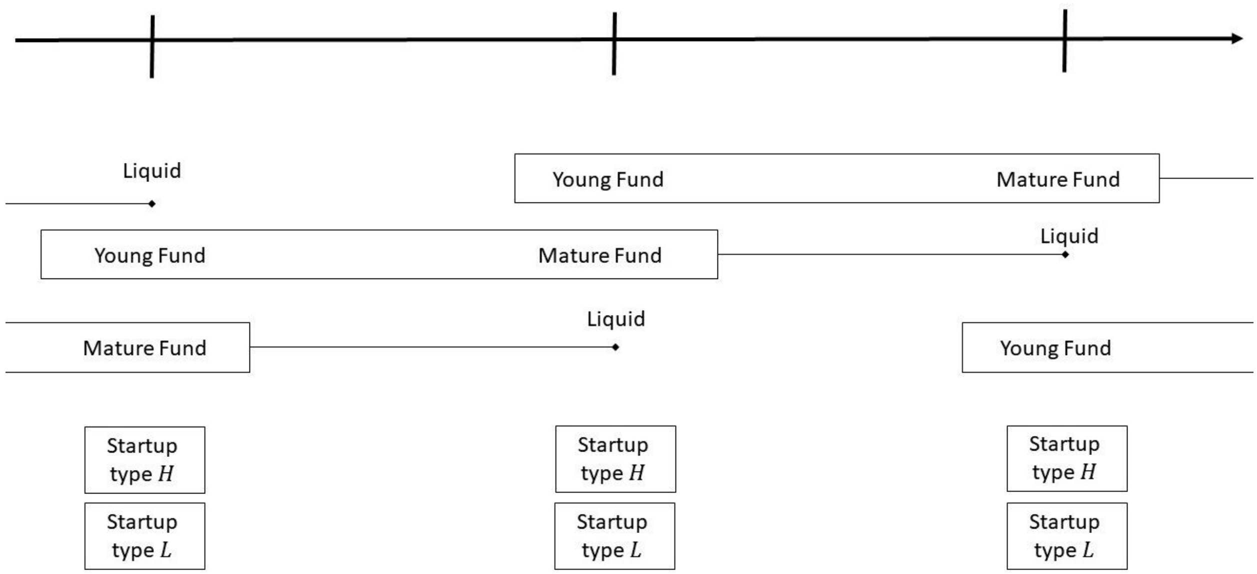

Figure 4. Stock of funds and startups in the model. Each mark on the timeline represents one period. The active status of funds and the entry of new startups are shown below the timeline. "Young", "Mature", and "Liquid" indicate different stages of the fund's life cycle, while "Startup type H" and "Startup type L" represent high-quality and low-quality startup types, respectively.

Tables

Table 1. Summary statistics

This table presents summary statistics for the investment dataset (Panel A) and startup dataset (Panel B).

Panel A: Investment Level - All Rounds					
	N	Exits	IPOs	M&As	
Startups	2,263	525	62	472	
		Num. of Startups per Fund			
	N	Mean	Min	Median	Max
Funds	413	8.76	2.00	7.00	35.00
		Fund Age			
	N	Mean	Min	Median	Max
Deals (Excl. Follow-ons)	3,618	2.00	0.00	1.58	22.00
		Investment Amount ($M)			
	N	Mean	Min	Median	Max
Total	3,618	11.96	0.01	5.00	1,300.00
Seed Round	1,787	5.57	0.01	3.00	600.00
First Round	947	9.30	0.02	5.00	143.00
Second Round	416	14.62	0.02	10.00	100.00
Third Round	236	24.89	0.20	16.00	250.00
Fourth Round	118	53.67	0.30	25.00	1,300.00
Fifth Round	59	50.90	0.10	30.00	250.00
Sixth Round	21	59.24	0.76	38.00	300.00
Seventh Round	10	51.76	2.50	38.00	238.00
Eighth Round	13	58.96	5.00	25.00	200.00
Ninth Round	11	63.03	10.00	46.50	320.00
Panel B: Startup Level - Single Investor, Seed Round Only					
	N	Exits	IPOs	M&As	
Startups	1,043	245	17	232	
		Num. of Startups per Fund			
	N	Mean	Min	Median	Max
Funds	202	5.16	2.00	4.00	25.00
		Fund Age			
	N	Mean	Min	Median	Max
Deals (Excl. Follow-ons)	1,043	1.95	0.00	1.58	15.12
		Num. of Follow-ons			
	N	Mean	Min	Median	Max
Follow-ons	1,088	1.04	0.00	1.00	8.00
		Investment Amount ($M)			
	N	Mean	Min	Median	Max
Seed Rounds	1,043	3.94	0.01	1.80	600.00

Table 2. Comparison of single-VC and multi-VC seed rounds

This table presents descriptive statistics for the key outcome variables in the baseline sample (single-VC investor seed rounds) and multi-VC investor seed rounds. It also shows differences in means between these two datasets and p-values from two-tailed t-tests.

	1 VC in round			>1 VC in round			Difference	
	Mean	SD	N	Mean	SD	N	Diff.	p-val
Deal Amount ($M)	3.938	19.577	1,043	7.521	11.698	392	-3.583	0.001
Deal Amount / Investor ($M)	3.938	19.577	1,043	4.401	8.849	392	-0.463	0.652
Number of Follow-ons	2.451	1.685	1,043	2.492	1.761	392	-0.042	0.680
Exit (%)	0.235	0.424	1,043	0.219	0.414	392	0.016	0.535
Num. of Portfolio Companies	9.233	6.810	1,043	7.927	4.850	392	1.306	0.001

Table 3. Baseline results - Fund age as the variable of interest

OLS regression results. The dependent variable in regressions (1), (3), (5), (7) is a dummy equal one if the startup undergoes an IPO or an M&A ("Exit"). In regression (2), the dependent variable is the number of follow-on investments the startup received. In regressions (4), the dependent variable is a dummy equal one if a partner from the VC firm holds a seat on the startup's board of directors. In regression (6), the dependent variable is a dummy equal one if at least one of a startup's founders was involved in another startup in the five years prior to the current one. *Fund Age* measures the fund's age at the time of investment, *Financial Intensity* is an industry-level inverse exit multiple, *Specialist* is a dummy turning one if the fund is a sector specialist, and *Fund Older than Mean* is a dummy turning one if the fund is older than the average active fund that year. Controls include the logarithm of the total deal amount and the number of portfolio companies in the fund at the time of investment, with fixed effects for deal year, investor country, industry, and fund. The sample includes only seed-stage startups that received investments from a single VC fund, provided the fund had invested in at least two different startups. In regression (4), the sample is further restricted to startups where VC representation on the board has been definitively established. In regression (6), the sample is further restricted to startups for which founder experience is definitively established and to deals starting in 2003. Standard errors clustered at the deal year and investor country levels are shown in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	Baseline	Financing		Monitoring		Selection	
	Exit	Follow-on	Exit	VC Board	Exit	Serial	Exit
Fund Age	-0.0506***	-0.2765***	-0.0156***	-0.0734*	-0.0381***	-0.0829**	-0.0482***
	(0.0073)	(0.0447)	(0.0036)	(0.0280)	(0.0073)	(0.0168)	(0.0066)
Fund Age × Financial Intensity			-0.0211***				
			(0.0047)				
Fund Age × Specialist					-0.0624***		
					(0.0100)		
Fund Older than Mean							-0.0655**
							(0.0189)
Num. of Port. Comp.	-0.0048***	0.0044	-0.0059***	-0.0001	-0.0059***	0.0031	-0.0032***
	(0.0007)	(0.0033)	(0.0008)	(0.0010)	(0.0011)	(0.0022)	(0.0002)
Ln(Deal Amount)	0.0112	0.1174***	0.0108	0.0062	0.0119	0.0449*	0.0114
	(0.0138)	(0.0258)	(0.0132)	(0.0030)	(0.0131)	(0.0146)	(0.0134)
Deal Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Investor Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,043	1,043	1,043	804	1,043	699	1,043
Adj. R^2	0.164	0.169	0.164	0.311	0.167	0.045	0.165

Table 4. Follow on investments regressed against years since inception

OLS regressions examining the number of follow-on investments made by the same fund as a function of the years since the fund's inception. Regression (1) is conducted at the startup level, while regressions (2) and (3) are conducted at the investment level. All models include controls for the logarithm of the deal amount and the number of portfolio companies in the fund at the time of investment. Additionally, regression (2) incorporates the age of the startup at the time of investment. Each model includes fixed effects for deal year, industry, investor country, and fund. Regression (2) further includes round fixed effects, and regression (3) adds startup fixed effects. The analyses include funds with investments in at least two distinct startups and firms backed by at least two different funds when startup fixed effects are applied. Standard errors clustered at the deal year and investor country levels are shown in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	Follow-on	Follow-on	Follow-on
Fund Age	-0.2765***	-0.2589***	-0.3402***
	(0.0447)	(0.0436)	(0.0250)
Num. of Port. Comp.	0.0044	0.0061***	0.0067***
	(0.0033)	(0.0019)	(0.0015)
Ln(Deal Amount)	0.1174***	0.0734***	-0.1753***
	(0.0258)	(0.0174)	(0.0457)
Firm Age on Deal Date		-0.0168***	
		(0.0050)	
Deal Year FE	Yes	Yes	Yes
Investor Country FE	Yes	Yes	Yes
Industry FE	Yes	Yes	No
Fund FE	Yes	Yes	Yes
Round FE	–	Yes	No
Startup FE	–	No	Yes
Observations	1,043	3,618	2,154
Adj. R^2	0.169	0.216	0.820
Sample Level	Startup	Investment	Investment

Table 5. Instrumental variable estimation

2SLS regression results. The dependent variable is a dummy equal one if the startup undergoes an IPO or an M&A ("Exit"). *Fund Older than Mean* is a dummy turning one if the fund is older than the average active fund that year, which we instrument with total US buyout fundraising twelve months prior. *Fund Age* measures the fund's age at the time of investment. Controls include the logarithm of the total deal amount and the number of portfolio companies in the fund at the time of investment, with fixed effects for deal year, investor country, industry, and fund. The sample includes only seed-stage startups that received investments from a single VC fund, provided the fund had invested in at least two different startups. Standard errors clustered at the deal year and investor country levels are shown in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	Exit	
	1st	2nd
Lagged US BO fundraising	0.0026***	
	(0.0007)	
Fund Older than Mean		-0.5452***
		(0.1186)
Controls	Yes	Yes
Deal Year FEs	Yes	Yes
Investor Country FEs	Yes	Yes
Industry FEs	Yes	Yes
Fund FEs	Yes	Yes
Observations	1,043	1,043
Adj. R^2	0.567	-0.133
Instrument F-stat	12.8	

Table 6. Alternative explanations

OLS regression results examining the effects of fund age on follow-on investments and exit outcomes for startups. In regressions (1), (3), (5), and (7), the dependent variable is a dummy equal one if the startup undergoes an IPO, sale, merger, or acquisition ("Exit"). In regressions (2), (4), (6), and (8), the dependent variable is the number of follow-on investments the startup received. The variable *Fund Age* represents the age of the fund at the time of investment. All control for the logarithm of the total deal amount and the number of portfolio companies in the fund at the time of investment. Additionally, regressions (2), (4), (6), and (8), incorporate the age of the startup at the time of investment. Each model includes fixed effects for deal year, industry, investor country, and fund. Regression (2), (4), (6), and (8) further include round fixed effects. The "Startup Level" sample is restricted to seed-stage startups receiving investment from a single VC fund, where the fund has invested in at least two different startups. Regressions (1) and (2) include only standalone funds or single-fund VC firms, (3) and (4) include only multi-fund VC firms, (5) and (6) exclude each fund's first investment, and (7) and (8) use a sample of US startups from PitchBook. Standard errors clustered at the deal year and investor country levels are shown in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	Standalone		Multi-fund VC		No First Inv.		PitchBook	
	Exit	Follow-on	Exit	Follow-on	Exit	Follow-on	Exit	Follow-on
Fund Age	-0.0518*	-0.4243***	-0.0844**	-0.2288***	-0.0763**	-0.3465***	-0.0204***	-0.0523***
	(0.0228)	(0.0963)	(0.0149)	(0.0295)	(0.0223)	(0.0403)	(0.0043)	(0.0109)
Num. of Port. Comp.	-0.0071**	-0.0006	-0.0009*	0.0150***	-0.0012	0.0132***	-0.0006	-0.0059***
	(0.0024)	(0.0039)	(0.0003)	(0.0029)	(0.0042)	(0.0010)	(0.0005)	(0.0003)
Ln(Deal Amount)	0.0066	0.0362	0.0129	0.0854***	0.0094	0.0756***	0.0292***	-0.0108***
	(0.0107)	(0.0303)	(0.0127)	(0.0106)	(0.0119)	(0.0135)	(0.0014)	(0.0027)
Firm Age on Deal Date		0.0040		-0.0254***		-0.0274***		-0.0254***
		(0.0195)		(0.0040)		(0.0027)		(0.0017)
Deal Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Investor Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Round FE	–	Yes	–	Yes	–	Yes	–	Yes
Observations	222	928	812	2,690	923	3,211	10,849	69,434
Adj. R^2	0.122	0.178	0.157	0.208	0.165	0.220	0.303	0.176
Sample Level	Startup	Investment	Startup	Investment	Startup	Investment	Startup	Investment

Appendix

Table A.1. Theoretical and Empirical Models Notation

Panel A: Theoretical Model

Variable	Notation	Description
Type	H, L	Startup type high and low, respectively
Investment	x	Investment made in a financing round
Time	t	Periods since the startup first matched with a fund
Startup Quality	θ_t	Quality of the startup
Contribution to Quality	ϵ_t^m, ϵ_t^f	Contribution to quality in period t through monitoring and financing, respectively
Expected Contribution	μ^m, μ^f	Expected contribution to quality through monitoring and financing, respectively
Variance of Contribution	σ_m^2, σ_f^2	Variance of contribution to quality through monitoring and financing, respectively
Financing Indicator	$\mathbb{I}_t^f$	Equals one if financing was provided in period t
Startup Value	V_t	Value of a startup in period t
Contribution to Value	b^m, b^f	Expected increase in value due to monitoring and financing, respectively
Follow-on Threshold	$T^{i,j}$	A threshold for quality above which a follow-on investment occurs
Risk-Free Rate	R	Gross risk-free rate, assumed to equal 1
Shares	$\lambda(\cdot)$	Ownership share given to investors

Panel B: Empirical Model		
Exits	$\mathbb{I}\{Exit_s\}$	A dummy variable turning one if the startup experienced a successful exit.
Fund Age	$FundAge_s$	Years since inception of the fund
Deal Amount	$Ln(DealAmount)_s$	Total dollar amount invested in a startup by all investors in a specific round of funding
Startup Age	$StartupAge_{s,t}$	Years since a startup received its initial seed investment
Financial Intensity Index	$Fin.Intensity_s$	An industry-level financial intensity measure capturing the inverse of the average investment multiples collapsed at the industry level
Specialist indicator	$\mathbb{I}\{Specialist_v\}$	A dummy variable turning one if the VC fund invested in two or less different industries

A Proofs

A.1 Proof of Proposition 1

Rearranging (6) yields that a fund will make a follow-on investment if and only if:

$$\lambda(V_0^i)[b^f - 1]V_1 + \underbrace{\lambda(V_1)V_1}_{\frac{xV_1}{V_1+x}} b^f > \lambda(V_0^j)V_0^j b^f \tag{11}$$

Note that the left-hand-side of the above equation is increasing in V_1. Thus, there is a threshold $T^F(V_0^i, V_0^j)$ such that (6) holds if and only if $V_1 > T^F$ and T^F is increasing in V_0^i and V_0^j.

Condition (7) for the entrepreneur to accept the contract is met if and only if:

$$\left[1 - \lambda(V_0^i)\right]\left[b^f - 1\right] > \lambda(V_1)b^f \tag{12}$$

Since $\lambda'(V_1) < 0$, there is a threshold $T^E(V_0^i)$ such Condition (7) holds if and only if $V_1 > T^E$, and T^E is decreasing in V_0^i.

Denote $T^{i,j} = \max\left\{T^F(V_0^i, V_0^j), T^E(V_0^i)\right\}$ then both agents agree to the follow-on contract if and only if $V_1 > T^{i,j}$. Furthermore, $T^{i,j}$ increases with V_0^j.

□

A.2 Proof of Proposition 2

If an entrepreneur of type i is matched with a mature fund, she will receive one round of financing and monitoring, with no option for a follow-on investment or additional monitoring period. Her expected profit is therefore given by:

$$U^E(mature|V_0^i) = [1 - \lambda(V_0^i)]E\left[V_1 \middle| V_0^i\right] = [1 - \lambda(V_0^i)]V_0^i b^m b^f. \tag{13}$$

Conversely, if the entrepreneur partners with a young fund that has the option to invest in a type j startup in the subsequent period, startup i will benefit from extended monitoring for an additional period and an option for follow-on investment. According to Proposition 1, a follow-on investment will not occur if $V_1 \leq T^{i,j}$. In this case, the entrepreneur's expected profit is:

$$[1 - \lambda(V_0^i)]V_1 b^m. \tag{14}$$

However, if $V_1 > T^{i,j}$, a follow-on investment will take place and provide the entrepreneur with an expected profit of:

$$[1-\lambda(V_0^i)-\lambda(V_1)]V_1 b^m b^f. \tag{15}$$

Let $G^E(V_1|V_0^i,V_0^j)$ denote the entrepreneur's expected gain from a follow-on investment above and beyond her outside option (see Equations 14 and 15), then:

$$G^E(V_1|V_0^i,V_0^j) \equiv \begin{cases} [1-\lambda(V_0^i)-\lambda(V_1)]V_1 b^m b^f - [1-\lambda(V_0^i)]V_1 b^m & \text{if } V_1 > T^{i,j} \\ 0 & \text{otherwise} \end{cases} \tag{16}$$

The definition of $T^{i,j}$ implies that $G^E(V_1|V_0^i,V_0^j) > 0$ for $V_1 > T^{i,j}$ (see Proposition 1). Thus, $E\left[G^E(V_1|V_0^i,V_0^j)\right] > 0$. In fact, this expression captures the option value of follow-on investment from the entrepreneur's point of view.

The expected profit for an entrepreneur matched with a young fund is therefore:

$$\begin{aligned}
&U^E(young|V_0^i,V_0^j) = \\
&\quad [1-\lambda(V_0^i)]E\left[V_1 b^m \middle| V_1 \leq T^{i,j}, V_0^i\right] \Pr\left(V_1 \leq T^{i,j} \middle| V_0^i\right) + \\
&\quad E\left([1-\lambda(V_0^i)-\lambda(V_1)]V_1 b^m b^f \middle| V_1 > T^{i,j}, V_0^i\right) \Pr\left(V_1 > T^{i,j} \middle| V_0^i\right) = \\
&\quad E\left[[1-\lambda(V_0^i)]V_1 b^m + G^E(V_1|V_0^i,V_0^j) \middle| V_1 \leq T^{i,j}, V_0^i\right] \Pr\left(V_1 \leq T^{i,j} \middle| V_0^i\right) + \\
&\quad E\left([1-\lambda(V_0^i)]V_1 b^m + G^E(V_1|V_0^i,V_0^j) \middle| V_1 > T^{i,j}, V_0^i\right) \Pr\left(V_1 > T^{i,j} \middle| V_0^i\right) = \\
&\quad E\Big([1-\lambda(V_0^i)]V_1 b^m + G^E(V_1|V_0^i,V_0^j) \Big| V_0^i\Big) = \\
&\quad [1-\lambda(V_0^i)]E[V_1|V_0^i]b^m + E\left[G^E(V_1|V_0^i,V_0^j)\right] = \\
&\quad U^E(mature|V_0^i)b^m + E\left[G^E(V_1|V_0^i,V_0^j)\right]
\end{aligned} \tag{17}$$

where $b^m > 1$ captures the value of an additional period of monitoring and $E\left[G^E(V_1|V_0^i,V_0^j)\right] > 0$ is the follow-on option value.

□

A.3 Proof of Proposition 3

Suppose the young fund's outside option when it is mature is match with a startup of type j. Suppose the fund matched with a startup of type i when it was young, and after the first investment, the startup's value is V_1. According to Proposition 1, a follow-on investment will not take place if $V_1 \leq T^{i,j}$. In this case, the fund will invest x in its outside option - the type-j startup. The expected value of this outside option, given V_1, is:

$$\lambda(V_0^i)V_1 b^m + \lambda(V_0^j)V_0^j b^m b^f - x. \tag{18}$$

However, if $V_1 > T^{i,j}$, a follow-on investment will take place and provide the fund with an expected profit of:

$$[\lambda(V_0^i) + \lambda(V_1)]V_1 b^m b^f$$

Let $G^F(V_1|V_0^i, V_0^j)$ denote the fund's expected gain above and beyond its outside option (18), then:

$$G^F(V_1|V_0^i, V_0^j) \equiv \begin{cases} [\lambda(V_0^i) + \lambda(V_1)]V_1 b^m b^f - \lambda(V_0^i)V_1 b^m - \lambda(V_0^j)V_0^j b^m b^f & \text{if } V_1 > T^{i,j} \\ 0 & \text{otherwise} \end{cases} \tag{19}$$

Now, let us consider the fund's incentives when it is young. Its expected profit from investing in type i is:

$$\begin{aligned} &\Pr(V_1 \leq T^{i,j}|V_0^i)\left[\lambda(V_0^i)E\left(V_1 b^m b^f \middle| V_1 \leq T^{i,j}, V_0^i\right) + \lambda(V_0^j)V_0^j b^m b^f\right] + \\ &\quad \Pr(V_1 > T^{i,j}|V_0^i)E\left([\lambda(V_0^i) + \lambda(V_1)]V_1 b^m b^f \middle| V_1 > T^{i,j}, V_0^i\right) - 2x = \\ &\quad \lambda(V_0^i)E\left[V_1 \middle| V_0^i\right] b^m + \lambda(V_0^j)V_0^j b^m b^f + E\left[G^F(V_1|V_0^i, V_0^j)\right] - 2x = \\ &\quad\quad \lambda(V_0^i)V_0^i(b^m)^2 b^f + \lambda(V_0^j)V_0^j b^m b^f + E\left[G^F(V_1|V_0^i, V_0^j)\right] - 2x \end{aligned} \tag{20}$$

Lemma 7. *The function $\lambda(V)V = \frac{xV}{x+V}$ is increasing in V.*

Lemma 7 implies that the first argument in (20) is increasing in V_0^i. It remains to show that $F(V_0^i) \equiv E\left[G^F(V_1|V_0^i, V_0^j)\right]$ is also increasing in V_0^i.

Recall that given V_0, the value V_1 is Log-Normal. Its probability density function is $\frac{1}{\sigma V_1}\phi\left(\frac{\ln V_1 - \ln V_0^i - c}{\sigma}\right)$, where $c \equiv \mu^m + \mu^f$ and $\sigma^2 \equiv \sigma_m^2 + \sigma_f^2$. Thus,

$$\begin{aligned} &F(V_0^i) = E\left[G^F(V_1|V_0^i, V_0^j)\right] = \\ &\quad \int_{T^{i,j}}^{\infty} G^F(V_1|V_0^i, V_0^j)\frac{1}{\sigma V_1}\phi\left(\frac{\ln V_1 - \ln V_0^i - c}{\sigma}\right) dV_1 \overset{\substack{substitution \\ V_1 = V_0^i \exp(c+\sigma z)}}{=} \\ &\quad \int_{\frac{\ln T^{i,j} - \ln V_0^i - c}{\sigma}}^{\infty} G^F\left(V_0^i \exp(c+\sigma z)\middle| V_0^i, V_0^j\right) \frac{\sigma V_0^i \exp(c+\sigma z) dz}{\sigma V_0^i \exp(c+\sigma z)}\phi(z) = \\ &\quad\quad \int_{\frac{\ln T^{i,j} - \ln V_0^i - c}{\sigma}}^{\infty} G^F\left(V_0^i \exp(c+\sigma z)\middle| V_0^i, V_0^j\right)\phi(z)\, dz \end{aligned}$$

Following the Leibniz integral rule:

$$F'(V_0^i) = \underbrace{-G^F(T^{i,j}|V_0^i, V_0^j)\phi\left(\frac{\ln T^{i,j} - \ln V_0^i - c}{\sigma}\right)\frac{\frac{\partial}{\partial V_0^i}\left(\ln T^{i,j} - \ln V_0^i\right)}{\sigma}}_{A} +$$
$$\underbrace{\int_{\frac{\ln T^{i,j} - \ln V_0^i - c}{\sigma}}^{\infty} \frac{\partial}{\partial V_0^i} G^F\left(V_0^i \exp(c + \sigma z)\middle|V_0^i, V_0^j\right)\phi\left(z\right)dz}_{B} \quad (21)$$

As for argument A in Equation (21), there are two possibilities. If $T^{i,j} = T^F(V_0^i, V_0^j)$ then by definition, $G^F(T^F) = 0$ and argument A nullifies. Otherwise, $T^{i,j} = T^E(V_0^i)$, in which case $\frac{\partial T^{i,j}}{\partial V_0^i} < 0$ (see proof of Proposition 1), which implies that $\frac{\partial}{\partial V_0^i}\left(\ln T^{i,j} - \ln V_0^i\right) = \frac{1}{T^{i,j}}\frac{\partial T^{i,j}}{\partial V_0^i} - \frac{1}{V_0^i} < 0$ and argument A is positive.

The positivity of argument B will follow from showing that $\frac{\partial}{\partial V_0^i}\left[G^F\left(V_0^i \exp(c + \sigma z)\middle|V_0^i, V_0^j\right)\right] > 0$ for $z > \frac{\ln T^{i,j} - \ln V_0^i - c}{\sigma}$. In that region:

$$G^F\left(V_0^i \exp(c + \sigma z)\middle|V_0^i, V_0^j\right) =$$
$$[\lambda(V_0^i) + \lambda(V_0^i \exp(c+\sigma z))]V_0^i \exp\left(c + \sigma z\right)b^m b^f - \lambda(V_0^i)V_0^i \exp\left(c + \sigma z\right)b^m - \lambda(V_0^j)V_0^j b^m b^f =$$
$$\lambda(V_0^i)V_0^i \exp(c + \sigma z)m[f-1] + \lambda(V_0^i \exp(c+\sigma z))V_0^i \exp(c+\sigma z)b^m b^f - \lambda(V_0^j)V_0^j b^m b^f$$

Lemma 7 implies that $\lambda(V_0^i)V_0^i$ and $\lambda(V_0^i \exp(c+\sigma z))V_0^i \exp(c+\sigma z)$ are increasing in V_0^i, so $G^F\left(V_0^i \exp(c + \sigma z)\middle|V_0^i, V_0^j\right)$ is also increasing in V_0^i.

□

A.4 Proof of Proposition 6

Note that $\ln V_1 \sim N\left(\ln V_0 + \mu^m + \mu^f\,,\, \sigma_m^2 + \sigma_f^2\right)$, so

$$\Pr\left(V_1 > T^{H,L}\middle|V_0^H\right)E\left(V_1\middle|V_1 > T^{H,L}, V_0^H\right) = V_0^H b^m b^f \tilde{\Phi}^H,$$

where $\tilde{\Phi}^i \equiv \Phi\left(\frac{\ln V_0^i + \mu^m + \mu^f + \sigma_m^2 + \sigma_f^2 - \ln T^{H,L}}{\sqrt{\sigma_m^2 + \sigma_f^2}}\right)$.[4] Thus, the expected value of a startup matched with a young fund equals:

[4]In all the decompositions we hold the threshold for follow on investment, $T^{H,L}$ constant.

$E[V|\text{matched with young}] =$

$$V_0^H (b^m)^2 b^f + \Pr\left(V_1 > T^{H,L} \middle| V_0^H\right) E\left(V_1 \middle| V_1 > T^{H,L}, V_0^H\right) b^m \left[b^f - 1\right] =$$
$$V_0^H (b^m)^2 b^f + \tilde{\Phi}^H V_0^H (b^m)^2 b^f \left[b^f - 1\right]. \quad (22)$$

We wish to compare this expression to the expected value of a startup matched with a mature fund:

$$E[V|\text{matched with mature}] = V_0^L b^m b^f \quad (23)$$

To simplify subsequent calculations, we divide Equations (22) and (23) by $b^m b^f$ and study the scaled the difference in startup valuations. That is, we study the difference between the following two expressions:

$$V_0^H b^m + \tilde{\Phi}^H V_0^H b^m \left[b^f - 1\right] - V_0^L. \quad (24)$$

Table A.2 presents the six possible orderings of the three channels—sorting, monitoring, and financing—and the expected startup valuation after each channel is added. In each row, Columns 1 and 4 display the scaled value of a startup matched with a mature fund and a young fund, respectively. The rows differ based on the sequence of "steps" required to transition between these two values. For instance, Row I corresponds to the ordering SMF as described in the main text (Equation 10). Column 2 shows the expected value after changing the startup type in Column 1 from L to H. Column 3 displays the value after adding an additional unit of monitoring to the value in Column 2. Column 4 shows the value after adding a follow-on investment option to the value in Column 3. Therefore, in Row I, the contribution of sorting is defined by the difference between Columns 2 and 1, the contribution of monitoring is the difference between Columns 3 and 2, and the contribution of financing is the difference between Columns 4 and 3.

Next, we turn to show that in each ordering, the contribution of all three channels is positive.

Sorting: Note that in Rows I-III, the contribution of sorting is proportional to $V_0^H - V_0^L$ which is positive. In Rows IV-VI, the contribution of sorting is proportional to:

$$\left[V_0^H - V_0^L\right] + [b^f - 1]\left[\tilde{\Phi}^H V_0^H - \tilde{\Phi}^L V_0^L\right]$$

where all the expressions within any set of square brackets are positive because $V_0^H > V_0^L$, $b^f > 1$ (Assumption 3), and $\tilde{\Phi}^H > \tilde{\Phi}^L$.

Monitoring: In all rows, the contribution of monitoring is proportional to b^m and thus positive.

Financing: In all rows, the contribution of financing is proportional to $b^f - 1$ which is positive (Assumption 3).

$\square$

Table A.2. Expected Startup Valuation for Different Channel Orderings

The table presents the six possible orderings of the three channels–sorting (S), monitoring (M), and financing (F)–and the expected startup valuation after each channel is added. Each row is labeled with a three-letter code representing the order in which the channels are applied. Columns 1 and 4 display the scaled values of a startup matched with a mature fund and a young fund, respectively (Equation 24). Each column displays the value after the relevant channel is applied to the value in the previous column. For example, Column 2 shows the expected value after the first channel is applied to the value in Column 1. The contribution of each channel is defined by the difference between the columns, which depends on the ordering of the channels in each row.

	Order	(1)	(2)	(3)	(4)
(I)	S M F	V_0^L	V_0^H	$V_0^H b^m$	$V_0^H b^m + \tilde{\Phi}^H V_0^H b^m \left[b^f - 1\right]$
(II)	S F M	V_0^L	V_0^H	$V_0^H + \tilde{\Phi}^H V_0^H \left[b^f - 1\right]$	$V_0^H b^m + \tilde{\Phi}^H V_0^H b^m \left[b^f - 1\right]$
(III)	M S F	V_0^L	$V_0^L b^m$	$V_0^H b^m$	$V_0^H b^m + \tilde{\Phi}^H V_0^H b^m \left[b^f - 1\right]$
(IV)	M F S	V_0^L	$V_0^L b^m$	$V_0^L b^m + \tilde{\Phi}^L V_0^L b^m \left[b^f - 1\right]$	$V_0^H b^m + \tilde{\Phi}^H V_0^H b^m \left[b^f - 1\right]$
(V)	F S M	V_0^L	$V_0^L + \tilde{\Phi}^L V_0^L \left[b^f - 1\right]$	$V_0^H + \tilde{\Phi}^H V_0^H \left[b^f - 1\right]$	$V_0^H b^m + \tilde{\Phi}^H V_0^H b^m \left[b^f - 1\right]$
(VI)	F M S	V_0^L	$V_0^L + \tilde{\Phi}^L V_0^L \left[b^f - 1\right]$	$V_0^L b^m + \tilde{\Phi}^L V_0^L b^m \left[b^f - 1\right]$	$V_0^H b^m + \tilde{\Phi}^H V_0^H b^m \left[b^f - 1\right]$

Table A.3. OLS robustness tests - Fund age as the variable of interest

OLS regression results. The dependent variable in regressions (1)-(5) is a dummy equal one if the startup undergoes an IPO, sale, merger, or acquisition (”Exit”). *Fund Age* measures the fund’s age at the time of investment. All regressions control for the logarithm of the total deal amount. Additionally, regressions include deal year, investor country, industry, fund fixed effects, and the number of portfolio companies, as mentioned in the table. The sample includes only seed-stage startups that received investments from a single VC fund, provided the fund had invested in at least two different startups. Standard errors clustered at the deal year and investor country levels are shown in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	Exit	Exit	Exit	Exit	Exit
Fund Age	-0.0072*	-0.0050*	-0.0043*	-0.0706***	-0.0506***
	(0.0041)	(0.0022)	(0.0019)	(0.0078)	(0.0073)
Ln(Deal Amount)	0.0321**	0.0403***	0.0360***	0.0120	0.0112
	(0.0129)	(0.0080)	(0.0079)	(0.0126)	(0.0138)
Num. of Port. Comp.					-0.0048***
					(0.0007)
Deal Year FE	Yes	Yes	Yes	Yes	Yes
Investor Country FE	No	Yes	Yes	Yes	Yes
Industry FE	No	No	Yes	Yes	Yes
Fund FE	No	No	No	Yes	Yes
Observations	1,151	1,149	1,149	1,043	1,043
Adj. R^2	0.090	0.101	0.122	0.164	0.164

Table A.4. Logit robustness tests - Fund age as the variable of interest

Logit regression results. The dependent variable in regressions (1)-(5) is a dummy equal one if the startup undergoes an IPO, sale, merger, or acquisition ("Exit"). *Fund Age* measures the fund's age at the time of investment. All regressions control for the logarithm of the total deal amount. Additionally, regressions include deal year, investor country, industry, fund fixed effects, and the number of portfolio companies, as mentioned in the table. The sample includes only seed-stage startups that received investments from a single VC fund, provided the fund had invested in at least two different startups. Standard errors clustered at the deal year level are shown in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	Exit	Exit	Exit	Exit	Exit
Fund Age	-0.0599**	-0.0413	-0.0466*	-0.6574**	-0.5543*
	(0.0245)	(0.0257)	(0.0282)	(0.3019)	(0.3306)
Ln(Deal Amount)	0.2158***	0.2781***	0.2690***	0.0612	0.0614
	(0.0817)	(0.0869)	(0.0945)	(0.1030)	(0.1057)
Num. of Port. Comp.					-0.0216
					(0.0368)
Deal Year FE	Yes	Yes	Yes	Yes	Yes
Investor Country FE	No	Yes	Yes	Yes	Yes
Industry FE	No	No	Yes	Yes	Yes
Fund FE	No	No	No	Yes	Yes
Observations	1,151	1,142	1,142	659	659

Table A.5. Board member representation and fund age

OLS regression results. The dependent variable is a dummy equal one if a partner from the VC firm holds a seat on the startup's board of directors. *Fund Age* measures the fund's age at the time of investment. *Fund Older than Mean* is a dummy turning one if the fund is older than the average active fund that year. *Serial Entrepreneur* is a dummy turning one if at least one of the startup's founders was involved in another startup in the five years prior to the current one. Controls include the logarithm of the total deal amount and the number of portfolio companies in the fund at the time of investment, with fixed effects for deal year, investor country, industry, and fund. The sample consists of seed-stage startups that received investments from a single VC fund, provided the fund had invested in at least two different startups. In regression (1), the sample is restricted to startups where VC representation on the board has been definitively established. In regression (2), the sample is further restricted to startups for which founder experience is definitively established. Standard errors clustered at the deal year and investor country levels are shown in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	VC Board Seat	VC Board Seat
Fund Age	-0.0713*	-0.1339**
	(0.0286)	(0.0287)
Num. of Port. Comp.	0.0019	0.0032
	(0.0010)	(0.0015)
Ln(Deal Amount)	0.0066**	0.0275**
	(0.0022)	(0.0058)
Fund Older than Mean	-0.0717**	-0.0326
	(0.0235)	(0.0287)
Serial Entrepreneur		-0.0272*
		(0.0092)
Deal Year FE	Yes	Yes
Investor Country FE	Yes	Yes
Industry FE	Yes	Yes
Fund FE	Yes	Yes
Observations	804	632
Adj. R^2	0.312	0.327

Table A.6. Board member representation and exits

OLS regression results. The dependent variable is a dummy equal one if the startup undergoes an IPO or an M&A ("Exit"). The independent variable is a dummy equal one if a partner from the VC firm holds a seat on the startup's board of directors. *Serial Entrepreneur* is a dummy turning one if at least one of the startup's founders was involved in another startup in the five years prior to the current one. Controls include the logarithm of the total deal amount and the number of portfolio companies in the fund at the time of investment, with fixed effects for deal year, investor country, industry, and fund. The sample consists of seed-stage startups that received investments from a single VC fund, provided the fund had invested in at least two different startups. The sample is restricted to startups where VC representation on the board has been definitively established. In regression (3) and (4), the sample is further restricted to startups for which founder experience is definitively established. Standard errors clustered at the deal year and investor country levels are shown in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	Exits	Exits	Exits	Exits
VC Board Seat	0.0720***	0.0699***	0.1003***	0.1004***
	(0.0053)	(0.0099)	(0.0126)	(0.0037)
Ln(Deal Amount)	0.0104	0.0108	-0.0020	-0.0025
	(0.0123)	(0.0146)	(0.0094)	(0.0061)
Fund Age		-0.0257**	0.0063	
		(0.0085)	(0.0082)	
Num. of Port. Comp.		-0.0046**	-0.0037	
		(0.0015)	(0.0059)	
Serial Entrepreneur			-0.0061	-0.0056
			(0.0258)	(0.0233)
Deal Year FE	Yes	Yes	Yes	Yes
Investor Country FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes	Yes
Observations	804	804	614	614
Adjusted R^2	0.125	0.125	0.137	0.140

Table A.7. Serial entrepreneur robustness tests

OLS regression results. The dependent variable in regression (1) is the logarithm of the total deal amount. In regression (2), it is the number of follow-on investments the startup received. In (3), it is a dummy equal one if the startup undergoes an IPO or an M&A ("Exit"). *Fund Age* measures the fund's age at the time of investment, *Financial Intensity* is an industry-level inverse exit multiple, *Specialist* is a dummy turning one if the fund is a sector specialist, and *Fund Older than Mean* is a dummy turning one if the fund is older than the average active fund that year. Controls include the logarithm of the total deal amount and the number of portfolio companies in the fund at the time of investment, with fixed effects for deal year, investor country, industry, and fund. The sample includes only seed-stage startups that received investments from a single VC fund, provided the fund had invested in at least two different startups. The sample is also restricted to startups for which founder experience is definitively established and to deals starting in 2003. Standard errors clustered at the deal year and investor country levels are shown in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	Deal Amount	Follow-on	Exit
Serial Entrepreneur	0.2076**	0.1387**	0.0099
	(0.0561)	(0.0268)	(0.0434)
Num. of Port. Comp.	0.0095	-0.0057	-0.0053
	(0.0117)	(0.0064)	(0.0026)
Ln(Deal Amount)		0.1617***	-0.0109
		(0.0152)	(0.0074)
Deal Year FE	Yes	Yes	Yes
Investor Country FE	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes
Observations	699	699	699
Adj. R^2	0.570	0.139	0.140

Table A.8. Cross-Investments

OLS regression results examining the effects of fund age on follow-on investments and exit outcomes for startups. In regressions (1) and (3), the dependent variable is a dummy equal one if the startup undergoes an IPO, sale, merger, or acquisition ("Exit"). In regressions (2) and (4), the dependent variable is the number of follow-on investments the startup received. The variable *Fund Age* represents the age of the fund at the time of investment. All control for the logarithm of the total deal amount and the number of portfolio companies in the fund at the time of investment. Additionally, regressions (2) and (4) incorporate the age of the startup at the time of investment. Each model includes fixed effects for deal year, industry, investor country, and fund. Regression (2) and (4), further include round fixed effects. The sample is restricted to seed-stage startups receiving investment from a single VC fund, where the fund has invested in at least two different startups. Regression (1) and (2) include only multi-fund VC firms with at least two active funds, and (3) and (4) with at least three. Standard errors clustered at the deal year and investor country levels are shown in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	Multi-fund>2		Multi-fund>3	
	Exit	Follow-on	Exit	Follow-on
Fund Age	-0.0648	-0.2243***	-0.1348***	-0.1895**
	(0.0333)	(0.0368)	(0.0129)	(0.0419)
Num. of Port. Comp.	-0.0017	0.0159**	0.0032*	0.0158*
	(0.0017)	(0.0040)	(0.0009)	(0.0060)
Ln(Deal Amount)	0.0110	0.0968***	0.0162	0.1266***
	(0.0169)	(0.0094)	(0.0156)	(0.0142)
Firm Age on Deal Date		-0.0305**		-0.0403***
		(0.0080)		(0.0080)
Deal Year FE	Yes	Yes	Yes	Yes
Investor Country FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes	Yes
Round FE	–	Yes	–	Yes
Observations	707	2,166	479	1,463
Adj. R^2	0.142	0.186	0.143	0.193
Sample Level	Startup	Investment	Startup	Investment

B Model with Experimentation

The model presented in this section extends our baseline model to an environment where VC funds and entrepreneurs engage in experimentation to determine the true value of a startup. We explore the equilibrium sorting in this market and demonstrate that, similar to the baseline model, it is characterized by VC funds closer to inception matching with higher-quality startups. Proofs of all propositions in this section are available upon request from the authors.

B.1 Setting

Time is discrete with an infinite horizon. There are two sorts of agents: VC funds and entrepreneurs.

VC Funds

A new VC fund is created in each period. This fund makes active investments over two periods and must liquidate all its positions in the third period. As a result, at any given time, there are three active VC funds of equal quality: one in its initial investment phase (young), one in its late investment phase (mature), and one in its liquidation phase (liquid).

In its investment phases, the fund operates under a periodic non-divisible budget constraint of x. Additionally, the fund creates value by actively monitoring its portfolio of startups. The fund aims to maximize its potential profit by increasing the returns from its portfolio companies in the liquidation phase.

Entrepreneurs

In each period, two new entrepreneurs launch a startup, one of high potential (type H) and one of low potential (type L). The quality of each startup, denoted by θ, is initially uncertain but is drawn from a known distribution:

$$\theta \sim N\left(\mu_0^i, \gamma_0^{-1}\right), \quad i \in \{H, L\},$$

where $\mu_0^H > \mu_0^L$.

The belief about the startup's quality determines its market value. Specifically, the value of a startup with expected quality μ is $V(\mu) = \exp(\mu)$. As will be made clear later, the assumption that valuations are exponential in μ implies that post-investment valuations have a Log-Normal distribution as documented by Cochrane (2005).

Assumption 6. *Once an entrepreneur has matched with a fund, she cannot receive funding from a different fund. If a startup has not matched with a fund, it will not survive to the next period.*

Assumption 6 implies that a startup can get up to two periods of monitoring and two funding units, depending on when the matching occurred in the fund's lifecycle.

Financing and monitoring enable the entrepreneur to realize her true potential by providing signals about the startup's quality. These signals arrive at the beginning of the subsequent period. Each unit of funding is valued at x and produces a signal $s^f \sim N\left(\theta, \frac{1}{\gamma^f}\right)$, and each period of monitoring generates a signal $s^m \sim N\left(\theta, \frac{1}{\gamma^m}\right)$. Conditional on θ, these signals are drawn independently of each other and across time. The signals are observable to both the entrepreneur and the fund, eliminating asymmetric information regarding the startup's quality. Following numerous discussions with venture capitalists and entrepreneurs, we depart from the more common assumption of information asymmetry between agents. These conversations highlighted themes similar to those in Gornall and Strebulaev (2022), which notes that "VC is a high-touch form of financing" and that, once invested, venture capitalists are deeply involved in a startup's daily operations. In all our discussions, VCs were consistently portrayed as highly engaged investors who, in addition to providing funding, dedicate approximately one-third of their time to working with their portfolio companies and understanding their businesses.

Let $t \in \{0, 1, 2\}$ denote the number of periods since the startup first matched with a fund, and let μ_t and γ_t denote the mean and precision of the startup's quality at the beginning of period t. During period t, the startup receives one unit of monitoring and up to one unit of funding. Let $\mathbb{I}_t^f$ equal one if the startup receives financing in period t and zero otherwise. We assume that first-time investment always entails financing, namely $\mathbb{I}_0^f = 1$, but follow-on investments will take place only if both agents accept the terms of the contract, namely, $\mathbb{I}_1^f \in \{0, 1\}$. A monitoring unit will be added in the second period regardless of the agents' decision on whether to pursue a follow-on investment.

After the signals resulting from t-period monitoring and financing are received (s_{t+1}^m and s_{t+1}^f, respectively), the entrepreneur and the fund use Bayesian inference to update their belief about the startup's quality to $N(\mu_{t+1}, \gamma_{t+1}^{-1})$, where:

$$\mu_{t+1} = \frac{\gamma_t \mu_t + \gamma^m s_{t+1}^m + \mathbb{I}_t^f \gamma^f s_{t+1}^f}{\gamma_t + \gamma^m + \mathbb{I}_t^f \gamma^f}, \quad \gamma_{t+1} = \gamma_t + \gamma^m + \mathbb{I}_t^f \gamma^f. \tag{25}$$

The evolution of beliefs depends on whether the entrepreneur and the fund sign their initial contract when the fund is young or mature and on their mutual decision to pursue a follow-on investment.

Note that given the t-period belief $N(\mu_t, \gamma_t^{-1})$ and $\mathbb{I}_t^f$, the next period's mean quality μ_{t+1} is normally distributed around μ_t:

$$\mu_{t+1}|(\mu_t, \gamma_t, \mathbb{I}_t^f) \sim N\left(\mu_t, \sigma^2_{t+1|\mathbb{I}_t^f}\right), \tag{26}$$

where:

$$\sigma^2_{t+1|\mathbb{I}_t^f} = Var\left(\mu_{t+1}\middle|\mu_t, \gamma_t, \mathbb{I}_t^f\right)$$

Since we assumed that $\mathbb{I}_0^f = 1$, we will sometimes abbreviate the notation by using $\sigma_1^2 \equiv \sigma^2_{1|1}$.

Recall that $V(\mu_{t+1}) = \exp(\mu_{t+1})$. Thus, conditional on t-period information, the value of the startup in period $t+1$ is Log-Normally distributed with a mean of:

$$E\left[V(\mu_{t+1})\middle|\mu_t, \mathbb{I}_t^f\right] = \exp\left(\mu_t + \tfrac{1}{2}\sigma^2_{t+1|\mathbb{I}_t^f}\right). \tag{27}$$

This characterization is consistent with the empirical findings in Cochrane (2005), which document a log-normal distribution of VC realized returns.

Equation (27) shows that an additional period of a match between a fund and an entrepreneur increases the startups value by a factor of $\exp(\frac{1}{2}\sigma^2_{t+1|\mathbb{I}_t^f})$. This added value arises from the informational gains of monitoring and financing operations. However, information gains exhibit decreasing returns to scale: the more information acquired in the past, the less valuable the next signal becomes. In our context, this is reflected in the decrease of $\sigma^2_{t+1|\mathbb{I}_t^f}$ over time, as $\sigma_1^2 > \sigma^2_{2|\mathbb{I}_1^f}$:

Lemma 8. $\sigma^2_{t+1|\mathbb{I}_t^f} = \frac{\gamma^m + \mathbb{I}_t^f \gamma^f}{\left(\gamma_t + \gamma^m + \mathbb{I}_t^f \gamma^f\right)\gamma_t}$ *and* $\sigma_1^2 > \sigma^2_{2|1} > \sigma^2_{2|0}$.

This property of decreasing informational gains may create a trade-off between benefiting from information and incurring the cost of delaying an exit. In this paper, we focus on the timing restrictions imposed by the contractual agreements of VC funds and their limited partners. Therefore, we assume that within the limited lifecycle of the fund, information gains do not decrease to the point where delaying an exit by one more period is not worthwhile. Specifically, let $R \geq 1$ denote the gross risk-free rate. We assume that the added value of monitoring in the second period is substantial enough to compensate for delaying the exit by one period:

Assumption 7. $\exp(\frac{1}{2}\sigma^2_{2|0}) = \exp\left(\frac{\gamma^m}{2(\gamma_0 + 2\gamma^m + \gamma^f)^2}\right) \geq R.$

Given Lemma 8, Assumption 7 ensures that the benefits of financing and monitoring outweigh the delay costs throughout the fund's lifecycle. For simplicity, we will assume that $R = 1$ from this point onward.

Investment Contracts

Entrepreneurs and VC funds may establish three types of contracts; each includes x units of funding: (1) an initial investment contract between a young fund and its matched startup, (2) a follow-on investment contract, and (3) an investment contract between a mature fund and a second startup. We assume that all contracts adhere to a similar structure, consistent with simplified common practices in real-world venture capital agreements. Specifically, we assume an all common-share ownership with no liquidation preferences, so the fund's ownership share is determined by the ratio of the investment amount to the startup's post-money valuation.[5]

Assumption 8. *Given that the expected quality of a startup at the time of investment is* μ_t, *an investment contract stipulates that the fund receives a share* $\lambda(\mu_t)$ *of the startup in exchange for an investment amount* x, *where* $\lambda(\mu_t) = \frac{x}{V(\mu_t)+x} = \frac{x}{\exp(\mu_t)+x}$.

The following assumption guarantees that first-time investments are viable, thereby eliminating uninteresting cases:

Assumption 9. *A new startup of type* $i \in \{H, L\}$ *has an expected positive NPV, even if it is expected to receive only one round of funding and monitoring, namely:*

$$\exp\left(\mu_0^i + \tfrac{1}{2}\sigma_1^2\right) - \exp(\mu_0^i) - x > 0. \tag{28}$$

The combination of Assumptions 8 and 9 guarantees that both the fund and the entrepreneur find the first investment beneficial. Namely, the fund prefers to invest in the startup rather than retain x as:

$$\lambda(\mu_0^i) E\left[V(\mu_1) \middle| \mu_0^i\right] = \frac{x \exp\left(\mu_0^i + \frac{1}{2}\sigma_1^2\right)}{\exp(\mu_0^i) + x} > x. \tag{29}$$

Additionally, the entrepreneur prefers to forfeit a share $\lambda(\mu_0^i)$ of the startup in exchange for an expected increase in its value rather than maintaining full ownership at the startup's initial value:

$$[1 - \lambda(\mu_0^i)] E\left[V(\mu_1) \middle| \mu_0^i\right] = \frac{\exp(\mu_0^i) \exp\left(\mu_0^i + \frac{1}{2}\sigma_1^2\right)}{\exp(\mu_0^i) + x} > \exp(\mu_0^i). \tag{30}$$

[5] The most common contract between entrepreneurs and VCs in practice is of convertible preferred equity. The literature (see Da Rin et al. (2013) for a survey) demonstrates the benefits of these contracts in addressing agency problems like double moral hazard (Casamatta, 2003; Schmidt, 2003; Hellmann, 2006) and incentive mismatches in continuation decisions (Cornelli and Yosha, 2003; Dessi, 2005). In our model, we use a simplified version of contracts, specifically common shares, because our primary focus is not on agency problems or incentive mismatches. Instead, our analysis centers on temporal aspects of the entrepreneur-VC relationship.

Equilibrium Concept

We study stable matches in the this setting, following Gale and Shapley (1962). In our setting, there are four elements that characterize this solution:

1. Strategies of entrepreneurs and funds for deciding when to accept a follow-on investment contract.
2. Entrepreneurs' preferences regarding the age of the fund when establishing the initial investment contract.
3. Funds' preferences regarding the type of startup in each investment period.
4. Stable matching (Gale and Shapley, 1962) between funds and startups in each period.

We now turn to analyzing each of these elements and show that there is a unique equilibrium in this model.

B.2 Follow-on Investments

Suppose that after the first investment, the mean of the startup's quality was updated to μ_1. Both parties are now contemplating a follow-on investment that will grant the fund an additional ownership share of $\lambda(\mu_1)$.

The VC fund has two outside options to consider if it decides against a follow-on investment: (1) retain the amount x without making any investment, or (2) reenter the market to match with a new startup of type j for a single period of investment and monitoring before having to liquidate. Given Assumption 9, investing in a new company is always more profitable than not investing. Thus, the expected value of the fund's outside option is:

$$\lambda(\mu_0^i) \exp\left(\mu_1 + \tfrac{1}{2}\sigma_{2|0}^2\right) + \lambda(\mu_0^j) \exp\left(\mu_0^j + \tfrac{1}{2}\sigma_1^2\right). \tag{31}$$

The fund will agree to the follow-on contract if it is expected to yield a higher profit than the outside option, namely if:

$$[\lambda(\mu_0^i) + \lambda(\mu_1)] \exp\left(\mu_1 + \tfrac{1}{2}\sigma_{2|1}^2\right) > \lambda(\mu_0^i) \exp\left(\mu_1 + \tfrac{1}{2}\sigma_{2|0}^2\right) + \lambda(\mu_0^j) \exp\left(\mu_0^j + \tfrac{1}{2}\sigma_1^2\right). \tag{32}$$

The entrepreneur's alternative to accepting a follow-on contract is to proceed to liquidation with one additional period of monitoring and no additional financing, which is expected to yield $[1 - \lambda(\mu_0^i)] \exp\left(\mu_1 + \frac{1}{2}\sigma_{2|0}^2\right)$. The entrepreneur will prefer to take the follow-on investment if:

$$\left[1 - \lambda(\mu_0^i) - \lambda(\mu_1)\right] \exp\left(\mu_1 + \tfrac{1}{2}\sigma_{2|1}^2\right) > \left[1 - \lambda(\mu_0^i)\right] \exp\left(\mu_1 + \tfrac{1}{2}\sigma_{2|0}^2\right). \tag{33}$$

The following proposition shows that the entrepreneur and the fund will agree to the follow-on contract only if they are sufficiently optimistic about the startup's quality. Specifically, this occurs when μ_1 exceeds a certain threshold determined by the fund's outside option. If rejecting the follow-on investment will allow the fund to match with a new startup of type H, it will require the incumbent startup to have a higher expected quality to pursue a follow-on investment than if the fund's outside option were a type-L startup.

Proposition 9. *Suppose a fund matched with a startup of type $i \in \{H, L\}$ when it was young. In addition, suppose that when it is mature, the fund's outside option is investing in a startup of type $j \in \{H, L\}$. There exists a threshold $T^{i,j} \in \mathbb{R}$, such that a follow-on investment is profitable for the entrepreneur of startup i and the fund if and only if the belief about startup i in period 1 satisfies $\mu_1 > T^{i,j}$. Furthermore, these thresholds satisfy $T^{i,H} \geq T^{i,L}$.*

B.3 Entrepreneurs' Preferences

Recall that entrepreneurs are only matched with a fund once, at the startup's foundation. Therefore, we focus on the entrepreneurs' preferences during this initial stage. If an entrepreneur is matched with a mature fund, she will receive one round of financing and monitoring, with no option for a follow-on investment or additional monitoring period.

Conversely, if the entrepreneur partners with a young fund, she will benefit from extended monitoring for an additional period and an option for follow-on investment. Both of these additional activities are expected to increase the value of the entrepreneur's share in the startup. Thus, she would prefer to match with a young fund:

Proposition 10. *An entrepreneur prefers to be matched with a young fund than a mature one.*

B.4 Funds' Preferences

The following proposition shows that young funds prefer to be matched with high-quality startups. At first glance, this might seem trivial, as higher-quality startups are generally expected to yield better returns than lower-quality ones. However, the intertemporal decision-making process for young funds is more nuanced. Young funds must also consider the informational gains from their initial investments, which are not necessarily higher for higher-quality startups. Additionally, they must consider the probability of securing a follow-on investment and the expected gains if it is secured. For example, it might be that two different L-type investments are more advantageous to the fund than a single H-type investment followed by a follow-on. However, in our setting, informational gains and follow-on investment considerations all align and contribute to funds' preference for higher quality startups:

Proposition 11. *A young fund prefers to be matched with a startup of type H rather than one of type L, irrespective of its outside option in the second investment period.*

B.5 Stable Matching and Startup Performance in Equilibrium

The following proposition characterizes the unique stable matching in this setting.

Proposition 12. *There is a unique stable matching where the young fund is paired with the high-type startup, and the mature fund, if it seeks a new investment, is paired with the low-type startup.*

We can now analyze the equilibrium outcomes of the model, which will serve as our main prediction for the empirical analysis. Specifically, our model sheds light on how the fund's age at the time of the initial contract with an entrepreneur relates to the startup's performance upon liquidation.

In equilibrium, a startup matched with a mature fund is of a low type and will get one round of funding and monitoring. Thus, the average valuation of such startups is:

$$E[V|\text{matched with mature}] = \exp\left(\mu_0^L + \tfrac{1}{2}\sigma_1^2\right) \tag{34}$$

However, a startup matched with a young fund is of a high type. It will get two monitoring periods and one or two rounds of funding. The average valuation of such startups is:

$$\begin{aligned} E[V|\text{matched with young}] &= \exp\left(\mu_0^H + \tfrac{1}{2}\sigma_1^2 + \tfrac{1}{2}\sigma_{2|0}^2\right) + \\ &\Pr\left(\mu_1 > T^{H,L}\middle|\mu_0^H\right) E\left(\exp(\mu_1)\middle|\mu_1 > T^{H,L}\right)\left[\exp\left(\tfrac{1}{2}\sigma_{2|1}^2\right) - \exp\left(\tfrac{1}{2}\sigma_{2|0}^2\right)\right] \end{aligned} \tag{35}$$

The following proposition captures the main prediction we will test in the data:

Proposition 13. $E[V|\textit{matched with young}] > E[V|\textit{matched with mature}]$

To prove Proposition 13, note that the difference between (35) and (34) can be decomposed into three components – sorting, additional monitoring, and additional financing:

$$
\begin{aligned}
&E[V|\text{matched with young}] - E[V|\text{matched with mature}] = \\
&\qquad \exp\left(\tfrac{1}{2}\sigma_1^2\right)\Bigg(\underbrace{\left[\exp(\mu_0^H) - \exp(\mu_0^L)\right]}_{Sorting} + \underbrace{\exp\left(\mu_0^H\right)\left[\exp\left(\tfrac{1}{2}\sigma_{2|0}^2\right) - 1\right]}_{Addtional\,monitoring} + \\
&\qquad\qquad \underbrace{\Phi\left(\frac{\mu_0^H + \sigma_1^2 - T^{H,L}}{\sigma_1}\right)\exp\left(\mu_0^H\right)\left[\exp\left(\tfrac{1}{2}\sigma_{2|1}^2\right) - \exp\left(\tfrac{1}{2}\sigma_{2|0}^2\right)\right]}_{Addtional\,financing}\Bigg). \qquad (36)
\end{aligned}
$$

Each of the components in Equation (36) is positive since $\mu_0^H > \mu_0^L$, $\sigma_{2|0}^2 > 0$ and $\sigma_{2|1}^2 > \sigma_{2|0}^2$. The decomposition to these three components is based on the following mental exercise: Suppose we take a startup matched with a mature fund and change its type from L to H, but leave it with only one unit of monitoring and financing. The added value from this change is attributed to sorting. Next, we give this hypothetical startup an additional unit of monitoring. The added value from this step is attributed to monitoring. Finally, we provide this hypothetical startup with an option for follow-on investment. The added value from this step is attributed to additional financing. Together, these hypothetical steps add up to the total gap between a startup matched with a young fund and one matched with a mature fund. However, this decomposition is not unique. Since the model is not linear, the order in which sorting, monitoring, and financing are added changes their attributed contributions. The following proposition shows that the contribution of each channel is positive, regardless of the decomposition order.

Proposition 14. *The contribution of each channel–sorting, monitoring, and financing–to the total value difference between a startup matched with a young fund and one matched with a mature fund is positive, regardless of the order in which these channels are added.*

C Survey Questions

We invite you to participate in a brief, anonymous survey designed for entrepreneurs. Your insights will help us understand how startup founders engage with venture capital (VC) funds. This survey is part of an international research project conducted by scholars worldwide. **The survey is short and should take approximately 5 minutes to complete.**

Important Notes:

- Participation is voluntary and anonymous.
- The collected data will be used solely for research purposes and will not be shared or sold for commercial use.
- Data will be de-identified and may be stored and distributed for future academic research.
- You may stop answering the survey at any time.

For any questions, please contact Jonathan Zandberg via email: `jonzand@wharton.upenn.edu`. By continuing, you agree to participate in the research.

Q1: Rank the importance of each factor in your decision to consider venture capital funding

	5 Not at all Important	4 Slightly Important	3 Moderately Important	2 Very Important	1 Extremely Important
The VC fund's available capital for future rounds of funding	☐	☐	☐	☐	☐
The VC fund's ability to mentor your company	☐	☐	☐	☐	☐
The age of the VC fund (time elapsed since fund inception)	☐	☐	☐	☐	☐

Q2: Scenario-Based Fund Selection

Your friend is an entrepreneur seeking advice. In each scenario, you will be presented with two VC funds. **Both are managed by experienced and well-connected partners who have already invested in many successful companies in the past.** Each fund offers your friend $1M for 15% of the company. Your friend's startup will be in one of two industries: Online Marketing, which has begun generating revenue and aims to bootstrap within three years, or Quantum Computing, which will require additional funding rounds to reach a self-sustaining stage. **A one-year-old fund typically has about nine years remaining** until the VC is contractually obligated to return capital to the fund's investors, while **a four-year-old fund has only six years remaining.**
Please select the fund you would recommend to your friend in each scenario.

Scenario I:

	A 1-year-old fund	A 4-year-old fund	Both funds are equally attractive
Online marketing startup	☐	☐	☐
Quantum computing startup	☐	☐	☐

Scenario II:

	A fund with $30M in dry powder	A fund with $8M in dry powder	Both funds are equally attractive
Online marketing startup	☐	☐	☐
Quantum computing startup	☐	☐	☐

** **Dry powder** refers to a fund's unallocated capital available for new opportunities and follow-on investments in existing portfolio companies.*

Scenario III:

	A 4-year-old fund with \$8M in dry powder	A 1-year-old fund with \$8M in dry powder	Both funds are equally attractive
Online marketing startup	☐	☐	☐
Quantum computing startup	☐	☐	☐

Scenario IV:

	A 4-year-old fund with \$30M in dry powder	A 1-year-old fund with \$8M in dry powder	Both funds are equally attractive
Online marketing startup	☐	☐	☐
Quantum computing startup	☐	☐	☐

Scenario V:

	A sector specialist	A generalist fund	Both funds are equally attractive
Online marketing startup	☐	☐	☐
Quantum computing startup	☐	☐	☐

* ***A specialist fund*** *invests in a specific industry. In contrast,* ***a general fund*** *invests in all types of companies.*

Scenario VI: Prior Investments

	Fund invested in 2 startups	Fund invested in 9 startups	Both funds are equally attractive
Online marketing startup	☐	☐	☐
Quantum computing startup	☐	☐	☐

* *Remember that both funds are run by experienced partners who have made* ***many successful investments in the past****.*

Q3: Rank the following VC fund characteristics in order of importance (1 = most important, 5 = least important)

- The VC's track record of successful exits: __________
- The fund's specialization in a specific industry/sector: __________
- The amount of capital available for follow-on investments: __________
- The support services offered by the fund (e.g., HR, legal, etc.): __________
- The offering of a reputable investor as a board member: __________

Q4: What additional VC fund traits or attributes are important when considering funding? (Optional)

____

Q5: How many companies have you founded or co-founded?

- 0 (I primarily invest in startups)
- 0 (I am neither an investor nor an entrepreneur)
- 1
- 2
- 3+

Q6: What is the total amount you have raised from VC funds across all ventures? (Optional)

- \$0 – No VC funding pursued
- \$0 – Tried but not yet secured VC funding
- \$1 - Up to \$1M
- \$1M - Up to \$5M
- \$5M - Up to \$10M
- \$10M or more

Q7: Enter the year your first company was established (Optional)

____

Q8: In which country is your current company's headquarters located? (Optional)

____

Q9: In which industry or industries does your latest company operate? (Select all that apply)

- Internet
- Cleantech
- Communications
- Life Sciences (including Health and Biotech)
- Semiconductors
- Other Manufacturing
- I am NOT an entrepreneur
- Other

Q10: How old are you?

- Under 18
- 18-24 years old
- 25-34 years old
- 35-44 years old
- 45-54 years old
- 55-64 years old
- 65+ years old

Q11: How do you describe yourself?

- Male
- Female
- Non-binary / third gender
- Prefer to self-describe
- Prefer not to say

D Summary of survey respondents characteristics

A total of 101 participants completed the survey, including 17 venture capitalists, 37 first-time founders, 41 serial entrepreneurs, and 6 who did not disclose their backgrounds. Among the respondents, 76 identified as male, 22 as female, and 3 chose not to disclose their gender. In terms of age distribution, 31 participants were between 25 and 34 years old, 37 were between 35 and 44, and 20 were between 45 and 54.

Of the 65 founders who reported the location of their startup's headquarters, 34 are based in Israel, 25 in the United States, 4 in the United Kingdom, 1 in Australia, and 1 in Colombia. Among the 68 founders who pursued VC funding, 38 secured more than \$10M, 10 raised between \$5M and \$10M, 7 obtained between \$1M and \$5M, 7 secured less than \$1M, and 6 attempted but have not yet secured any VC funding. In terms of industry experience, 27 respondents operated in the internet sector, 14 in life sciences, 4 in cleantech, 4 in communications, 3 in semiconductors, 3 in manufacturing, and 39 in other industries.

The first survey question used a Likert scale to assess the importance of three VC fund characteristics: the fund's available capital for future rounds, its ability to mentor startups, and its age at the time of investment. Respondents ranked each characteristic on a scale from 1 to 5, with 1 being "Extremely important" and 5 being "Not at all Important." The primary purpose of this question was to direct respondents' attention to these three factors before presenting them with hypothetical scenarios.

As reported in Table A.9, in the overall ranking across all participants, available capital was rated the most important factor with an average score of 2.584, followed by the fund's ability to mentor startups at 2.663, and fund age at 3.455. However, these differences in mean scores are not statistically significant. Notably, there are differences in how various subgroups prioritize mentoring versus financing. Investors, first-time founders, and female participants ranked the fund's mentoring ability as the most important factor, while entrepreneurs, serial founders, and male participants placed greater emphasis on the fund's available capital for follow-on investments, ranking it first.

Table A.9. Likert scale on participants preferences

All	N=101		
Category	**Rank**	**Mean**	**Std. Dev.**
VC fund's available capital for future rounds of funding	1	2.584	0.941
VC fund's ability to mentor your company	2	2.663	1.116
Age of the VC fund (time elapsed since fund inception)	3	3.455	0.922
Investor	N=17		
VC fund's ability to mentor your company	1	2.059	0.899
VC fund's available capital for future rounds of funding	2	2.235	1.033
Age of the VC fund (time elapsed since fund inception)	3	3.294	0.772
Entrepreneur	N=78		
VC fund's available capital for future rounds of funding	1	2.705	0.913
VC fund's ability to mentor your company	2	2.782	1.101
Age of the VC fund (time elapsed since fund inception)	3	3.513	0.964
First Time	N=37		
VC fund's ability to mentor your company	1	2.703	0.812
VC fund's available capital for future rounds of funding	2	2.811	1.050
Age of the VC fund (time elapsed since fund inception)	3	3.595	0.927
Serial	N=41		
VC fund's available capital for future rounds of funding	1	2.610	0.771
VC fund's ability to mentor your company	2	2.854	1.315
Age of the VC fund (time elapsed since fund inception)	3	3.439	1.001
Male	N=76		
VC fund's available capital for future rounds of funding	1	2.592	0.912
VC fund's ability to mentor your company	2	2.684	1.146
Age of the VC fund (time elapsed since fund inception)	3	3.487	0.931
Female	N=22		
VC fund's ability to mentor your company	1	2.455	0.912
VC fund's available capital for future rounds of funding	2	2.591	1.054
Age of the VC fund (time elapsed since fund inception)	3	3.364	0.953

E Survey Responses

Figure 5. Scenario 1: Fund Age

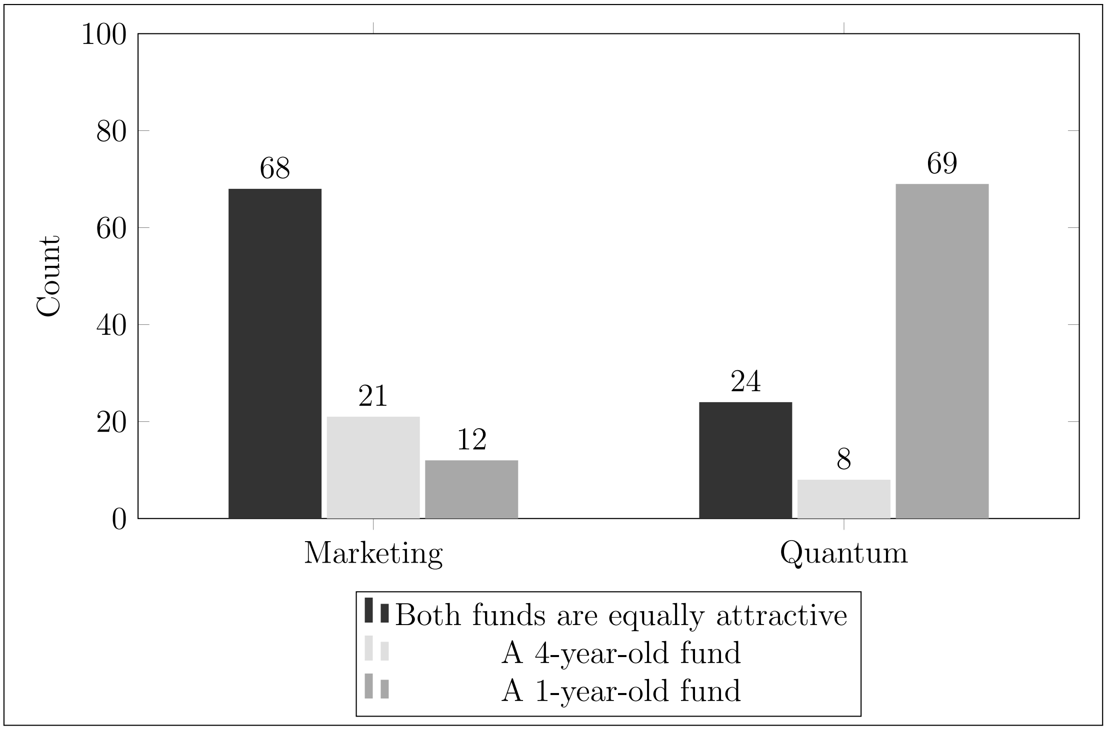

Figure 6. Scenario 2: Financing

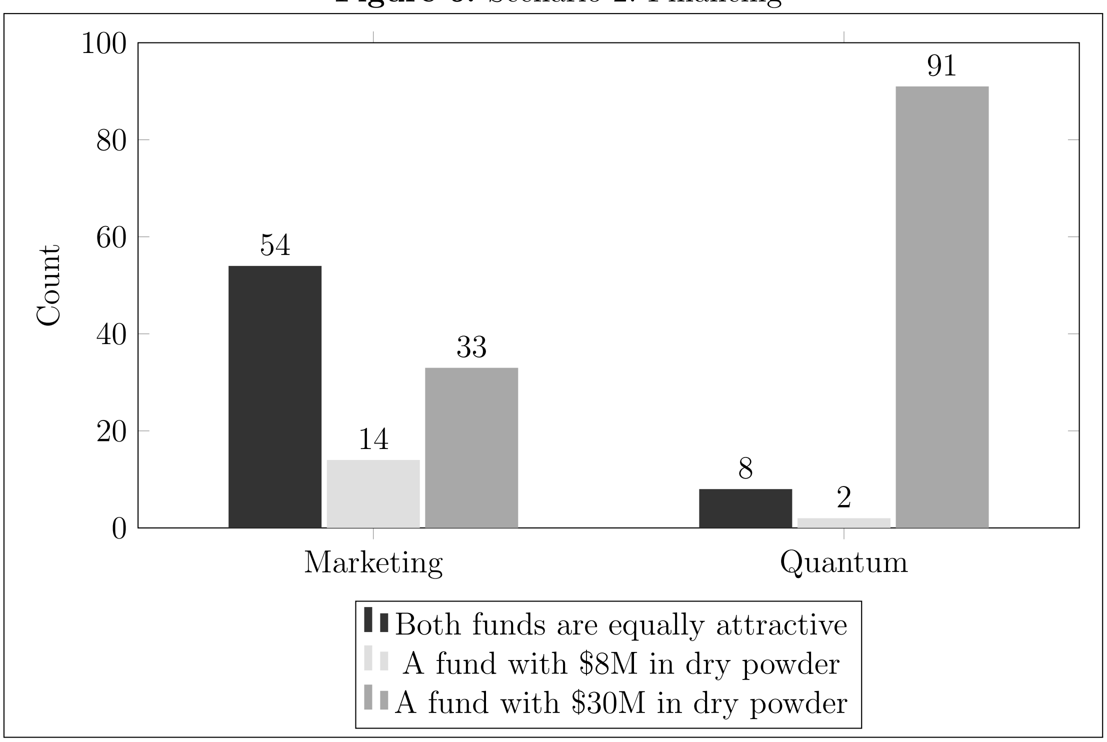

Figure 7. Scenario 3: Monitoring with limited financing

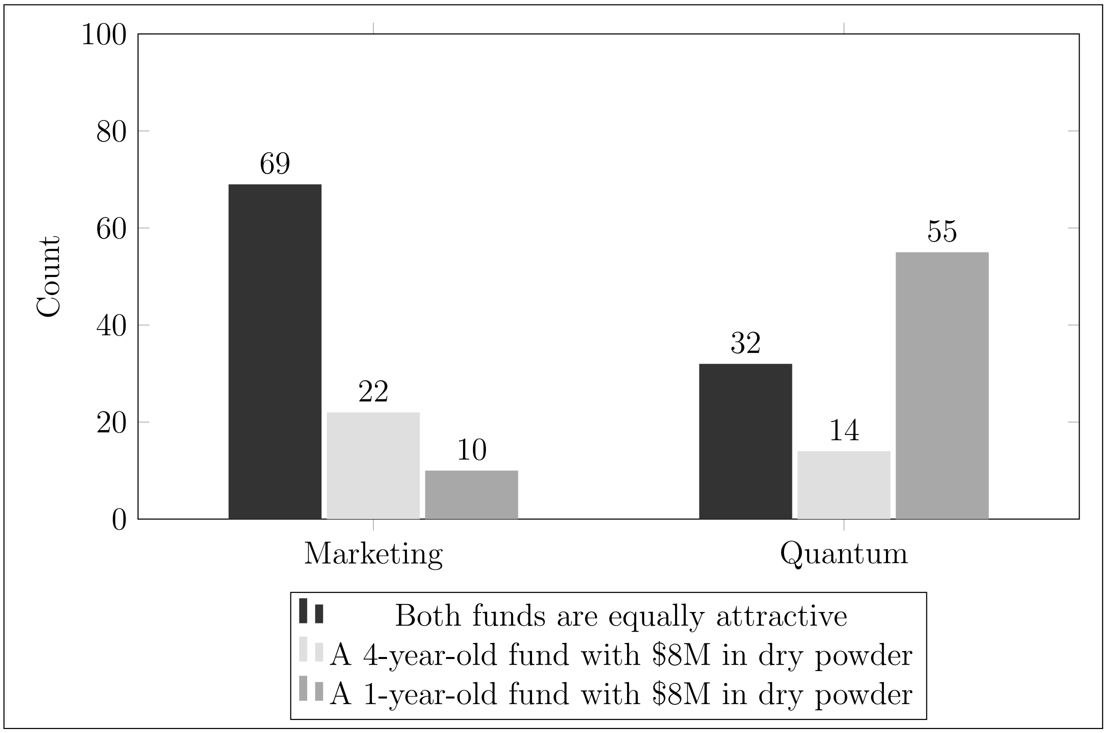

Figure 8. Scenario 4: Monitoring Vs. Financing

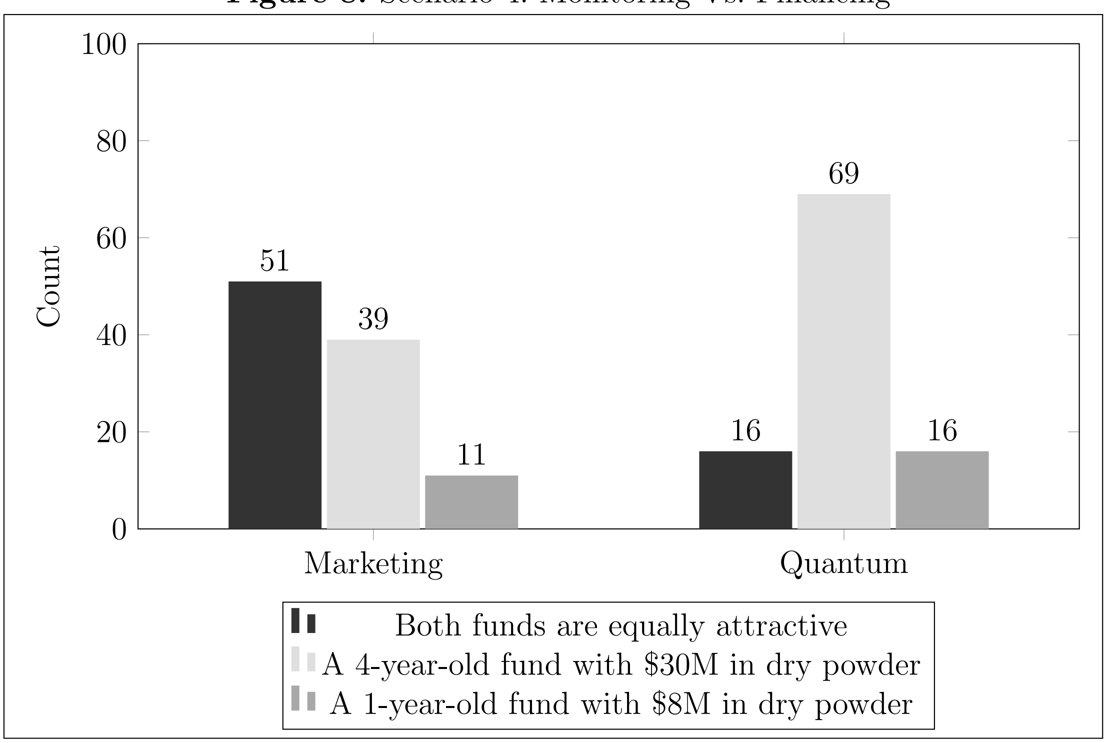

Figure 9. Scenario 5: Monitoring

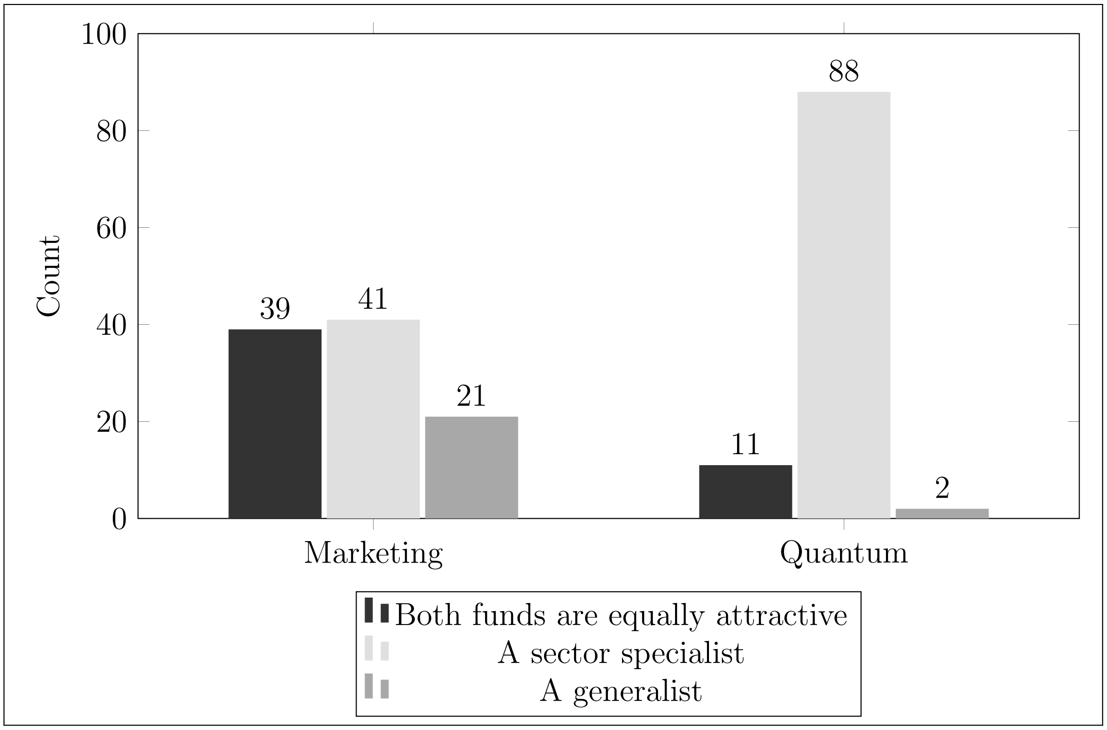

Figure 10. Scenario 6: Portfolio Size

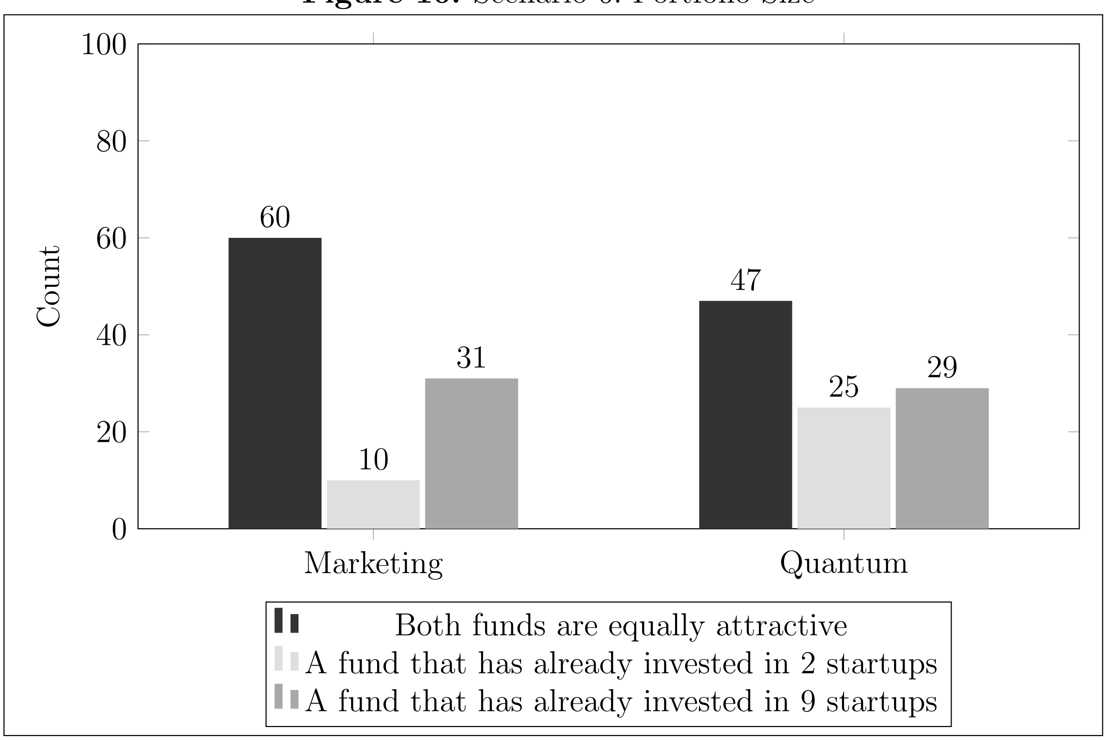

Table A.10. VC fund characteristics ranked in order of importance

Category	Rank	Average	Std. Dev.	Median
The fund's specialization in a specific industry/sector	1	2.406	1.320	2
The offering of a reputable investor as a board member in your startup	2	2.802	1.233	3
The VC's track record of successful exits	2	2.802	1.497	3
The amount of capital available for follow-on investments	4	3.188	1.354	3
The support services offered by the fund (e.g., HR, legal, etc.)	5	3.802	1.281	4