The Lifecycle of Venture Capital Funds

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Abstract

We document a previously unexplored lifecycle pattern in venture capital: the success of portfolio companies systematically declines as funds age. Using comprehensive fund-level data, we show that startups backed earlier in a fund's life are more likely to achieve successful exits through IPOs and M&As. We attribute this pattern to three reinforcing mechanisms: financing, monitoring, and sorting. We provide empirical evidence for each mechanism and further support them with a theoretical model and a survey of investors and entrepreneurs. Together, our results highlight the central role of fund age in shaping financing dynamics, entrepreneurial matching, and value creation in venture capital.

Keywords: Venture Capital, Fund Lifecycle, M&As, IPOs, Entrepreneurship

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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 economic growth (Aghion and Howitt, 1992; Romer, 1990). We introduce a previously undocumented factor that shapes the value proposition of VC funds and their investment outcomes - the age of the fund. Specifically, we find that investments made earlier in a fund's lifecycle are significantly more likely to achieve successful exits through initial public offerings (IPOs) or mergers and acquisitions (M&As). We attribute this lifecycle pattern to three interrelated mechanisms - financing, monitoring, and sorting - and provide evidence on how these channels evolve over the lifespan of a fund to drive the link between fund age and portfolio outcomes.

Our hypothesis that fund age shapes VCs' value proposition rests on two fundamental industry characteristics. First, a VC investment entails more than the provision of capital; it also includes the option of follow-on funding (Hsu, 2010) and 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). Second, VC funds are structured as limited partnerships with finite lifespans, typically around ten years (Sahlman, 1990; Metrick and Yasuda, 2010). Within this structure, early investments benefit from longer-term guidance and greater access to follow-on capital.

We argue that these characteristics affect startup outcomes through three channels: (1) the financing channel, where younger funds have greater flexibility to provide follow-on capital; (2) the monitoring channel, where early investments receive extended oversight and guidance; and (3) the sorting channel, where high-potential startups prefer to match with younger funds in order to secure longer-term support via the financing and monitoring channels.

The contribution of this paper is two-fold. First, we show that a fund's limited lifespan significantly impacts its value proposition. This finite structure, grounded in contractual agreements between general partners (GPs) and limited partners (LPs), is designed to prevent LPs from being held up by GPs once they have committed capital to the fund. In a frictionless world, VCs could overcome this limitation by raising additional capital and hiring additional talent to provide further monitoring whenever they identify strong investment opportunities. However, our findings suggest that these operations are subject to frictions, making investment timing within a fund's lifecycle a key factor influencing exit outcomes. Second, we demonstrate that fund age shapes the matching process between startups and VCs. While prior research focuses on quality-based matching (Sorensen, 2007; Gompers et al., 2020; Ewens et al., 2022; Sannino, 2024), we show that entrepreneurs prefer younger funds for their ability to provide sustained support. This highlights a novel dimension of matching dynamics led by the entrepreneur and driven by the industry's contractual structure and lifecycle constraints.

We analyze the temporal dynamics of VC funds using a comprehensive dataset that encompasses the near-universe of Israeli VC-backed startups for the last twenty years. Unlike commonly used databases like PitchBook or Crunchbase, which link most 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 the near-universe coverage is particularly useful for our analysis of the potential underlying mechanisms.

Our primary empirical finding is that each additional year in a VC fund's age at the time of the initial investment in a startup reduces the probability of a successful exit by as much as 5pp, corresponding to 21.5% relative 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 several additional control variables 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 show that initial 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% decline in follow-on investments by that fund relative to the sample mean of 1.04 per startup, and a 16% decline in follow-ons from all funds relative to the sample mean of 2.46. This result supports our hypothesis that investments made earlier in a fund's lifecycle are more likely to lead to follow-on investments.

To identify the effect of fund age on startup outcomes through the financing channel and to 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 with a fund is proportional to a startup's industry-specific capital needs. Specifically, a one-standard-deviation increase in industry financial intensity is associated with a 5% increase in the probability of a successful exit for each additional year with a fund. Put differently, startups in more capital-intensive industries are more likely to achieve successful exits when they receive initial investments from younger funds. If financing had no temporal effect, exit outcomes should not vary with financial intensity once fund age is held constant.

Next, we examine the monitoring channel and start by studying VCs' representation on startups' boards of directors. Having a VC serve as director on a startup's board allows the fund to engage more closely with the company's operations, thereby enabling more intense monitoring. VCs often demand 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, 2025), and when risks and uncertainties are greater (Kaplan and Strömberg, 2004).

Utilizing unique administrative data on board members from the Israeli Company Registrar, we examine the relationship between fund age and board representation. We find that each additional year in a fund's life is associated with a 10% decline relative to the unconditional probability of 73% for VC board participation. Further analysis suggests that this decline reflects both reduced monitoring capacity in older funds and a sorting effect, whereby younger funds are more likely to attract higher-quality startups that VCs prefer to monitor more closely through board involvement.

While board representation enables VCs to work closely with their portfolio companies, it is not a necessary condition for monitoring. To identify the temporal aspects of the monitoring channel, we compare specialist and generalist funds. Specialists have historically outperformed generalists (Gompers et al., 2009), which may reflect superior selection, stronger monitoring, or both. We exploit this distinction to test whether specialists' active involvement contributes meaningfully to startup success and how this effect evolves over time. If monitoring does not add significant value, time should not differentially affect outcomes by investor type. However, if monitoring matters, specialists should experience 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 relative to the sample's unconditional mean, indicating that monitoring is an important component of the fund's intertemporal value proposition. Furthermore, our results provide novel evidence that specialists' superior performance cannot be attributed solely to selection. By including both a specialist dummy (or fund fixed effect) and its interaction with time, we disentangle specialists' superior selection ability from their capacity to generate value through monitoring, as any time-invariant selection advantage is absorbed by the dummy (or the fund fixed effect).

The third mechanism is the sorting channel, which captures how high-quality founders select among available VC funds. All else equal, entrepreneurs who recognize the value of time spent with a particular fund prefer younger funds, as these funds offer a longer runway for follow-on investments and extended monitoring. We provide empirical evidence supporting this mechanism through two primary identification strategies and present an additional, suggestive test in the extensions section that further reinforces the sorting channel.

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 arguably 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 likely 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 sample.

In our second and primary identification strategy, we exploit cross-sectional variation in fund age to assess how startup performance differs under different relative market conditions. We flag all funds older than the average active fund in a given year and test whether investments made by these relatively older funds are less likely to result in successful exits even after controlling for the funds' absolute age. By including absolute age, we account for the possibility that older funds select weaker startups as they mature. Any remaining effect of relative age, therefore, reflects differences in the startups' choices rather than in the VCs' age-dependent selection. Conceptually, a fund's attractiveness to entrepreneurs depends not only on its own maturity but also on the relative age distribution of active funds in the market. A fund that becomes one year older may suddenly appear more or less appealing to founders if the overall pool of competing funds shifts older or younger in that year. As expected, 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, consistent with higher-quality startups systematically matching with the youngest available funds.

We illustrate the VC fund lifecycle and summarize the three channels, along with their corresponding empirical tests, in Figure 1.

Lastly, we address three alternative explanations for our baseline results and five relevant extensions to our core analysis. 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 address concerns related to the endogenous timing of new fund formations. A possible explanation for our findings is that VC firms strategically establish new funds when attractive investment opportunities arise, making the earliest investment systematically more successful. To address this concern, we exclude each fund's first investment, whose age is mechanically determined by the initiation of the fund, whereas the ages of all subsequent investments are determined by the time elapsed since that initial investment. The results remain consistent with our baseline findings, indicating that the strategic timing of fund formations does not drive our results.

Third, we test the extent to which funds' pressure to deploy capital toward the end of their investment period can explain our results. The concern is that the negative relationship between fund age and exit outcomes might be driven by underperforming investments made late in a fund's life, rather than better-performing ones made earlier. To address this, we exclude investments that were potentially made under pressure to deploy capital. Specifically, we re-run our baseline specifications after dropping each fund's initial investments made (i) during the fund year of the last initial investment, (ii) during the fund year of the last investment overall, and (iii) from fund year six onward, as most investment periods last five years (Sahlman, 1990). Results remain similar across all three specifications, suggesting that end-of-period investment pressure is not driving our results.

These additional tests show that alternative stories cannot fully explain the financing, monitoring, and sorting mechanisms documented in our paper, although they may very well exist in parallel.

Next, we address five relevant extensions to our baseline analysis. First, we examine whether the negative correlation between fund age and VC board representation reflects sorting or capacity constraints. Using measures of startup quality and fund attractiveness, we find that older funds are less likely to obtain board seats, while younger funds attract higher-quality startups and engage more intensively, consistent with sorting. The negative correlation persists even after controlling for startup quality, which points to capacity constraints as an additional factor. Overall, we find that both sorting and capacity limitations shape board seat allocation.

Second, we test whether cross-investments, where portfolio companies receive financing from multiple funds managed by the same VC firm, undermine 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 represent a significant value proposition, their mere presence 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 limited time horizon assumption.

Third, 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.

Fourth, we adopt an instrumental variable (IV) approach to strengthen the causal interpretation of the sorting mechanism 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 predictor of whether a fund is older than the market mean. 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. While this test should be interpreted with caution, it provides additional, complementary evidence that entrepreneurs systematically select younger funds, reinforcing the role of relative age in shaping investment outcomes.

Fifth, we conduct a mediation analysis to examine whether the relationship between fund age and startup performance operates through the proposed mechanisms of financing, monitoring, and selection. While this exercise should be interpreted with caution given the potential endogeneity of the mediating variables, it provides suggestive evidence on their importance. We find that including variables capturing these three channels attenuates the effect of fund age, and that incorporating all three jointly eliminates it altogether. These results suggest that the temporal dynamics of financing, monitoring, and selection, at least partially, explain the negative relationship between fund age and startup outcomes.

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 conduct a survey to explore how entrepreneurs and investors evaluate VC fund characteristics. The survey asks participants to rank key fund attributes 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 highlight how entrepreneurs and investors internalize the value of time when selecting VC investors, further supporting our hypothesis that fund age influences the startup–VC matching process. Specifically, founders and investors show a clear preference for funds with a longer time horizon and greater available dry powder.

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) models the conflict of interest between LPs and GPs in the decision to continue projects, stemming from the fund's limited lifespan and GPs' 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 the finite horizon of VC funds affects their value proposition to portfolio companies and, consequently, their ability to attract high-quality startups.

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 and the entrepreneur's choice.

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) interviews 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) analyzes 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.

Taken together, our empirical evidence, theoretical framework, and survey results highlight fund age as a central determinant of startup–VC matching and outcomes, adding a novel lifecycle dimension to the study of venture capital. 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 describing our data sources and presenting summary statistics. We then document the empirical relationship between fund age and startup exit outcomes, analyze three potential mechanisms—financing, monitoring, and sorting—and examine three alternative explanations as well as five extensions.

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 comprise VC funds (31.2%), angels (17.4%), corporate venture capital (4.5%), private equity funds (1.5%), and government agencies (1.2%). The investments span all funding stages, ranging from 24,788 seed-round investments to a single fifteenth-round investment. The data also include 2,072 IPOs and M&As between 2002 and 2024.

We focus on first-time investments by VC firms from funds that have invested in at least two startups between 2002 and 2023. Funds with a single investment are excluded as the fund fixed effects would absorb them. Our sample starts in 2002, 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 lifecycle stages, providing a cleaner setting to identify the underlying 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 a 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. 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 seed rounds appear reasonably similar. While syndicated rounds involve higher absolute deal amounts, investment sizes on a per-investor basis are nearly identical. Startups in single-investor and syndicated rounds also exhibit similar trajectories in terms of follow-on financing and exit rates. Combined with a set of empirical tests—discussed later in the paper—conducted on the full dataset, this suggests that the tighter identification afforded by our restriction to single-investor seed rounds comes at little cost in terms of representativeness relative to VC-backed seed rounds more broadly.

2.2 Empirical Strategy and 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 and address potential alternative explanations and extensions.

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:

$$\mathbb{I}\{Exit_s\} = \beta_1 FundAge_s + \beta_2 Ln(DealAmount)_s + \beta_3 InvestmentOrder_s \\ + FundFE + DealYearFE + Inv.CountryFE + IndustryFE + \epsilon_s \tag{1}$$

where s indexes startups. $\mathbb{I}\{Exit_s\}$ is a dummy variable equal to one if a startup achieves an exit through an M&A or an IPO. As illustrated in Figure 2, *FundAge* measures the number of years since a fund's inception as the difference between the investment date and the fund's first recorded investment. Our controls include the logarithmic transformation of the total deal amount, that is, the total dollar amount invested in that round, to facilitate comparisons across investments of similar scale. We include *InvestmentOrder*, which counts the number of startups already in the fund's portfolio at the time of each investment. This variable captures the fund's sequencing of initial investments by comparing the relative position of startups within a fund and helps distinguish ranking effects from investment timing. Including this control helps mitigate concerns that systematic sequencing in capital deployment could influence the estimated relationship between fund age and exit outcomes. All results remain unchanged when this variable is used as a fixed effect or excluded from the regression.

In our *Startup-Level Dataset*, we do not control for startup age because all startups in this sample are raising their first seed investment, resulting in minimal age variability. 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.

Our baseline empirical result, presented in Column 1 of Table 3, shows that the coefficient on fund age is negative. 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.2 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 sorting based on fund quality.

In the second set of robustness tests, reported in Table A.3, 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.

In a third set of robustness tests, we analyze the strength of the negative correlation between fund age and exit outcomes in the *Investment-Level Dataset*. While this approach is econometrically problematic because the dependent variable, exit outcome, is identical for all observations associated with a given startup, which gives startups with more investment records disproportionate weight in the regression, it can still indicate whether the negative association between fund age and exit outcomes is unique to single-investor seed rounds. Table A.4 in the Appendix shows a consistently statistically significant negative correlation between fund age and exit outcomes of similar magnitude when including fixed effects and control variables sequentially, implying that our baseline results are not unique to our chosen subsample. Taken together, all four approaches yield consistent results, supporting a negative correlation between fund age and exit probability.

2.2.2 The Financing Channel

In our second empirical setting, we examine the temporal dynamics of the financing channel and assess 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 at least one future round of funding is most likely made by an existing investor.

We then replace our dependent variable, $\mathbb{I}\{Exit_s\}$, 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. 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.[1] 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.

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:

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

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

[1] 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.

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. As reported in Table 4 Column 2, exploiting the richness of the data through the *Investment-Level Dataset* yields results consistent in direction and magnitude with those at the startup level.

In an alternative approach, possible only with the *Investment-Level Dataset*, we include both fund and startup fixed effects to isolate the fund lifecycle impact while controlling for both fund and startup quality. This specification restricts the analysis to funds investing in at least two different startups and startups receiving investments from at least two different VC funds. As shown in Table 4 Column 3, the inclusion of both fixed effects enables us to compare two or more initial investments from different VC funds within the same startup, with fund age as the only distinguishing factor. We find that the negative correlation between fund age and follow-on investments persists, even when comparing investments made by funds at different stages of their lifecycle in the same startup. That is, when a startup receives investments from two different funds, it is more likely to secure a follow-on investment from the younger fund among the two. This result aligns closely in both direction and magnitude with our previous findings that do not include startup fixed effects.

Finally, as reported in Columns 4 and 5 of Table 4, we test for a potential substitution effect by redefining the dependent variable to include follow-on investments received from any fund, not just the original investor. We repeat both specifications from Columns 2 and 3 and obtain coefficients of similar magnitude, suggesting that the effect of fund age is not offset by follow-on financing from other investors. We do not estimate the model with startup fixed effects in this setting because variation at the startup level disappears once all possible follow-ons are included.

Next, we turn to identification by analyzing the 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 financial intensity index. To evaluate this index, we look at exit multiples. 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:

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

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

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 × std. dev. / unconditional prob. of exit = 0.0211 × 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.

2.2.3 The Monitoring Channel

We analyze the temporal dynamics of the monitoring channel by first 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. As reported in Table A.5 in the Appendix, we 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 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, either due to capacity constraints or due to selection, potentially limiting their ability to provide hands-on monitoring and oversight. Consistent with this and 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%.

We next identify the monitoring channel by comparing the effect of fund age on the performance of generalist and specialist funds. We classify funds that invest in at least three different industries as generalists, and those that invest in at most two industries as specialists. This analysis relies on the hypothesis that the monitoring channel is more pronounced 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 estimate the following regression:

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

where $\mathbb{I}\{Specialist_v\}$ is a dummy variable equal to 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 on the interaction term, $FundAge \times \mathbb{I}\{Specialist\}$, β_4. The standalone $\mathbb{I}\{Specialist_v\}$ variable is absorbed by fund fixed effects. The presence of a time-dependent monitoring channel implies that each additional year with a specialist fund is associated with better startup performance.

As presented in Table 3, Column 5, a specialist fund that is one year older is 6.24pp less likely to experience an exit, representing 26.6% of the sample's unconditional mean. This result suggests that additional time spent with specialist funds is more valuable for startups, which benefit from increased 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 marginal difference in performance between generalist and specialist VCs.

Moreover, this analysis provides novel evidence that the superior performance of specialist funds is not driven solely by their ability to select high-potential startups, but also by their ability to monitor. If the superior performance were driven solely by selection, only the coefficient on the standalone $\mathbb{I}\{Specialist\}$ variable, which is absorbed by the fund fixed effects in our setting, would be significant. However, the negative coefficient on the interaction term between the Specialist dummy and fund age indicates that the additional value of a specialist fund accumulates over time, likely due to its enhanced capacity to monitor and mentor portfolio companies. Finally, in an unreported analysis, we reran our regression without fund fixed effects to recover the standalone *Specialist* variable and obtained results similar in direction and statistical significance to those reported above.

2.2.4 The Sorting Channel

The preferential sorting channel of startups 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 examine this selection channel using three empirical strategies. Two detailed below and one detailed in the extensions section.

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. 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. 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.6 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. Importantly, 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.

In this section's main empirical test, we use a cross-sectional lifecycle measure. As illustrated in Figure 3, we use all initial investments by VC funds to estimate market conditions at the time of investment by examining the age distribution of all active funds in a given year and flagging those older than the annual mean. By identifying funds that are older than the mean, we capture variation in the relative competitiveness of the venture capital market with respect to fund age.

Our null hypothesis within the selection channel is that if selection were driven solely by the VC's choice—where fund age affects performance only through the VC's own selection of startups, and startup preferences over investors are irrelevant—then only a fund's absolute age should matter for startup outcomes. In that case, once we control for absolute fund age, relative age should have no additional explanatory power. Conversely, if relative age remains significant after controlling for absolute age, this suggests that startups themselves play an active role in the matching process, systematically preferring younger funds over older ones. By controlling for absolute fund age, we isolate the effect of relative age and effectively shut down the VC-side age-dependent selection mechanism.

Specifically, we regress *Exits* on the *OlderThanMean* variable while controlling for a fund's age in our more restrictive *Startup-Level Dataset*:

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

A negative correlation between the *OlderThanMean* dummy and exits, even after controlling for the fund age, constitutes evidence for 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 of an equilibrium where higher-quality startups choose younger available funds, and lower-quality startups end up matching with older ones. This empirical setting 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.

As shown in Table 3 Column 7, 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.

2.3 Alternative Explanations and Extensions

In our final set of empirical analyses, we address three alternative explanations for our baseline results and explore five extensions of our core analysis. The first alternative explanation tests whether funds engage in "Window Dressing" by allocating their most promising startups to newly raised funds to showcase strong performance to prospective investors. The second examines whether our findings are driven by the VC firm's endogenous decision to launch a new fund when an attractive investment opportunity arises. The third considers whether VCs, under pressure to deploy remaining capital, make lower-quality investments toward the end of their investment period.

We then turn to five extensions. First, we examine whether the negative relationship between fund age and VC board representation is driven by capacity constraints, sorting effects, or both. Second, we assess whether our assumption of a limited time horizon is invalidated when cross-investments are possible, namely, when VC firms can offer continued support through subsequent funds. Third, we test the external validity of our results by analyzing whether the documented mechanisms are specific to the Israeli market. Fourth, we replicate the strategy of Nanda and Rhodes-Kropf (2013) to provide suggestive evidence in support of the selection channel. Finally, we conduct a mediation exercise by regressing exit outcomes on fund age while sequentially adding variables that capture, at least partially, the three underlying channels.

2.3.1 Alternative Explanation 1: Window Dressing

One 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 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 the 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 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.

Regardless, such behavior is more likely among young VC firms and less likely among reputable VCs who maintain ongoing relationships with LPs. VCs who engage in "Window Dressing" risk losing their investors' trust and could severely damage their brand as they have a fiduciary duty to maximize returns for their investors in every single fund. Such behavior can 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 follow-on investments with coefficient estimates similar in magnitude to those in our baseline regressions (Column 1 of Table 5), suggesting "Window Dressing" does not drive our results.

2.3.2 Alternative Explanation 2: Timing of Fund Initiation

A second 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 endogenous 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 (Column 2 of Table 5).

2.3.3 Alternative Explanation 3: Pressure to Deploy Capital

A third potential concern relates to the pressure funds face to deploy uninvested capital toward the end of their investment period. The finite lifespan of VC funds implies that the later a fund makes its initial investment in a portfolio company, the less time remains to support that company and achieve a successful exit. To allow sufficient time for this process, funds typically have a dedicated investment period, usually the first five years of the fund's life. However, significant amounts of uninvested capital may remain toward the end of this period, creating pressure to invest quickly. Arcot et al. (2015), in the context of secondary buyouts, show that investments made under such pressure tend to underperform.

It is therefore conceivable that the negative relationship we document between a fund's age at the time of initial investment and a startup's likelihood of a successful exit is driven by underperforming investments made toward the end of the investment period. To address this concern, we exclude initial investments that were potentially made under pressure to deploy capital. Specifically, we re-estimate our baseline specification after excluding investments made by each fund (i) during the year it made its last initial investment, which likely corresponds to the final year of its investment period (Column 3 of Table 5), (ii) during the final year of the fund's life overall (Column 4), and (iii) during the sixth year and beyond (as most investment periods last five years, Sahlman (1990); Column 5).

In all three specifications, we continue to find negative and statistically significant associations between fund age at the time of initial investment and both the likelihood of exit and the probability of follow-on financing. These findings suggest that our baseline results are not solely driven by end-of-period investment pressure.

2.3.4 Extension 1: VC Board Representation

The negative correlation between fund age and VCs taking a board seat 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 startups perceived as higher quality, which in turn prefer younger funds.

To distinguish between these explanations, we employ measures related to perceived startup quality and fund attractiveness from Section 2.2.4. Specifically, we re-estimate the equation for board representation, incorporating the serial entrepreneur and *OlderThanMean* dummy variables as additional explanatory variables. As reported in Table 6, Column 1, and consistent with the sorting hypothesis, we find that older-than-mean funds, which have fewer remaining active years, are less likely to obtain board representation. This is consistent with older funds struggling to attract high-quality startups and therefore claiming less board involvement. Interestingly, Column 2 suggests that startups with a serial entrepreneur on the founding team, while perceived as higher quality, are less likely to obtain VC board representation. This could be because their experience reduces the need for intensive VC involvement

Nonetheless, Columns 1 and 2 in Table 6 show that the negative correlation between board representation and fund age remains even after controlling for startup-quality measures, indicating that capacity constraints also contribute to the observed pattern. Taken together, these findings suggest that both sorting and capacity constraints shape a fund's decision to take a board seat, with startups backed by younger funds more likely to receive intensive monitoring through VC board representation.

2.3.5 Extension 2: Cross-Investments

A potential limitation of our analysis concerns the assumption of a limited time horizon. VC firms managing multiple active funds may extend their financing and monitoring activities through cross-investments. First, it is important to note that this phenomenon, while theoretically relevant, is extremely rare in our data. Among the 1,043 startups in our sample, such cross-investments occur in only 24 instances across all funding rounds. Of these, only 16 cases (1.5% of the sample) involve a VC firm investing in a startup's seed round with one fund and providing additional financing in later rounds with another. Despite their rarity, the mere possibility of cross-investments could, in theory, weaken the relationship between fund age and startup outcomes.

To address this concern, we restrict the sample to VC firms managing multiple funds, where cross-investments are theoretically feasible. The coefficient on fund age remains similar in magnitude and statistical significance when limiting the sample to VC firms with more than one fund (Columns 3 and 5 of Table 6), or more than two or three funds (Table A.7 in the Appendix), ruling out the possibility that our results are solely driven by single-fund VCs being unable to offer continued support to their portfolio companies.

2.3.6 Extension 3: External Validity

Lastly, we test whether our results are unique to the Israeli market. The effect of fund age might be specific to Israeli startups due to unobserved or context-specific factors. To examine this possibility and assess the external validity of our findings, we replicate our baseline tests using a sample of VC-backed startups from the United States, constructed from PitchBook data.

While PitchBook is widely used in academic studies of the VC industry (Gompers et al., 2021; Lerner and Nanda, 2023; Yimfor and Garfinkel, 2023, to name a few), it presents several limitations in the context of our analysis. First, PitchBook does not cover the full universe of VC deals in the U.S., whereas the IVC dataset provides near-comprehensive coverage of VC-backed startups in Israel. This is particularly important for our mechanism tests. In particular, having population-level data on active VC funds and startup exits allows us to construct key variables, such as the *OlderThanMean* indicator and the industry financial intensity index, with precision. Second, 62% of VC investments in U.S. startups in the PitchBook data lack fund identifiers. Since our identification strategy relies on variation in fund age, it is essential to link each investment to a specific VC fund, not just a VC firm.

Despite these limitations, the PitchBook data still support the construction of the key variables required for our baseline regressions, namely, fund age, exit outcomes, and follow-on investments. We apply the same sample construction procedures used with the IVC data. The resulting *PitchBook Investment-Level Dataset* includes 69,434 investments in 26,411 startups by 6,479 VC funds, while the *PitchBook Startup-Level Dataset* contains 10,849 single-investor seed-round investments by 2,729 VC funds, with roughly one third of these startups achieving a successful exit.

Consistent with our findings in the Israeli setting, we find negative and statistically significant correlations between fund age at the time of initial investment and both the likelihood of exit and follow-on financing, suggesting that our baseline results are not unique to the Israeli market (Columns 4 and 6 of Table 6).

2.3.7 Extension 4: Instrumenting the Selection Channel

As an additional robustness test to our main identification strategy of 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. 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 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 the rest of the world's 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 this strategy.

The instrumented *OlderThanMean* variable captures variation in a given VC fund's competitiveness due to shifts in the average age of other active VC funds. If limited partners allocate more capital to buyout funds, VC fundraising will also increase. 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 fund's absolute 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.

Table A.8 in the Appendix, presents the results for 2SLS estimation of Equation 5.[2] Col-

[2]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 *OlderThanMean*, are unaffected by the partialling out in IV estimation.

umn 1 shows a negative correlation between lagged buyout fundraising and *OlderThanMean*, with significant conventional and Kleibergen-Paap instrument F-statistics. Column 2 shows a negative effect of the instrumented *OlderThanMean* variable on a startup's likelihood to exit successfully.[3] 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.

The combination of evidence from the serial entrepreneur test and the "*OlderThanMean*" specification in Section 2.2.4, as well as this additional IV analysis, yields a consistent and robust pattern. Taken together, these complementary analyses strongly support the selection channel, whereby higher-quality entrepreneurs systematically match with younger VC funds.

2.3.8 Extension 5: Mediation

We conclude by examining whether the observed relationship between fund age and startup performance operates through the proposed mechanisms of financing, monitoring, and selection. This exercise is inherently imperfect, as the inclusion of mediating variables in the outcome regression introduces "bad controls" (Angrist and Pischke, 2009) that may themselves be endogenous to fund age. Moreover, the variables we include only partially capture each channel. *VC Board* participation reflects one dimension of monitoring but does not encompass all forms of non-financial support VCs provide. *Follow-on* investments capture a key aspect of the financing channel, but not the inherent option for follow-ons which comes with younger funds. Similarly, the *Serial Entrepreneur* indicator measures only one facet of the selection channel.

With these limitations in mind, Table A.9 reports the results of a sequential mediation analysis. Adding individual mediators (*VC Board*, *Follow-on*, and *Serial*) in Columns 2

[3] The adjusted R^2 in the second stage of the IV regression (Column 2) is negative, however, Wooldridge (2019) states that "Unlike in the case of OLS, the R-squared from IV estimation can be negative because SSR for IV can actually be larger than SST. Although it does not really hurt to report the R-squared for IV estimation, it is not very useful, either. We report the adjusted R^2 values for full transparency.

and 3 reduces the economic magnitude of the *Fund Age* coefficient, suggesting that part of the effect operates through these channels. When all three mediators are included jointly in Column 4, the coefficient on *Fund Age* becomes economically and statistically indistinguishable from zero, suggesting that the proposed mechanisms collectively account for the observed relationship between fund age and exit outcomes.

3 Model

Our empirical findings reveal systematic differences in startup 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: financing, monitoring, and sorting.

The model features overlapping generations of VC funds of the same quality, alongside startups that differ in quality. Younger funds have a longer remaining horizon and greater capacity, and therefore provide sustained monitoring and the option of follow-on funding. High-quality entrepreneurs anticipate these benefits and, due to mutual preferences, endogenously match with younger funds. Crucially, we show that this sorting arises even if only the higher-quality type internalizes the long-term advantage of partnering with a younger fund.

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. Each fund remains active for three periods: it makes new investments in the first two periods and liquidates all positions in the third. Accordingly, at any point in time, there are three active funds in the market–one in its initial investment phase (young), one in its subsequent investment phase (mature), and one in its liquidation phase (liquid).

In each of the two investment periods, the fund operates under a fixed, non-divisible budget constraint of x. This structure reflects the staged financing typical of venture capital, which, as shown by Kerr et al. (2014), enhances expected project value by embedding an option to terminate underperforming ventures.

Beyond financial investment, each fund contributes value through active monitoring of its portfolio companies. All funds are identical in quality and thus provide the same level of monitoring in each period. This abstraction allows the model to isolate the role of fund age in value proposition and the matching process, as quality-based matching has been studied extensively in prior work (Sorensen, 2007; Ewens et al., 2022). This assumption is also consistent with our empirical strategy, which controls for fund-level fixed effects and holds fund quality constant.

Each fund seeks to maximize returns through the eventual exit of its investments, which occurs exclusively during the liquidation phase.

Entrepreneurs and Startups

In each period, two entrepreneurs launch startups: 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 model's notation. Let $\theta_0 \in \{\theta_0^H, \theta_0^L\}$ denote the startup's initial quality, with $\theta_0^H > \theta_0^L$.

Assumption 1. *Once an entrepreneur matches with a fund, she cannot receive funding from a different fund. If a startup fails to match with a fund, it does not survive to the next period.*

Assumption 1 is motivated by empirical evidence on the persistence of VC-startup relationships, as discussed in Section 2.2.2. It implies that a startup can receive up to two periods of monitoring and at most two funding units, depending on when the initial match occurs in the fund's lifecycle. Both financing and monitoring are assumed to increase the value of the startup.

Let $t \in \{0, 1, 2\}$ denote the number of periods since the startup matched with a fund, and let $\mathbb{I}_t^f \in \{0, 1\}$ indicate whether the startup receives funding in period t. We assume that first-time investment always entails funding, so $\mathbb{I}_0^f = 1$. Follow-on funding in period $t = 1$ occurs only if both the fund and the entrepreneur agree to proceed, i.e., $\mathbb{I}_1^f \in \{0, 1\}$. Monitoring is provided in both investment periods $t \in \{0, 1\}$, regardless of whether follow-on funding occurs. For instance, if a fund provides monitoring via board participation, it continues to do so even without additional financing.

The startup's quality evolves over time based on the monitoring and financing provided. Specifically, in each period t, quality evolves as:

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

where $\epsilon_t^m \sim N(\mu^m, \sigma_m^2)$ and $\epsilon_t^f \sim N(\mu^f, \sigma_f^2)$ are random components resulting from monitoring and financing in period $t - 1$, respectively, and are mutually independent.

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

Let $V_0^i = \exp(\theta_0^i)$ denote the initial startup value. Following Assumption 2, the value in period $t \geq 1$ can be written as:

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

which implies that

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

This formulation implies that post-investment valuations follow a log-normal distribution, consistent with empirical evidence on VC-backed firm valuations (Cochrane, 2005).

Define the expected value multipliers from monitoring and financing as:

$$v^m = \mathbb{E}[\exp(\epsilon_t^m)] = \exp\left(\mu^m + \tfrac{1}{2}\sigma_m^2\right), \quad v^f = \mathbb{E}[\exp(\epsilon_t^f)] = \exp\left(\mu^f + \tfrac{1}{2}\sigma_f^2\right).$$

The conditional expected value of the startup is then:

$$\mathbb{E}\left[V_t \middle| V_{t-1}, \mathbb{I}_{t-1}^f\right] = \begin{cases} V_{t-1} \cdot v^m \cdot v^f & \text{if } \mathbb{I}_{t-1}^f = 1, \\ V_{t-1} \cdot v^m & \text{if } \mathbb{I}_{t-1}^f = 0. \end{cases}$$

Thus, each period of monitoring increases expected value by a factor of v^m, and each unit of financing increases it by v^f. This formulation implies that the startup's expected liquidation value 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.

We acknowledge a potential trade-off between the benefit of continued investment and the cost of delayed exit. However, our focus is on frictions arising from funds' limited lifespans, so we assume that the value added from monitoring or financing exceeds the opportunity cost of delaying exit by one period:

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

For simplicity, we normalize the risk-free rate to $R = 1$ throughout the analysis.

In an extension of the baseline model that incorporates experimentation, we allow financing and monitoring to improve the accuracy of startup quality assessment. This formulation captures the joint learning dynamics by VCs and entrepreneurs as in Kerr et al. (2014); Kerr and Nanda (2015); Manso (2016). Unlike the baseline model, where the value added by financing and monitoring is constant, in this extension, the incremental contribution diminishes over time as uncertainty resolves. Nonetheless, the qualitative insights of the model remain unchanged. See Appendix C for details.

Investment Contracts

Entrepreneurs and VC funds may enter into three types of contracts, each involving an investment of size x: (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 new startup.

We assume that all contracts follow a common structure, consistent with simplified representations of standard venture capital agreements. Specifically, we model contracts as involving common equity with no liquidation preferences. The fund's ownership share is therefore determined by the investment amount relative to the startup's post-money valuation.

In practice, the most common financial instrument used in VC contracts is convertible preferred equity. The literature (see Da Rin et al. (2013) for a survey) emphasizes the role of such contracts in mitigating agency frictions, including double moral hazard (Casamatta, 2003; Schmidt, 2003; Hellmann, 2006) and continuation incentives (Cornelli and Yosha, 2003; Dessi, 2005). However, we adopt a simplified contract form of common equity since our focus lies in the temporal structure of the VC-startup relationship rather than in contract design or the resolution of agency problems.

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

To ensure that first-time investments are always mutually beneficial, we impose the following:

Assumption 5. *A new startup of type $i \in \{H, L\}$ has a positive expected net present value, even if it receives only one round of funding and monitoring: $\mathbb{E}[V_1 \mid V_0^i] - V_0^i - x = V_0^i \cdot v^m v^f - V_0^i - x > 0$.*

Together, Assumptions 4 and 5 ensure that both the fund and the entrepreneur prefer to engage in a first-time investment. The fund compares the expected return from investing to the outside option of retaining the capital: $\lambda(V_0^i) \cdot \mathbb{E}[V_1 \mid V_0^i] = \frac{x \cdot V_0^i \cdot v^m v^f}{V_0^i + x} > x$. The entrepreneur, in turn, prefers receiving funding in exchange for giving up equity rather than keeping full ownership at the startup's initial value: $(1-\lambda(V_0^i))\cdot\mathbb{E}[V_1 \mid V_0^i] = \frac{(V_0^i)^2\cdot v^m v^f}{V_0^i+x} > V_0^i$. Thus, both parties are strictly better off by agreeing to the first investment.

Equilibrium Concept

We analyze stable matches in this setting by building on the classic framework of Gale and Shapley (1962). In our model, the equilibrium is characterized by the following four elements:

1. The strategies of entrepreneurs and funds for deciding whether to accept a follow-on investment contract.
2. Entrepreneurs' preferences over fund age when forming an initial investment contract.
3. Funds' preferences over startup types.
4. A stable matching between funds and startups in each period (Gale and Shapley, 1962).

We now analyze each of these components and demonstrate that a unique stable matching arises in equilibrium. The resulting sorting pattern is primarily driven by the preferences of high-quality entrepreneurs, as they are favored by VC funds.

3.2 Follow-on Investments

Suppose that a fund, while young, matched with a startup of type $i \in \{H, L\}$, and that after the first investment, the startup's value is $V_1 = V_0^i \cdot \exp\left(\epsilon_1^m + \epsilon_1^f\right)$. Both parties now consider a follow-on investment that grants the fund an additional ownership share of $\lambda(V_1)$.

The VC fund faces two outside options if it declines to reinvest: (1) retain the amount x without reinvesting, or (2) reenter the market to match with a new startup of type j for one final period of investment and monitoring before liquidation.

Following Assumption 5, investing in a new company always yields higher expected value than retaining the capital. Therefore, the fund's outside option is to match with a startup of type j, while continuing to monitor the incumbent startup. The expected value of the fund's portfolio under this strategy is $\lambda(V_0^i)V_1 v^m + \lambda(V_0^j)V_0^j v^m v^f$. The fund agrees to a follow-on investment if the expected return from increasing its stake in the current startup and providing it with additional financing exceeds this outside option:

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

The entrepreneur, in turn, will accept the follow-on contract if the benefit of additional funding outweighs the dilution of ownership. If she declines, she proceeds to liquidation after an additional period of monitoring. Thus, she accepts the follow-on contract if:

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

The following proposition shows that a follow-on investment is mutually beneficial if the current startup value exceeds a threshold. Moreover, this threshold increases with the value of the fund's outside option when it is mature.

Proposition 1. *Suppose a fund matched with a startup of type $i \in \{H, L\}$ during its young phase. Suppose further that when mature, the fund's outside option is to invest in a new startup of type $j \in \{H, L\}$. Then there exists a threshold $T^{i,j} \in \mathbb{R}_+$ such that a follow-on investment is mutually profitable if and only if $V_1 > T^{i,j}$. Moreover, $T^{i,j}$ is increasing in V_0^j.*

Proof. See Section B.1 in the Appendix.

3.3 Entrepreneurs' Preferences

Entrepreneurs are matched with a fund only once, at the startup's inception. If matched with a mature fund, the entrepreneur receives one round of financing and monitoring, with no option for follow-on investment or continued guidance. In contrast, a match with a young fund offers two periods of monitoring and the option of a follow-on investment, both of which increase the expected value of the startup. Hence:

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

Proof. See Section B.2 in the Appendix.

3.4 Funds' Preferences

The following proposition establishes that young funds prefer high-type startups. While this result may seem intuitive, the underlying incentives are more nuanced. Because $\lambda(V_0)$ is decreasing in V_0, a fund acquires a smaller initial stake in higher-type startups. This could, in principle, diminish the fund's incentive to pursue follow-on investments. One might imagine a scenario in which investing in a lower-type startup (with a larger initial stake) is preferable due to higher follow-on returns. However, in our setting, the expected gains from monitoring and follow-on investment in high-quality startups are sufficiently large to offset the smaller initial stake.

Proposition 3. *A young fund strictly prefers to match with a startup of type H rather than type L, regardless of its outside option in the second period.*

Proof. See Section B.3 in the Appendix.

3.5 Stable Matching

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

Proposition 4. *There is a unique stable matching in which 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 shows that entrepreneurs prefer young funds over mature ones, and Proposition 3 shows that young funds prefer high-type startups. Consider the two versions of the deferred acceptance algorithm (Gale and Shapley, 1962): entrepreneur-proposing and fund-proposing. In the entrepreneur-proposing version, both entrepreneurs initially apply to their top choice, which is the young fund. The young fund prefers type H and therefore rejects type L. As a result, the stable matching is H-young, L-mature. In the fund-proposing version, the young fund proposes to H. If the mature fund also proposes to H, it is rejected. In either case, the outcome is again H-young, L-mature. Since both versions of the algorithm yield the same matching, it is the unique stable matching. □

The following proposition highlights that the equilibrium sorting pattern is driven primarily by the preferences of high-quality entrepreneurs. Because young funds prefer high-type startups over low-type ones, the high-type's choice of partner determines the matching outcome. Even if low-type entrepreneurs have no preference over fund age, the unique stable matching still obtains. This insight emphasizes the novel role of high-type entrepreneur preferences in shaping the matching equilibrium.

Proposition 5. *The stable matching in Proposition 4 is sustained even if only the high-type entrepreneur internalizes the benefit of matching with a younger fund.*

Proof. Suppose that the low-type entrepreneur prefers mature funds over young ones. In the entrepreneur-proposing version of the deferred acceptance algorithm, the high-type entrepreneur applies to her top choice–the young fund–while the low-type entrepreneur applies to her preferred partner–the mature fund. The resulting matching is H–young, L–mature. In the fund-proposing version, the young fund proposes to H. If the mature fund also proposes to H, it is rejected. In either case, the outcome remains H-young, L-mature. Thus, both algorithms yield the same matching as in Proposition 4, establishing it as the unique stable match. □

3.6 Fund Age and Startup Value in Equilibrium

We conclude the theory section by showing how the equilibrium matching patterns give rise to systematic differences in startup outcomes. This mirrors the empirical analysis in

Section 2, which examines the effect of fund age on startup performance through three channels: sorting, monitoring, and financing. In particular, we use the model to illustrate how the timing of initial investment—specifically, whether a startup is backed by a young or mature fund—affects its expected valuation upon liquidation via these three channels.

In equilibrium, a startup matched with a mature fund is of low type and receives one round of financing and monitoring. Its expected liquidation value is:

$$\mathbb{E}[V \mid \text{matched with mature}] = \mathbb{E}[V_1 \mid V_0^L] = V_0^L \cdot v^m v^f. \tag{8}$$

In contrast, a startup matched with a young fund is of high type and receives two periods of monitoring and either one or two rounds of funding. Its expected liquidation value is:

$$\begin{aligned}
\mathbb{E}[V \mid \text{matched with young}] = \mathbb{E}[V_2 \mid V_0^H] = &\\
&\mathbb{P}(V_1 \leq T^{H,L} \mid V_0^H) \cdot \mathbb{E}[V_1 \cdot v^m \mid V_1 \leq T^{H,L}, V_0^H] + \\
&\mathbb{P}(V_1 > T^{H,L} \mid V_0^H) \cdot \mathbb{E}[V_1 \cdot v^m v^f \mid V_1 > T^{H,L}, V_0^H] = \\
&V_0^H \cdot (v^m)^2 v^f + \mathbb{P}(V_1 > T^{H,L} \mid V_0^H) \cdot \mathbb{E}[V_1 \mid V_1 > T^{H,L}, V_0^H] \cdot v^m \cdot (v^f - 1).
\end{aligned} \tag{9}$$

The following proposition establishes that startups matched with young funds outperform those matched with mature funds in expectation:

Proposition 6. $\mathbb{E}[V \mid \textit{matched with young}] > \mathbb{E}[V \mid \textit{matched with mature}]$*.*

Proof. The gap in valuation, captured by the difference between Equations 9 and 8, can be decomposed into three distinct channels—sorting, monitoring, and financing:

$$\mathbb{E}[V \mid \text{matched with young}] - \mathbb{E}[V \mid \text{matched with mature}] =$$

$$\underbrace{(V_0^H - V_0^L) \cdot v^m v^f}_{\text{Sorting}} + \underbrace{V_0^H \cdot v^m v^f \cdot (v^m - 1)}_{\text{Monitoring}} +$$

$$\underbrace{\mathbb{P}(V_1 > T^{H,L} \mid V_0^H) \cdot \mathbb{E}[V_1 \mid V_1 > T^{H,L}, V_0^H] \cdot v^m \cdot (v^f - 1)}_{\text{Financing}}. \quad (10)$$

Each of the three components in Equation 10 is positive as $v^m > 1$ and $v^f > 1$ (Assumption 3). □

To interpret the decomposition in Equation 10, imagine hypothetically upgrading a startup matched with a mature fund through three steps: first, changing its type from L to H; second, giving it an additional period of monitoring; and third, providing the option of follow-on financing. Each step yields a strictly positive increase in expected value.

While the decomposition in Equation 10 depends on the order in which channels are applied, the sign of each term is robust. The following proposition formalizes this invariance and determines the positive contribution of each channel:

Proposition 7. *The contribution of each channel—sorting, monitoring, and financing—to the valuation gap between startups matched with young versus mature funds is strictly positive, regardless of the order in which channels are applied.*

Proof. See Section B.4 in the Appendix.

In conclusion, this section shows how the stable matching framework leads to performance outcomes consistent with our empirical findings. Startups matched with younger funds achieve higher expected valuations at exit due to a combination of higher initial quality, more sustained monitoring, and the option for follow-on investment.

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 divided 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 D in the Appendix, and summary statistics of the respondents' characteristics can be found in Section E.

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 aim 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 a fund 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.12, (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 a track record of successful exits over financing, suggesting that high-quality monitoring is also a key consideration. These findings indicate that while entrepreneurs prioritize capital when facing direct trade-offs, they still value strong industry expertise and governance, particularly when choosing between funds with comparable financial strength. Overall, the results provide further evidence that both financing and monitoring shape the startup-VC temporal matching process, with their relative importance varying by 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 being 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 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 time frame, 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 that 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.

Our findings also relate to the recent emergence of evergreen VC funds, which do not have a finite lifespan. The open-ended structure of these funds may enable continued follow-on funding and long-term mentoring. However, it is not clear *ex ante* to what extent the evergreen model can mitigate all underlying frictions. For example, evergreen funds may still face constraints in raising additional capital from LPs or in recycling invested capital by exiting portfolio companies when liquidity is needed for new opportunities. Moreover, the ability to provide ongoing mentorship depends on the fund's capacity to scale its team by hiring sufficient partners as the portfolio grows. We leave for future research the question of how, and to what extent, the fund age dynamics documented in this paper apply to evergreen VC structures.

References

Aghion, P., Howitt, P., 1992. A Model of Growth Through Creative Destruction. Econometrica 60, 323–351.

Amornsiripanitch, N., Gompers, P.A., Xuan, Y., 2019. More than money: Venture capitalists on boards. The Journal of Law, Economics, and Organization 35, 513–543.

Angrist, J.D., Pischke, J.S., 2009. Mostly harmless econometrics: An empiricist's companion. Princeton university press.

Arcot, S., Fluck, Z., Gaspar, J.M., Hege, U., 2015. Fund managers under pressure: Rationale and determinants of secondary buyouts. Journal of Financial Economics 115, 102–135.

Barrot, J.N., 2017. Investor horizon and the life cycle of innovative firms: Evidence from venture capital. Management Science 63, 3021–3043.

Bernstein, S., Giroud, X., Townsend, R.R., 2016. The impact of venture capital monitoring. The Journal of Finance 71, 1591–1622.

Bottazzi, L., Da Rin, M., Hellmann, T., 2008. Who are the active investors? Evidence from venture capital. Journal of Financial Economics 89, 488–512.

Bottazzi, L., Da Rin, M., Hellmann, T., 2009. What is the role of legal systems in financial intermediation? Theory and evidence. Journal of Financial Intermediation 18, 559–598.

Bottazzi, L., DaRin, M., Hellmann, T., 2016. The Importance of Trust for Investment: Evidence from Venture Capital. The Review of Financial Studies 29, 2283–2318.

Brav, A., Lakan, G., Yafeh, Y., 2023. Private equity and venture capital fund performance: evidence from a large sample of israeli limited partners. European Corporate Governance Institute–Finance Working Paper .

Casamatta, C., 2003. Financing and advising: optimal financial contracts with venture capitalists. The Journal of Finance 58, 2059–2085.

Chakraborty, I., Ewens, M., 2018. Managing Performance Signals Through Delay: Evidence from Venture Capital. Management Science 64, 2875–2900.

Cochrane, J.H., 2005. The risk and return of venture capital. Journal of Financial Economics 75, 3–52.

Conti, A., 2018. Entrepreneurial Finance and the Effects of Restrictions on Government R&D Subsidies. Organization Science 29, 134–153.

Conti, A., Guzman, J.A., 2023. What Is the US Comparative Advantage in Entrepreneurship? Evidence from Israeli Migration to the United States. Review of Economics and Statistics , 1–45.

Cornelli, F., Yosha, O., 2003. Stage financing and the role of convertible securities. The Review of Economic Studies 70, 1–32.

Crain, N.G., 2018. Venture capital and career concerns. Journal of Corporate Finance 49, 168–185.

Da Rin, M., Hellmann, T., Puri, M., 2013. A Survey of Venture Capital Research, in: Constantinides, G.M., Harris, M., Stulz, R.M. (Eds.), Handbook of the Economics of Finance. Elsevier. volume 2, pp. 573–648.

Dessi, R., 2005. Start-up finance, monitoring, and collusion. RAND Journal of Economics , 255–274.

Ewens, M., Gorbenko, A., Korteweg, A., 2022. Venture capital contracts. Journal of Financial Economics 143, 131–158.

Ewens, M., Malenko, N., 2025. Board dynamics over the startup life cycle. Journal of Finance, Forthcoming .

Falik, Y., Lahti, T., Keinonen, H., 2016. Does startup experience matter? Venture capital selection criteria among Israeli entrepreneurs. Venture Capital 18, 149–174.

Fu, J.X., 2024. How does active involvement benefit investors? evidence from 85 billion cell phone signals. Working Paper .

Gale, D., Shapley, L.S., 1962. College admissions and the stability of marriage. The American Mathematical Monthly 69, 9–15.

Gompers, P., Gornall, W., Kaplan, S.N., Strebulaev, I.A., 2021. Venture capitalists and covid-19. Journal of Financial and Quantitative Analysis 56, 2474–2499.

Gompers, P., Kovner, A., Lerner, J., 2009. Specialization and success: Evidence from venture capital. Journal of Economics & Management Strategy 18, 817–844.

Gompers, P., Kovner, A., Lerner, J., Scharfstein, D.S., 2006. Skill vs. luck in entrepreneurship and venture capital: Evidence from serial entrepreneurs. NBER, Working Paper .

Gompers, P.A., 1996. Grandstanding in the venture capital industry. Journal of Financial economics 42, 133–156.

Gompers, P.A., Gornall, W., Kaplan, S.N., Strebulaev, I.A., 2020. How do venture capitalists make decisions? Journal of Financial Economics 135, 169–190.

Gornall, W., Strebulaev, I.A., 2022. The contracting and valuation of venture capital-backed companies. Forthcoming, Handbook of the Economics of Corporate Finance 1.

Hellmann, T., 2006. Ipos, acquisitions, and the use of convertible securities in venture capital. Journal of Financial Economics 81, 649–679.

Hellmann, T., Puri, M., 2002. Venture capital and the professionalization of start-up firms: Empirical evidence. The Journal of Finance 57, 169–197.

Hopp, C., Rieder, F., 2011. What drives venture capital syndication? Applied Economics 43, 3089–3102.

Hsu, Y.W., 2010. Staging of venture capital investment: a real options analysis. Small Business Economics 35, 265–281.

Kandel, E., Leshchinskii, D., Yuklea, H., 2011. VC Funds: Aging Brings Myopia. Journal of Financial and Quantitative Analysis 46, 431–457.

Kaplan, S.N., Strömberg, P., 2001. Venture capitalists as principals: Contracting, screening, and monitoring. American Economic Review 91, 426–430.

Kaplan, S.N., Strömberg, P., 2003. Financial Contracting Theory Meets the Real World: An Empirical Analysis of Venture Capital Contracts. The Review of Economic Studies 70, 281–315.

Kaplan, S.N., Strömberg, P., 2004. Characteristics, Contracts, and Actions: Evidence from Venture Capitalist Analyses. The Journal of Finance 59, 2177–2210.

Kerr, W.R., Nanda, R., 2015. Financing Innovation. Annual Review of Financial Economics 7, 445–462.

Kerr, W.R., Nanda, R., Rhodes-Kropf, M., 2014. Entrepreneurship as experimentation. Journal of Economic Perspectives 28, 25–48.

Kortum, S., Lerner, J., 2000. Assessing the Contribution of Venture Capital to Innovation. RAND Journal of Economics 31, 674–692.

Lakonishok, J., Shleifer, A., Thaler, R., Vishny, R., 1991. Window dressing by pension fund managers. The American Economic Review 81, 227–231.

Lerner, J., Nanda, R., 2023. Venture capital and innovation, in: Handbook of the Economics of Corporate Finance. Elsevier. volume 1, pp. 77–105.

Li, X., Wang, S., Xu, J., Zheng, X., 2024. How does vc specialization backfire in startup experimentation? Working Paper .

Lockett, A., Wright, M., 2001. The syndication of venture capital investments. Omega 29, 375–390.

Manso, G., 2016. Experimentation and the Returns to Entrepreneurship. The Review of Financial Studies 29, 2319–2340.

Metrick, A., Yasuda, A., 2010. The economics of private equity funds. The Review of Financial Studies 23, 2303–2341.

Nanda, R., Rhodes-Kropf, M., 2013. Investment cycles and startup innovation. Journal of Financial Economics 110, 403–418.

NVCA, 2024. Venture monitor .

Romer, P.M., 1990. Endogenous Technological Change. Journal of Political Economy 98, S71–S102.

Sahlman, W.A., 1990. The structure and governance of venture-capital organizations. Journal of Financial Economics 27, 473–521.

Samila, S., Sorenson, O., 2011. Venture Capital, Entrepreneurship, and Economic Growth. The Review of Economics and Statistics 93, 338–349.

Sannino, F., 2024. The equilibrium size and value-added of venture capital. The Journal of Finance 79, 1297–1352.

Schmidt, K.M., 2003. Convertible securities and venture capital finance. The Journal of Finance 58, 1139–1166.

Shaw, K., Sørensen, A., 2019. The productivity advantage of serial entrepreneurs. ILR Review 72, 1225–1261.

Sorensen, M., 2007. How Smart Is Smart Money? A Two-Sided Matching Model of Venture Capital. The Journal of Finance 62, 2725–2762.

Wooldridge, J.M., 2019. Introductory Econometrics: A Modern Approach. 7 ed., Cengage Learning.

Yao, T., O'Neill, H., 2022. Venture capital exit pressure and venture exit: A board perspective. Strategic Management Journal 43, 2829–2848.

Yimfor, E., Garfinkel, J.A., 2023. Predicting success in entrepreneurial finance research. Journal of Corporate Finance 81, 102359.

Figures

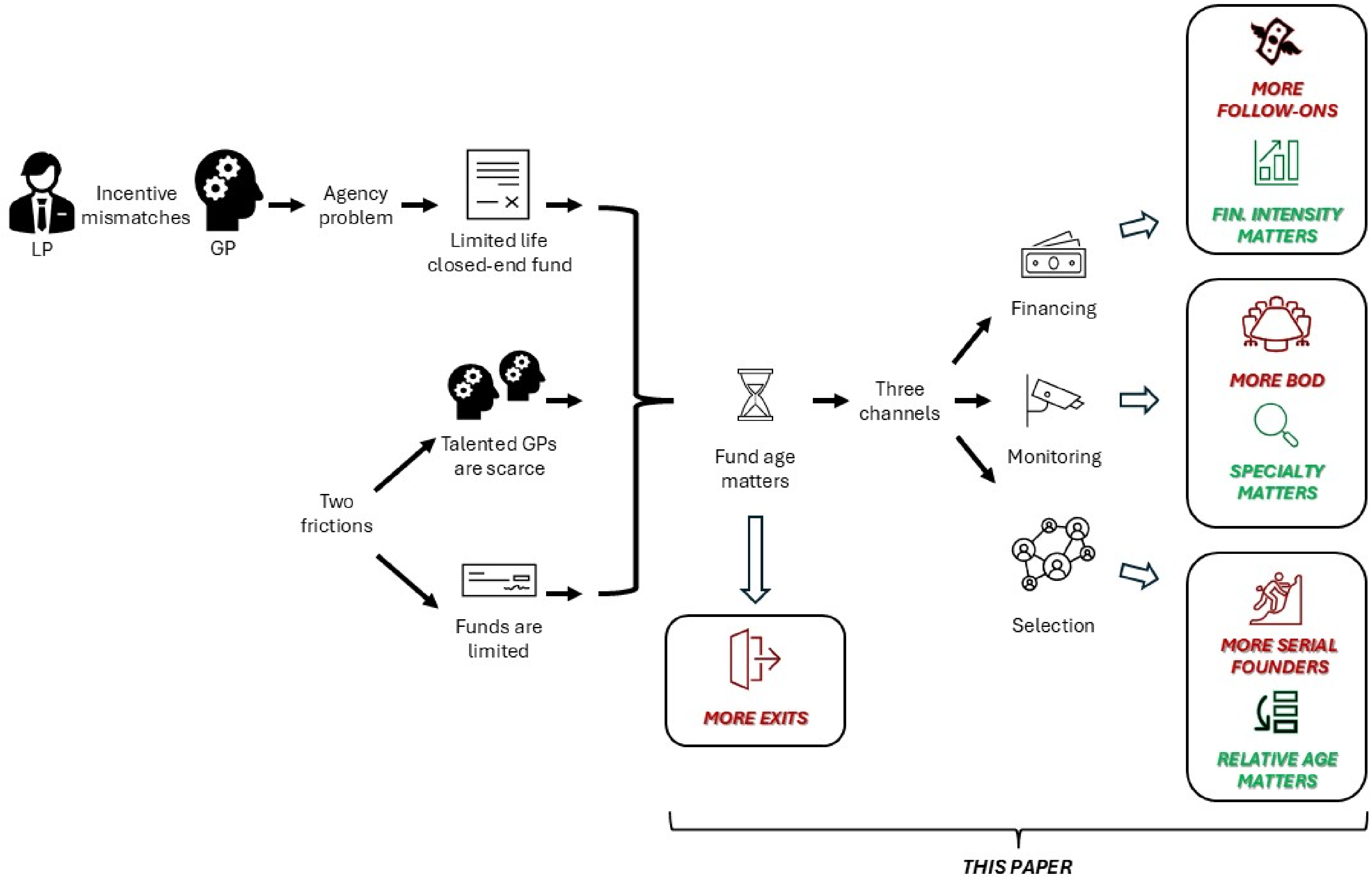

Figure 1. Summary of the mechanisms analyzed in our study. Incentive mismatches generate an agency problem between LPs and GPs. To mitigate this problem, funds adopt a limited-life, closed-end structure, which amplifies two frictions: constrained access to additional capital and high-quality GPs. These 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 a higher probability of successful exits.

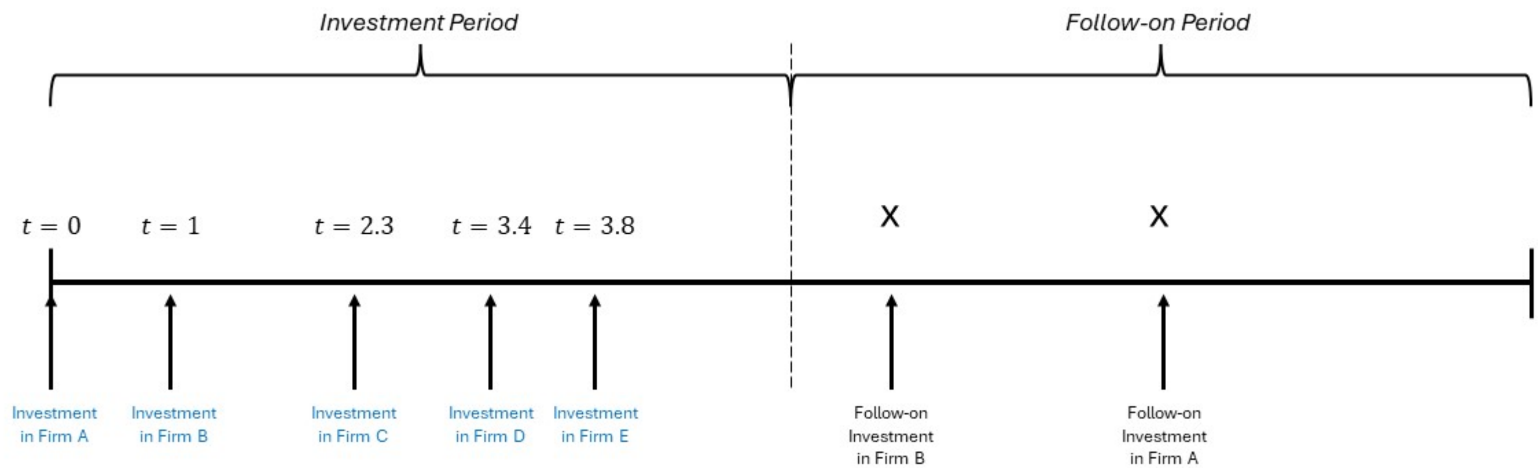

Figure 2. Fund Age. The variable '*Fund Age*' marks the initial investment of each fund as time zero and measures the number of days between that investment and every subsequent investment made by the same fund. These days are then converted into years for analysis, with any follow-on investments excluded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

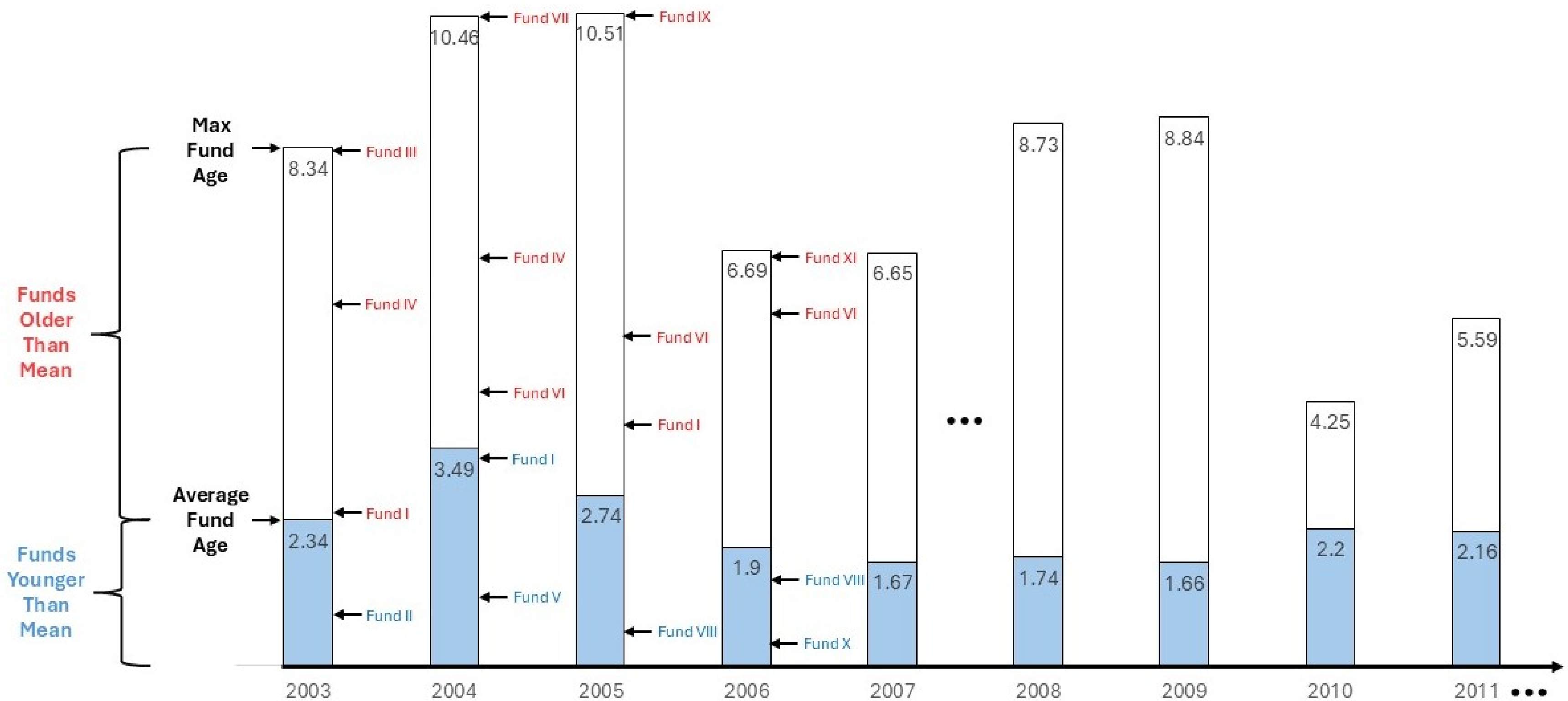

Figure 3. Older than Mean. The variable '*Fund Older than Mean*' is a dummy that flags funds older than the average age of all active funds in a given year. For each year, we identify all active funds, calculate their average age, and classify funds as "old" if they exceed this average. All follow-on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

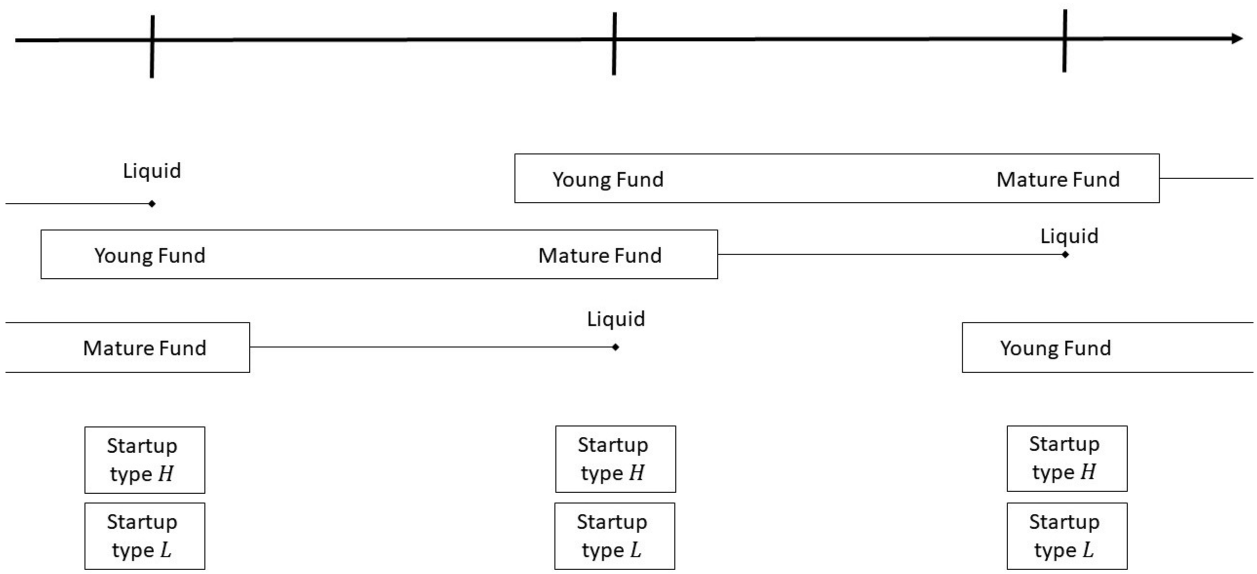

Figure 4. Stock of funds and startups in the model. Each mark on the timeline represents one period. The active status of funds and the entry of new startups are shown below the timeline. “Young”, “Mature”, and “Liquid” indicate different stages of the fund’s life cycle, while “Startup type H” and ”Startup 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 regression (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 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. 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	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	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)
Investment Order	-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 as a function of the years since the fund's inception. Regressions (1) to (3) use follow-on investments made by the same fund, whereas regressions (4) and (5) use those made by all funds. Regressions (1) and (4) are conducted at the startup level, while regressions (2), (3), and (5) 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, regressions (2) and (5) incorporate the age of the startup at the time of investment. Each model includes fixed effects for deal year, industry, investor country, and fund. Regressions (2) and (5) further include round fixed effects, and regression (3) adds startup fixed effects. The analyses include funds with investments in at least two distinct startups and startups 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.

	Same fund			All funds	
	(1) Follow-on	(2) Follow-on	(3) Follow-on	(4) Follow-on	(5) Follow-on
Fund Age	-0.2765***	-0.2589***	-0.3402***	-0.3941***	-0.2920***
	(0.0447)	(0.0436)	(0.0250)	(0.0247)	(0.0091)
Investment Order	0.0044	0.0061***	0.0067***	0.0006	0.0098*
	(0.0033)	(0.0019)	(0.0015)	(0.0069)	(0.0050)
Ln(Deal Amount)	0.1174***	0.0734***	-0.1753***	0.1694***	0.1351***
	(0.0258)	(0.0174)	(0.0457)	(0.0270)	(0.0230)
Firm Age on Deal Date		-0.0168***			-0.0498***
		(0.0050)			(0.0131)
Deal Year FE	Yes	Yes	Yes	Yes	Yes
Investor Country FE	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	No	Yes	Yes
Fund FE	Yes	Yes	Yes	Yes	Yes
Round FE	No	Yes	No	No	Yes
Startup FE	No	No	Yes	No	No
Observations	1,043	3,618	2,154	1,043	3,618
Adj. R^2	0.169	0.216	0.820	0.140	0.530
Sample Level	Startup	Investment	Investment	Startup	Investment

Table 5. Alternative explanations

OLS regression results examining the effects of fund age on exit outcomes and follow-on investments for startups. In Panel A, the dependent variable is a dummy equal one if the startup undergoes an IPO, sale, merger, or acquisition ("Exit"). In Panel B, 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 in Panel B incorporate the age of the startup at the time of investment. Each model includes fixed effects for deal year, industry, investor country, and fund. Regressions in Panel B further include round fixed effects. The "Startup Level" sample in Panel A is restricted to seed-stage startups receiving investment from a single VC fund, where the fund invests in at least two different startups. Panel B uses the "Investment Level" sample. In both panels, regression (1) includes only standalone funds or single-fund VC firms, (2) excludes each fund's first investment, (3) excludes each fund's initial investments during the fund year of the last initial investment, (4) excludes each fund's initial investments during the fund year of the last investment, and (5) excludes each fund's initial investments from the sixth fund year onward. 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.

Panel A: Startup-Level Dataset

	Standalone	No First Inv.	No Last Inv.		
	(1)	(2)	(3)	(4)	(5)
	Exit	Exit	Exit	Exit	Exit
Fund Age	-0.0518*	-0.0763**	-0.0593*	-0.0470***	-0.0607*
	(0.0228)	(0.0223)	(0.0207)	(0.0093)	(0.0198)
Investment Order	-0.0071**	-0.0012	-0.0043	-0.0058**	-0.0009*
	(0.0024)	(0.0042)	(0.0026)	(0.0016)	(0.0003)
Ln(Deal Amount)	0.0066	0.0094	0.0143	0.0123	0.0141
	(0.0107)	(0.0119)	(0.0141)	(0.0147)	(0.0122)
Deal Year FE	Yes	Yes	Yes	Yes	Yes
Investor Country FE	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes	Yes	Yes
Observations	222	923	866	997	976
Adj. R^2	0.122	0.165	0.133	0.157	0.168

Panel B: Investment-Level Dataset					
	Standalone	No First Inv.	No Last Inv.		
	(1) Follow-on	(2) Follow-on	(3) Follow-on	(4) Follow-on	(5) Follow-on
Fund Age	-0.4243***	-0.3465***	-0.2314***	-0.2765***	-0.2183***
	(0.0963)	(0.0403)	(0.0435)	(0.0479)	(0.0515)
Investment Order	-0.0006	0.0132***	0.0034	0.0066***	0.0010
	(0.0039)	(0.0010)	(0.0025)	(0.0019)	(0.0026)
Ln(Deal Amount)	0.0362	0.0756***	0.0632***	0.0790***	0.0829***
	(0.0303)	(0.0135)	(0.0186)	(0.0195)	(0.0201)
Firm Age on Deal Date	0.0040	-0.0274***	-0.0193***	-0.0216***	-0.0220***
	(0.0195)	(0.0027)	(0.0044)	(0.0040)	(0.0032)
Deal Year FE	Yes	Yes	Yes	Yes	Yes
Investor Country FE	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes	Yes	Yes
Round FE	Yes	Yes	Yes	Yes	Yes
Observations	928	3,211	2,886	3,375	3,381
Adj. R^2	0.178	0.220	0.179	0.188	0.216

Table 6. Extensions

OLS regression results examining the effects of fund age on VC board representation, exit outcomes, and follow-on investments for startups. Panel A shows results using the "Startup Level" sample, which is restricted to seed-stage startups receiving investment from a single VC fund, where the fund invests in at least two different startups. Panel B shows results using the "Investment Level" sample. In Panel A, 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 ("VC Board") in models (1) and (2), and a dummy equal one if the startup undergoes an IPO, sale, merger, or acquisition ("Exit") in models (3) and (4). In Panel B, 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. *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. Additionally, regressions in Panel B incorporate the age of the startup at the time of investment. Each model includes fixed effects for deal year, industry, investor country, and fund. Regressions in Panel B further include round fixed effects. In Panel A, regression (1) includes startups where VC representation on the board has been definitively established, (2) further restricts startups to those for which founder experience is definitively established, (3) includes only multi-fund VC firms, and (4) uses a sample of US startups from PitchBook. In Panel B, regression (1) includes only multi-fund VC firms, and (2) uses 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.

Panel A: Startup-Level Dataset

	Monitoring		Multi-fund VC	PitchBook
	(1) VC Board	(2) VC Board	(3) Exit	(4) Exit
Fund Age	-0.0713*	-0.1339**	-0.0844**	-0.0204***
	(0.0286)	(0.0287)	(0.0149)	(0.0043)
Investment Order	0.0019	0.0032	-0.0009*	-0.0006
	(0.0010)	(0.0015)	(0.0003)	(0.0005)
Ln(Deal Amount)	0.0066**	0.0275**	0.0129	0.0292***
	(0.0022)	(0.0058)	(0.0127)	(0.0014)
Fund Older than Mean	-0.0717**	-0.0326		
	(0.0235)	(0.0287)		
Serial Entrepreneur		-0.0272*		
		(0.0092)		
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	632	812	10,849
Adj. R^2	0.312	0.327	0.157	0.303

Panel B: Investment-Level Dataset		
	Multi-fund VC	PitchBook
	(5)	(6)
	Follow-on	Follow-on
Fund Age	-0.2288***	-0.0523***
	(0.0295)	(0.0109)
Investment Order	0.0150***	-0.0059***
	(0.0029)	(0.0003)
Ln(Deal Amount)	0.0854***	-0.0108***
	(0.0106)	(0.0027)
Firm Age on Deal Date	-0.0254***	-0.0254***
	(0.0040)	(0.0017)
Deal Year FE	Yes	Yes
Investor Country FE	Yes	Yes
Industry FE	Yes	Yes
Fund FE	Yes	Yes
Round FE	Yes	Yes
Observations	2,690	69,434
Adj. R^2	0.208	0.176

Appendix

A Appendix Tables

Table A.1. Theoretical and Empirical Models Notation

Panel A: 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

Panel B: 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	v^m, v^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

Table A.2. 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 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.

	(1) Exit	(2) Exit	(3) Exit	(4) Exit	(5) 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)
Investment Order					-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.3. 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 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.

	(1) Exit	(2) Exit	(3) Exit	(4) Exit	(5) 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)
Investment Order					-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.4. Baseline result in investments-level dataset

OLS regression results. The dependent variable 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. Sequentially included controls include the logarithm of the deal amount, the number of portfolio companies in the fund at the time of investment, and the age of the startup at the time of investment. Sequentially included fixed effects are for deal year, industry, investor country, fund, and round. The analyses include funds with investments in at least two distinct 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.

Panel A: Sequential inclusion of fixed effects

	(1) Exit	(2) Exit	(3) Exit	(4) Exit	(5) Exit
Fund Age	-0.0256***	-0.0298***	-0.0298***	-0.0271***	-0.0300***
	(0.0049)	(0.0064)	(0.0064)	(0.0078)	(0.0084)
Deal Year FE	No	Yes	Yes	Yes	Yes
Investor Country FE	No	No	Yes	Yes	Yes
Industry FE	No	No	No	No	Yes
Fund FE	Yes	Yes	Yes	Yes	Yes
Round FE	No	No	No	Yes	Yes
Observations	4,176	4,176	4,176	4,175	4,175
Adj. R^2	0.206	0.214	0.210	0.213	0.218

Panel B: Sequential inclusion of control variables

	(1) Exit	(2) Exit	(3) Exit	(4) Exit
Fund Age	-0.0300***	-0.0310***	-0.0525***	-0.0490***
	(0.0084)	(0.0082)	(0.0124)	(0.0130)
Num. of Port. Comp.				-0.0010
				(0.0009)
Ln(Deal Amount)			0.0255***	0.0256***
			(0.0056)	(0.0056)
Firm Age on Deal Date		0.0091***	0.0070***	0.0070***
		(0.0026)	(0.0023)	(0.0023)
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	Yes	Yes
Observations	4,175	4,175	3,618	3,618
Adj. R^2	0.218	0.219	0.209	0.209

Table A.5. 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 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.

	(1) Exits	(2) Exits	(3) Exits	(4) 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)	
Investment Order		-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.6. 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 invested in at least two different startups. The sample is also 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.

	(1) Deal Amount	(2) Follow-on	(3) Exit
Serial Entrepreneur	0.2076**	0.1387**	0.0099
	(0.0561)	(0.0268)	(0.0434)
Investment Order	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.7. 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 invests 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	
	(1) Exit	(2) Follow-on	(3) Exit	(4) Follow-on
Fund Age	-0.0648	-0.2243***	-0.1348***	-0.1895**
	(0.0333)	(0.0368)	(0.0129)	(0.0419)
Investment Order	-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

Table A.8. 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 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.

	(1)	(2)
	Exit	
	1^{st} stage	2^{nd} stage
Lagged US BO fundraising	0.0026***	
	(0.0007)	
Fund Older than Mean		-0.5452***
		(0.1186)
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	21.2	
Kleibergen-Paap F-stat	12.8	

Table A.9. Mediation analysis

OLS regression results examining mediation effects. The dependent variable is a dummy equal one if the startup undergoes an IPO or an M&A ("Exit"). Regression (1) shows our baseline result from Table 3. In regressions (2) to (4), we sequentially regress the prospective mediator variables (*VC Board*, *Follow-on*, and *Serial*). *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 invested in at least two different startups. In regressions (2) to (4), the sample is further restricted to startups where VC representation on the board has been definitively established. In regression (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.

	(1) Exit	(2) Exit	(3) Exit	(4) Exit
Fund Age	-0.0506***	-0.0257**	-0.0380***	-0.0005
	(0.0073)	(0.0062)	(0.0081)	(0.0042)
Investment Order	-0.0048***	-0.0046**	-0.0045*	-0.0032
	(0.0007)	(0.0015)	(0.0018)	(0.0046)
Ln(Deal Amount)	0.0112	0.0108	0.0162	0.0038
	(0.0138)	(0.0130)	(0.0128)	(0.0070)
VC Board		0.0699***	0.0771***	0.1160***
		(0.0106)	(0.0115)	(0.0170)
Follow-on			-0.0378***	-0.0414***
			(0.0050)	(0.0055)
Serial				-0.0023
				(0.0254)
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	1,043	804	804	624
Adj. R^2	0.164	0.122	0.132	0.143

B Proofs

B.1 Proof of Proposition 1

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

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

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:

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

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.

□

B.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:

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

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:

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

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

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

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:

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

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, $\mathbb{E}\left[G^E(V_1|V_0^i, V_0^j)\right] > 0$. 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:

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

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

□

B.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 $V_1 \le T^{i,j}$. 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:

$$
\lambda(V_0^i)V_1 v^m + \lambda(V_0^j)V_0^j v^m v^f - x. \qquad (18)
$$

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

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

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:

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

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

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

Lemma 8. *The function $\lambda(V)V = \frac{xV}{x+V}$ is increasing in V.*

Lemma 8 implies that the first argument in (20) is increasing in V_0^i. It remains to show that $F(V_0^i) \equiv \mathbb{E}\left[G^F(V_1|V_0^i, V_0^j)\right]$ 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,

$$F(V_0^i) = \mathbb{E}\left[G^F(V_1|V_0^i, V_0^j)\right] =$$

$$\int_{T^{i,j}}^{\infty} G^F(V_1|V_0^i, V_0^j)\frac{1}{\sigma V_1}\phi\left(\frac{\ln V_1 - \ln V_0^i - c}{\sigma}\right) dV_1 \overset{\substack{substitution \\ V_1 = V_0^i \exp(c+\sigma z)}}{=}$$

$$\int_{\frac{\ln T^{i,j} - \ln V_0^i - c}{\sigma}}^{\infty} G^F\left(V_0^i \exp(c+\sigma z)\middle| V_0^i, V_0^j\right) \frac{\sigma V_0^i \exp(c+\sigma z) dz}{\sigma V_0^i \exp(c+\sigma z)} \phi(z) =$$

$$\int_{\frac{\ln T^{i,j} - \ln V_0^i - c}{\sigma}}^{\infty} G^F\left(V_0^i \exp(c+\sigma z)\middle| V_0^i, V_0^j\right) \phi(z)\, dz$$

Following the Leibniz integral rule:

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

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:

$$G^F\left(V_0^i \exp(c+\sigma z)\middle| V_0^i, V_0^j\right) =$$

$$[\lambda(V_0^i) + \lambda(V_0^i \exp(c+\sigma z))]V_0^i \exp\left(c+\sigma z\right) v^m v^f - \lambda(V_0^i)V_0^i \exp\left(c+\sigma z\right) v^m - \lambda(V_0^j)V_0^j v^m v^f =$$

$$\lambda(V_0^i)V_0^i \exp(c+\sigma z) m[f-1] + \lambda(V_0^i \exp(c+\sigma z))V_0^i \exp(c+\sigma z) v^m v^f - \lambda(V_0^j)V_0^j v^m v^f$$

Lemma 8 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.

$\square$

B.4 Proof of Proposition 7

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

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

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:

$$\begin{aligned}
&\mathbb{E}[V|\text{matched with young}] = \\
&\qquad V_0^H (v^m)^2 v^f + \Pr\left(V_1 > T^{H,L}\middle|V_0^H\right)\mathbb{E}\left(V_1\middle|V_1 > T^{H,L}, V_0^H\right) v^m \left[v^f - 1\right] = \\
&\qquad\qquad V_0^H (v^m)^2 v^f + \tilde{\Phi}^H V_0^H (v^m)^2 v^f \left[v^f - 1\right]. \qquad (22)
\end{aligned}$$

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

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

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

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

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

Table A.10 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:

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

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

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

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

$\square$

Table A.10. 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	$V_0^H v^m$	$V_0^H v^m + \tilde{\Phi}^H V_0^H v^m \big[v^f - 1\big]$
(II)	S F M	V_0^L	V_0^H	$V_0^H + \tilde{\Phi}^H V_0^H \big[v^f - 1\big]$	$V_0^H v^m + \tilde{\Phi}^H V_0^H v^m \big[v^f - 1\big]$
(III)	M S F	V_0^L	$V_0^L v^m$	$V_0^H v^m$	$V_0^H v^m + \tilde{\Phi}^H V_0^H v^m \big[v^f - 1\big]$
(IV)	M F S	V_0^L	$V_0^L v^m$	$V_0^L v^m + \tilde{\Phi}^L V_0^L v^m \big[v^f - 1\big]$	$V_0^H v^m + \tilde{\Phi}^H V_0^H v^m \big[v^f - 1\big]$
(V)	F S M	V_0^L	$V_0^L + \tilde{\Phi}^L V_0^L \big[v^f - 1\big]$	$V_0^H + \tilde{\Phi}^H V_0^H \big[v^f - 1\big]$	$V_0^H v^m + \tilde{\Phi}^H V_0^H v^m \big[v^f - 1\big]$
(VI)	F M S	V_0^L	$V_0^L + \tilde{\Phi}^L V_0^L \big[v^f - 1\big]$	$V_0^L v^m + \tilde{\Phi}^L V_0^L v^m \big[v^f - 1\big]$	$V_0^H v^m + \tilde{\Phi}^H V_0^H v^m \big[v^f - 1\big]$

C 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.

C.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 $\sigma_1^2 \equiv \sigma_{1|1}^2$.

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 9. $\sigma^2_{t+1|\mathbb{I}_t^f} = \frac{\gamma^m + \mathbb{I}_t^f \gamma^f}{\left(\gamma_t + \gamma^m + \mathbb{I}_t^f \gamma^f\right)\gamma_t}$ *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 9, 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:

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

[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.

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:

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

Equilibrium Concept

We study stable matches in 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.

C.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 10. *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 $T^{i,H} \geq T^{i,L}$.*

C.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 11. *An entrepreneur prefers to be matched with a young fund than a mature one.*

C.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 12. *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.*

C.5 Stable Matching and Startup Performance in Equilibrium

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

Proposition 13. *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 14. $E[V|\textit{matched with young}] > E[V|\textit{matched with mature}]$

To prove Proposition 14, note that the difference between (35) and (34) can be decomposed into three components – sorting, additional monitoring, and additional financing:

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

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 15. *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.*

D 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

E 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.11, 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.11. 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

F Survey Responses

Figure 5. Scenario 1: Fund Age

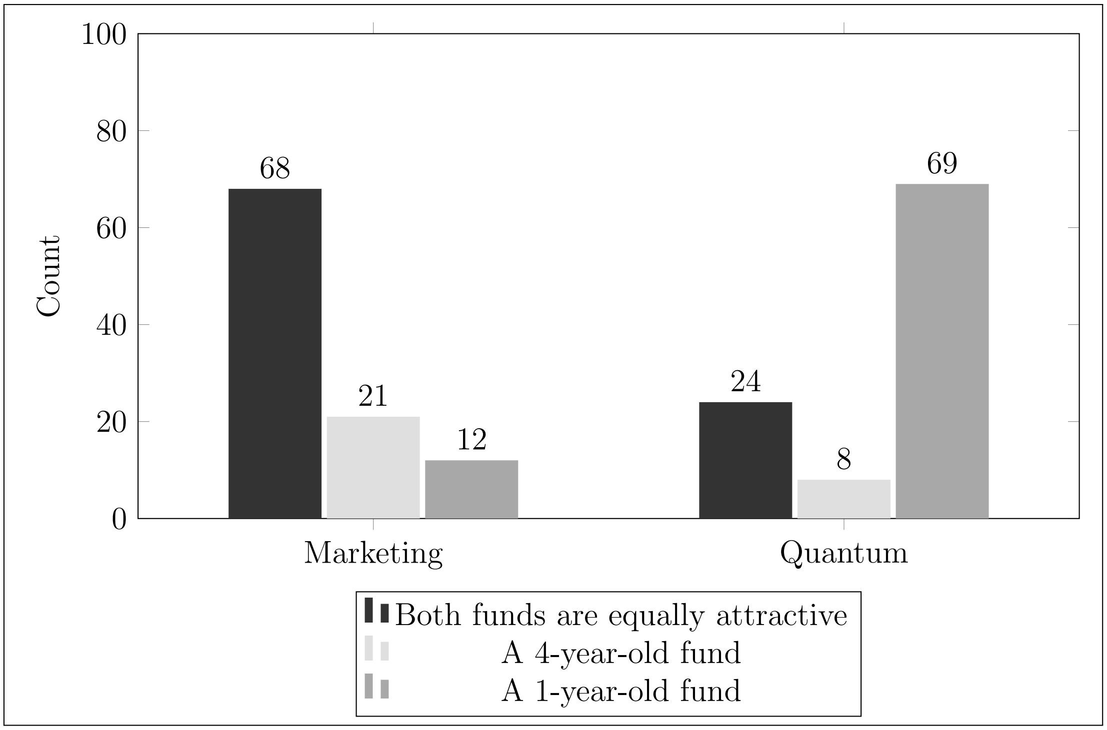

Figure 6. Scenario 2: Financing

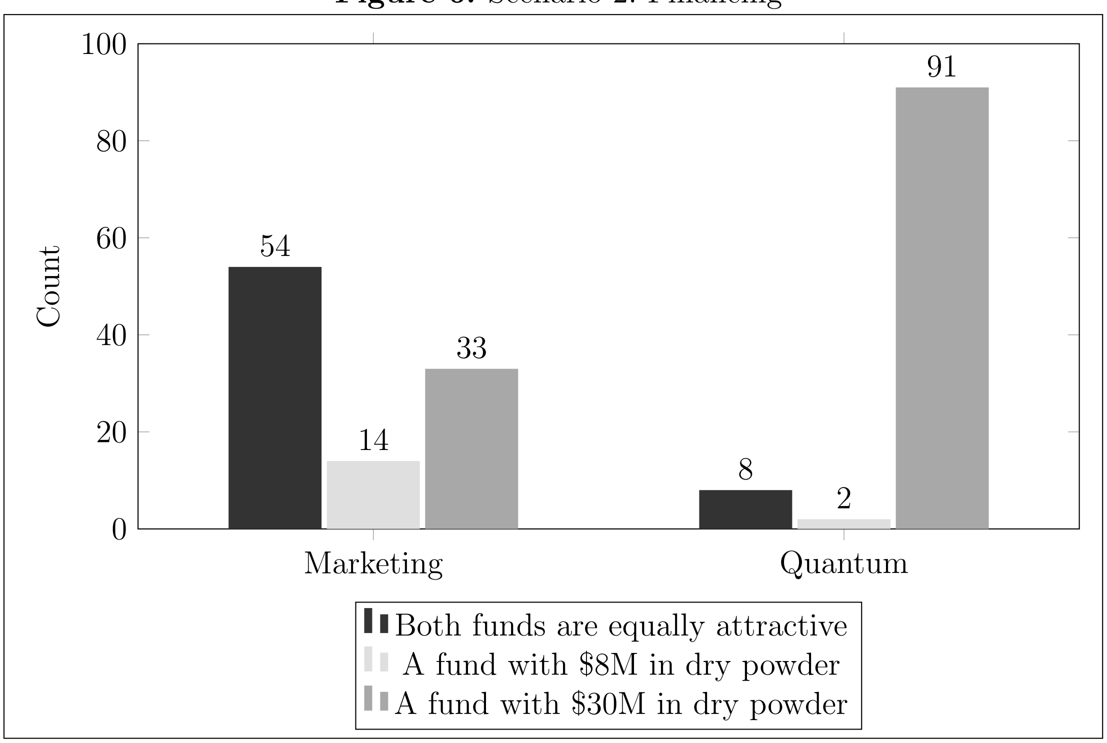

Figure 7. Scenario 3: Monitoring with limited financing

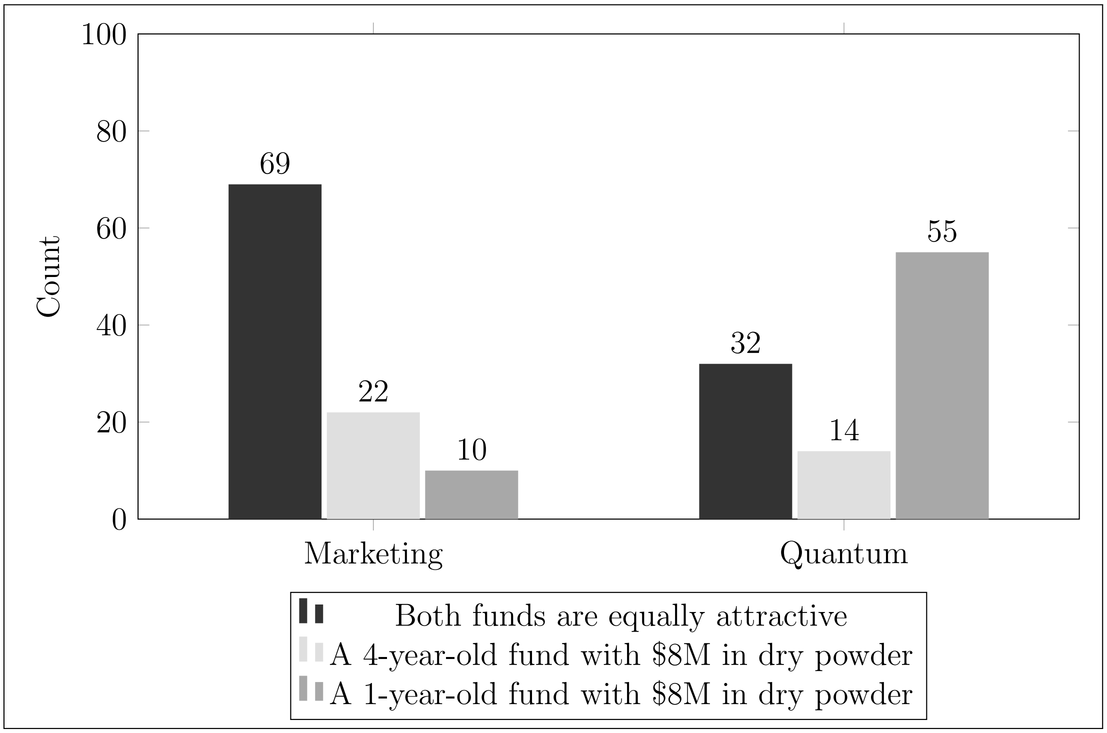

Figure 8. Scenario 4: Monitoring Vs. Financing

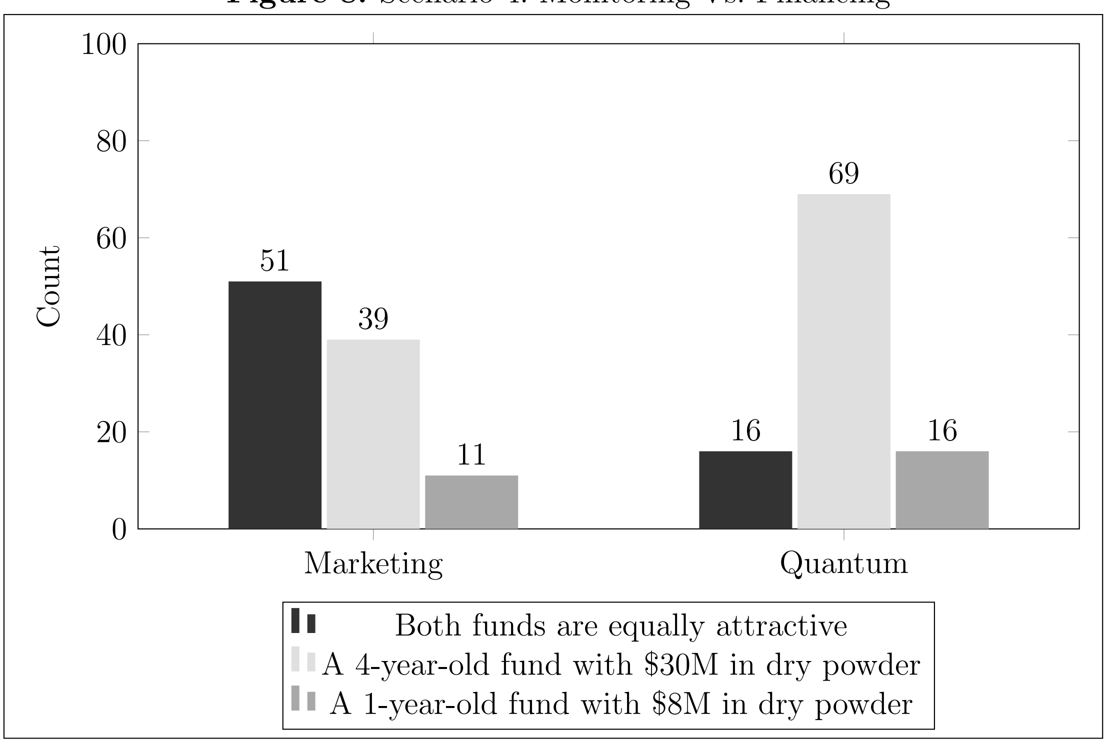

Figure 9. Scenario 5: Monitoring

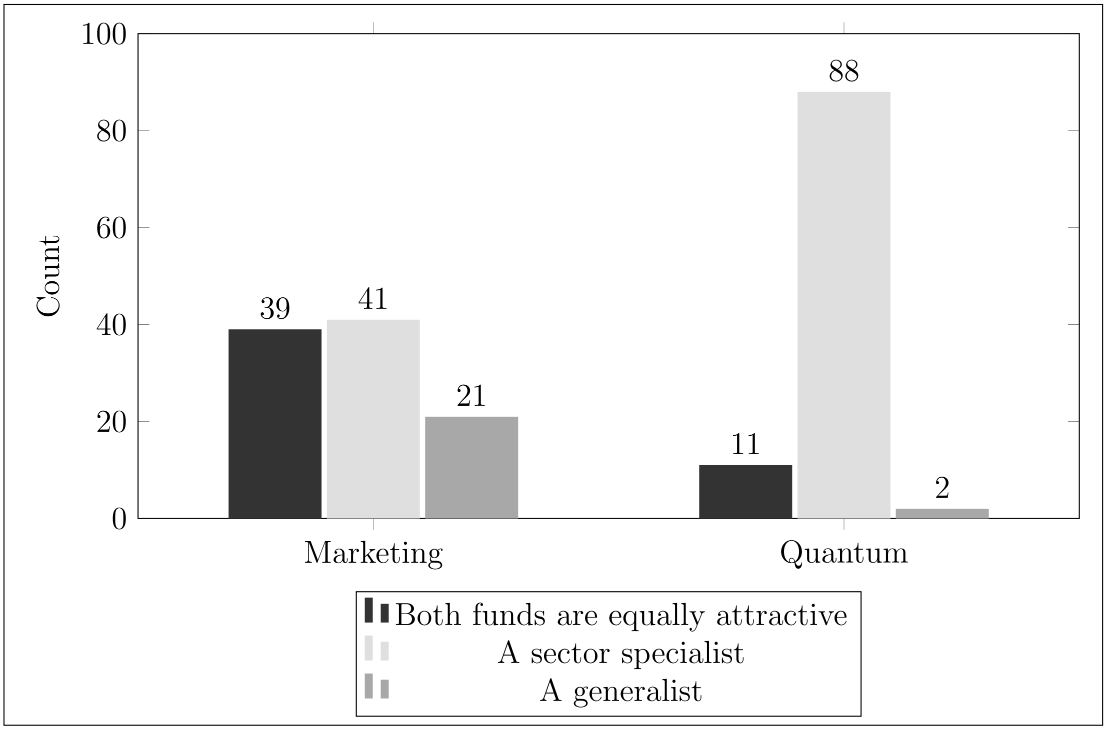

Figure 10. Scenario 6: Investment Order

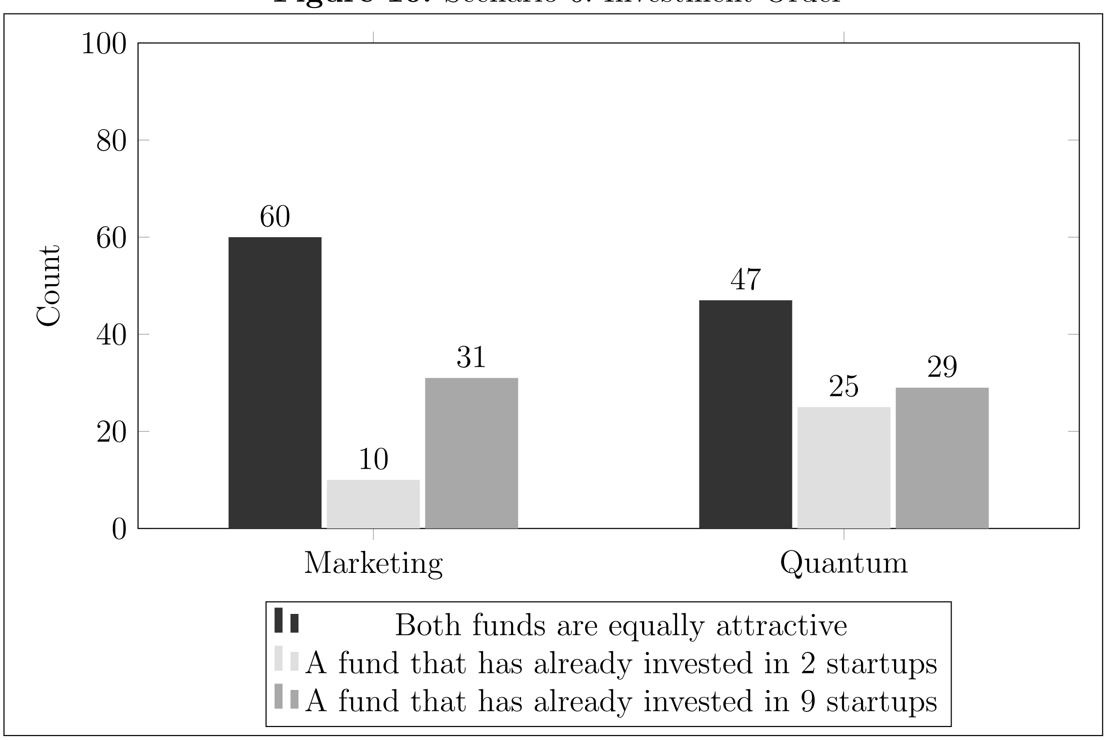

Table A.12. VC fund characteristics ranked in order of importance

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