Temporal Dynamics of Venture Capital Funds: Investment Timing and Performance

Alexander Montag, Maya Haran Rosen, Jonathan Zandberg, Osnat Zohar*

First version June 2023
Current version December 2, 2024

Abstract

This study investigates how venture capital (VC) fund age influences investment outcomes, focusing on younger funds' ability to attract higher-quality startups and increase the likelihood of successful exits. We present a theoretical model suggesting that funds attract high-quality startups early in the funds' lifecycle by offering extended monitoring and greater opportunities for follow-on investments—channels that are further strengthened by entrepreneurs' selection of younger funds. Using a comprehensive dataset of VC funds, we find empirical evidence supporting our model, showing that investments made earlier in a fund's lifecycle achieve significantly higher exit rates and receive more follow-on funding. By controlling for fund and startup characteristics and interacting fund age with industry-level financial intensity and fund specialization, we identify the two channels and quantify the role of entrepreneurs' selection of funds in the startup-VC matching process. This research provides novel insights into the temporal dynamics of VC value creation and how investment timing and entrepreneurial choices influence startup outcomes.

*Alexander Montag is from the Kelley School of Business, Indiana University; Jonathan Zandberg is from The Wharton School of the University of Pennsylvania; and Maya Haran Rosen and Osnat Zohar are from the Bank of Israel. The authors gratefully acknowledge financial support from the Sapir Center at Tel Aviv University. We thank Yuval Kreynes and Eitan Fink for their excellent research assistance. The paper greatly benefited from Alexey Khazanov's discussion and comments from participants at a seminar at the Bank of Israel. We also thank Alon Brav, Sylvain Catherine, Brian Gibbons, Song Ma, Nadya Malenko, Daniel Nathan, Philip Strahan, Lucian Taylor, Clara (Chi) Xu, and Xiang Zheng for their invaluable comments. The views expressed in this paper do not necessarily reflect those of the Bank of Israel.

1 Introduction

Venture capital (VC) funds play a pivotal role in financing high-growth startups, which disproportionately contribute to innovation and are key drivers of economic growth (Kortum and Lerner, 2000; Aghion and Howitt, 1992; Romer, 1990). The sorting process between startups and VC funds is of first-order importance for value creation, with startups seeking funding from the most reputable VC funds and top VC funds aiming to invest in the highest-potential startups (Sorensen, 2007; Gompers et al., 2020; Sannino, 2024). While this positive sorting has been well-documented, the temporal dynamics of how VC fund age influences this process have not been thoroughly explored. This paper addresses this gap by investigating how the age of a VC fund affects the startup-VC matching process and investment outcomes, emphasizing the significant role of entrepreneurs' choices in these outcomes.

We develop a theoretical model to examine how the timing of investments within a VC fund's lifecycle impacts outcomes. Our model reveals a novel insight: higher-quality startups tend to match with younger VC funds. This equilibrium matching arises from mutual preferences. Startups prefer younger funds in anticipation of more monitoring and a higher likelihood of follow-on funding, given the finite lifespan of VC funds. VC funds prefer investing in higher-quality startups to maximize potential returns.

Our theoretical framework is based on fundamental characteristics of the VC industry, where investments involve three key components: (1) the provision of capital, (2) the option for follow-on investments (Hsu, 2010), and (3) the supply 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). Most VC funds are structured as limited partnerships with a finite lifespan, typically ten years (Metrick and Yasuda, 2010; Kandel et al., 2011; Barrot, 2017). Therefore, the earlier a startup secures investment within a fund's lifecycle, the longer the VC firm's commitment to providing professional guidance and the greater the likelihood of receiving follow-on investments.

Building on these institutional details, our model considers 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. 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 investment, entrepreneurs prefer to partner with younger funds. VC funds, on their part, prefer investing in higher-quality startups to maximize returns. This mutual selection leads to an equilibrium of stable matching (Gale and Shapley, 1962) where higher-quality startups partner with younger VC funds.

Our model predicts diminishing returns in VC investments as fund age increases, implying that startups funded earlier in a fund's lifecycle tend to achieve better outcomes. This effect is attributed to three factors: (1) additional monitoring provided to these startups, (2) additional funding through follow-on investments, and (3) sorting of higher-quality startups into younger funds. To the best of our knowledge, this paper is the first to explore how these three channels relate to fund age and startup outcomes.

Importantly, this result is not trivial. The extent to which these equilibrium matches arise depends on the ability of VC funds to differentiate between lower- and higher-quality startups before investing. In practice, even experienced VC partners find this task challenging (Kerr et al., 2014). Early-stage investments, the context within which we test our theory's predictions, are characterized by high levels of uncertainty, making it difficult to identify startups of varying quality. In response, many VC investment committees adopt a 'championing' rule for initial early-stage investments, where a single partner's vote in favor of investing is sufficient for the fund to proceed (Malenko et al., 2024). Furthermore, considerations such as the overall quality of the fund or fund diversification strategies may outweigh temporal factors. Taken together, these factors suggest that the extent to which higher-quality startups match with younger VC funds in practice is uncertain.

We empirically test our model's predictions using a comprehensive dataset of Israeli VC-backed startups (IVC), which offers an ideal setting for our analysis. The dataset encompasses nearly the entire universe of Israeli VC-backed startups since the beginning of the 1990s and includes detailed information on which VC funds invest in each startup. Unlike commonly used databases like PitchBook or Crunchbase, which typically link investments to VC firms rather than individual funds or lack investment details, 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.

Our primary empirical finding is that startups receiving funding early in a VC fund's lifecycle are more likely to achieve successful exits, supporting our model's prediction that higher-quality startups match with younger VC funds. To ensure the robustness of this result and rule out alternative explanations, we impose stringent sample restrictions and controls. Specifically, we focus exclusively on first-time, seed-stage, single-VC-investor investments, excluding all follow-on investments and restricting our analysis to funds with two or more 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). Across all empirical analyses, we control for the total amount invested in the round, the number of other portfolio companies managed by the VC fund, and include fixed effects for deal year, investor country, industry, and funding round (when applicable). This combination of sample restrictions and control variables enables us to isolate and analyze the age-dependent mechanism independently of previously documented sorting dynamics.

First, we examine whether investments made closer to a fund's inception are associated with a higher likelihood of a successful exit. We find that each additional year in the fund's age reduces the probability of an exit by as much as 21% compared to the sample's unconditional mean of 23% exits.

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

Next, we turn to identify and establish the existence of a time-dependent financing channel. We address potential endogeneity concerns by examining how the fund's age affects industries with different financial intensities. We find that the marginal benefit from each additional year spent together is proportionate to the startup's industry financial needs. Specifically, a one standard deviation increase in the startup's industry financial intensity is associated with a 5% increase in the probability of a successful exit for each additional year with the fund. Startups operating in financially intensive industries are relatively more likely to have a successful exit if they receive their initial investments from younger funds. If financing had no temporal effect, we should not observe any difference in performance based on financial intensity while holding the fund's age and investment amount constant. The fact that we find a difference proves the existence of a financing channel.

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

We identify the sorting channel by analyzing the competitiveness of the VC market using a panel approach that examines the relative age of each fund in a given year. We compile data on all operating funds within each specific year and calculate the average active VC fund age, reflecting the VC industry's collective maturity for that period. We then compare each fund's age against this annual average, identifying those older than the mean. Our analysis reveals that startups funded by older-than-average funds are 34% less likely to achieve a successful exit than the sample's unconditional mean, even after controlling for the fund's absolute age at the time of investment. This finding suggests that funds older than other currently active funds are more effective at attracting higher-quality startups, highlighting the fund's competitiveness beyond any lifecycle-driven advantages.

Finally, we address three potential concerns relating to our empirical findings: window dressing, timing selection, and external validity. First, to address the possibility that fund managers engage in 'window dressing' to make their funds appear more attractive to potential limited partners (Lakonishok et al., 1991), we restrict our sample to standalone funds that cannot allocate promising late-stage opportunities to newer funds. In this context, 'window dressing' refers to fund managers allocating their most promising investments to new funds to showcase strong performance and attract investors for raising subsequent funds. Our results remain robust, with fund age negatively correlated with both the likelihood of exits and the number of follow-on rounds. Second, to mitigate the potential selection bias from VC firms timing the initiation of new funds based on attractive initial investment opportunities, we exclude each fund's first investment and rerun our analysis. We find results consistent with our baseline findings, implying that timing cannot fully explain our results. Third, to test the external validity of our findings and assess whether the effect of fund age might be unique to the Israeli market, we replicate our analysis on a sample of VC-backed startups in the United States using data from PitchBook. The PitchBook data, however, have some significant limitations for the context of our study—incomplete coverage and missing fund IDs. More specifically, almost two-thirds of investments have missing fund IDs (and only identify VC firms), which is a problem given that our identifying variation comes from changes in fund age. Despite these limitations, the PitchBook data allow us to construct the key variables for our baseline regressions (fund age, exits, and follow-on investments) for a subsample of deals, and we follow the same sample construction steps as with the IVC data.

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.

Our paper contributes to the literature on the finite horizon of VC funds, which has been extensively surveyed by Da Rin et al. (2013). 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. Arcot et al. (2015) uses a private equity fund's age as one of multiple inputs to construct a proxy for the pressure a fund is under and relates this measure to deal characteristics. Kandel et al. (2011) model the conflict of interest between limited and general partners in the decision to continue projects, stemming from the fund's limited lifespan and general partners' informational advantage. Chakraborty and Ewens (2018) and Crain (2018) analyze how raising a new fund impacts the investment decisions at a VC investor's current fund. Our paper complements these studies by showing that higher-quality startups sort with younger VC funds. Importantly, by focusing on seed rounds only, we hold the maturity of startups constant, which implies that our sorting mechanism is different from that in Barrot (2017).

We also contribute to the theoretical VC literature. Our model builds upon the frameworks established by Kerr et al. (2014) and Nanda and Rhodes-Kropf (2017), who conceptualize VC funds as entities engaged in a series of investments and experiments. From the entrepreneurs' perspective, Manso (2016) models entrepreneurship as the experimentation with new ideas. Our model integrates these approaches by considering mutual experimentation resulting from the sorting process between entrepreneurs and VC funds. Fu and Taylor (2024) focus on the pre-investment period, demonstrating how the intensity of a fund's due diligence process influences its investment decisions. We depart from the Fu and Taylor (2024) model by incorporating the startup's choice in a general equilibrium framework. The novelty of our approach lies in accounting for startups' responses to the timing restrictions imposed on VC funds by their contractual agreements with limited partners. These contractual obligations, which require VC funds to return capital after a finite period, make the timing of investments a crucial factor in the fund's value proposition, ultimately affecting startups' selection of funds.

Admati and Pfleiderer (1994) show how venture capitalists help resolve agency problems in the multi-stage financing of startups. Sorensen (2007) develop a two-sided sorting model to analyze the relative importance of selection and treatment in the likelihood of a startup going public. Hellmann and Thiele (2015) study the interactions between angel and venture capital investors. Piacentino (2019) demonstrate that VC investors' motivation to build a reputation can reduce the number of startups they invest in, potentially increasing or decreasing welfare depending on the abundance of high-quality startups. Hellmann and Thiele (2023) analyze a startup's decision to scale as a standalone venture or sell to an established firm. Sannino (2024) develop a model for the sorting of entrepreneurs and VC investors, 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. A key contribution of our theoretical model is the finding that startups prefer younger VC funds even in the absence of heterogeneity in fund quality, legal systems, trust, or information asymmetry.

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

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

2 Model

The model presented in this section describes an environment of overlapping generations of VC funds alongside startups that vary in quality. We explore the equilibrium sorting in this market and show that it is characterized by VC funds closer to inception matching with higher-quality startups.

2.1 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). Figure 1 illustrates the stock of startups and funds in each period. Table A.1 in the Appendix summarizes the notation used in the model.

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

Assumption 1 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:

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

Figure 2 illustrates how beliefs about startup quality update over the lifecycle of its matched fund. This evolution 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:

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

where:

$$\sigma^2_{1|1} = Var(\mu_1 | \mu_0, \mathbb{I}_0^f = 1) = \frac{\gamma^m + \gamma^f}{(\gamma_0 + \gamma^m + \gamma^f)^2}$$

and:

$$\sigma^2_{2|\mathbb{I}_1^f} = Var(\mu_2 | \mu_1, \mathbb{I}_1^f) = \frac{\gamma^m + \mathbb{I}_1^f \gamma^f}{\left(\gamma_0 + 2\gamma^m + (1 + \mathbb{I}_1^f)\gamma^f\right)^2}.$$

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:

$$E\left[V(\mu_{t+1})\middle|\mu_t, \mathbb{I}_t^f\right] = \exp\left(\mu_t + \tfrac{1}{2}\sigma^2_{t+1|\mathbb{I}_t^f}\right). \tag{3}$$

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

Equation (3) 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 $\sigma_1^2 > \sigma^2_{2|\mathbb{I}_1^f}$. This property of 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 2. $\exp(\frac{1}{2}\sigma^2_{2|0}) = \exp\left(\frac{\gamma^m}{2(\gamma_0+2\gamma^m+\gamma^f)^2}\right) \geq R$

Given that $\sigma_1^2 > \sigma_{2|1}^2 > \sigma_{2|0}^2$,[1] Assumption 2 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

[1] The fact that $\sigma_{2|1}^2 > \sigma_{2|0}^2$ follows from the fact that the function $\frac{y}{(c+y)^2}$ is increasing for $y < c$.

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.[2]

Assumption 3. *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 4. *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:*

$$\exp\left(\mu_0^i + \tfrac{1}{2}\sigma_1^2\right) - \exp(\mu_0^i) - x > 0. \tag{4}$$

The combination of Assumptions 3 and 4 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:

$$\lambda(\mu_0^i)E\left[V(\mu_1)\middle|\mu_0^i\right] = \frac{x\exp\left(\mu_0^i + \frac{1}{2}\sigma_1^2\right)}{\exp(\mu_0^i) + x} > x. \tag{5}$$

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:

$$[1 - \lambda(\mu_0^i)]E\left[V(\mu_1)\middle|\mu_0^i\right] = \frac{\exp(\mu_0^i)\exp\left(\mu_0^i + \frac{1}{2}\sigma_1^2\right)}{\exp(\mu_0^i) + x} > \exp(\mu_0^i). \tag{6}$$

Equilibrium Concept

The following elements characterize equilibrium in this model:

1. Strategies of entrepreneurs and funds for deciding when to accept a follow-on investment contract.

[2] 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.

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.

2.2 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 4, investing in a new company is always more profitable than not investing. Thus, the expected value of the fund's outside option is:

$$\lambda(\mu_0^i) \exp\left(\mu_1 + \tfrac{1}{2}\sigma_{2|0}^2\right) + \lambda(\mu_0^j) \exp\left(\mu_0^j + \tfrac{1}{2}\sigma_1^2\right). \tag{7}$$

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

$$[\lambda(\mu_0^i) \; + \; \lambda(\mu_1)] \exp\left(\mu_1 + \tfrac{1}{2}\sigma_{2|1}^2\right) \;\; > \;\; \lambda(\mu_0^i) \exp\left(\mu_1 + \tfrac{1}{2}\sigma_{2|0}^2\right) \; + \; \lambda(\mu_0^j) \exp\left(\mu_0^j + \tfrac{1}{2}\sigma_1^2\right). \tag{8}$$

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:

$$\left[1 - \lambda(\mu_0^i) - \lambda(\mu_1)\right] \exp\left(\mu_1 + \tfrac{1}{2}\sigma_{2|1}^2\right) > \left[1 - \lambda(\mu_0^i)\right] \exp\left(\mu_1 + \tfrac{1}{2}\sigma_{2|0}^2\right). \tag{9}$$

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 1. *Suppose a fund matched with a startup of type $i \in \{H, L\}$ when it was young. In addition, suppose that when it is mature, the fund's outside option is investing in a startup of type $j \in \{H, L\}$. There 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 $T^{i,H} \geq T^{i,L}$.*

Proof. See Section A.1 in the Appendix.

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

Proof. 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:

$$U^E(mature|\mu_0^i) = [1 - \lambda(\mu_0^i)]E\left[V(\mu_1)\middle|\mu_0^i\right] = [1 - \lambda(\mu_0^i)]\exp\left(\mu_0^i + \tfrac{1}{2}\sigma_1^2\right) \tag{10}$$

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 $\mu_1 \leq T^{i,j}$. In this case, the entrepreneur will enjoy one period of monitoring, and her expected value, given μ_1, is:

$$[1 - \lambda(\mu_0^i)]\exp\left(\mu_1 + \tfrac{1}{2}\sigma_{2|0}^2\right). \tag{11}$$

However, if $\mu_1 > T^{i,j}$, a follow-on investment will take place and provide the entrepreneur with an expected profit of:

$$[1 - \lambda(\mu_0^i) - \lambda(\mu_1)] \exp\left(\mu_1 + \tfrac{1}{2}\sigma_{2|1}^2\right). \tag{12}$$

Thus, the entrepreneur's expected profit from matching with a young fund is:

$$\begin{aligned} U^E(young|\mu_0^i, \mu_0^j) = \\ & [1 - \lambda(\mu_0^i)] E\left[\exp\left(\mu_1 + \tfrac{1}{2}\sigma_{2|0}^2\right) \Big| \mu_1 \leq T^{i,j}, \mu_0^i\right] \Pr(\mu_1 \leq T^{i,j}) + \\ & E\left([1 - \lambda(\mu_0^i) - \lambda(\mu_1)] \exp\left(\mu_1 + \tfrac{1}{2}\sigma_{2|1}^2\right) \Big| \mu_1 > T^{i,j}, \mu_0^i\right) \Pr(\mu_1 > T^{i,j}) \end{aligned} \tag{13}$$

The following lemma (proof provided in Appendix A.2) shows that $U^E(young|\mu_0^i, \mu_0^j) > U^E(mature|\mu_0^i, \mu_0^j)$ due to the benefits of extended monitoring and the option value of a follow-on investment. Thus, an entrepreneur prefers to be matched with a young fund than a mature one.

Lemma 3. *$U^E(young|\mu_0^i, \mu_0^j) = U^E(mature|\mu_0^i) \exp(\frac{1}{2}\sigma_{2|0}^2) + C(\mu_0^i, \mu_0^j)$, where $\exp(\frac{1}{2}\sigma_{2|0}^2) > 1$ is the value of an additional period of monitoring and $C(\mu_0^i, \mu_0^j) > 0$ denotes the follow-on option value.*

□

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

Proof. See Section A.3 in the Appendix.

2.5 Stable Matching and Startup Performance in Equilibrium

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

Proposition 5. *There is a unique stable matching where the young fund is paired with the high-type startup, and the mature fund, if it seeks a new investment, is paired with the low-type startup.*

Proof. Proposition 2 states that entrepreneurs prefer young funds over mature ones. Proposition 4 shows that young funds prefer high-type startups over low. Consider the two possible deferred acceptance algorithms (Gale and Shapley, 1962): "entrepreneur proposing" and "fund proposing." In the "entrepreneur proposing" version, both entrepreneurs initially approach their first priority, which is the young fund. The young fund rejects L, so the stable matching is H-young, L-mature. In the "fund proposing" version, the young fund initially approaches H. If the mature fund also approaches H, it is rejected, and in any case, the resulting matching is H-young, L-mature. Since both versions yield the same matching, it is the unique stable matching. □

We 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:

$$E[V|\text{matched with mature}] = \exp\left(\mu_0^L + \tfrac{1}{2}\sigma_1^2\right) \tag{14}$$

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:

$$\begin{aligned} E[V|\text{matched with young}] = \exp\left(\mu_0^H + \tfrac{1}{2}\sigma_1^2 + \tfrac{1}{2}\sigma_{2|0}^2\right) + \\ \Pr\left(\mu_1 > T^{H,L}\middle|\mu_0^H\right) E\left(\exp(\mu_1)\middle|\mu_1 > T^{H,L}\right)\left[\exp\left(\tfrac{1}{2}\sigma_{2|1}^2\right) - \exp\left(\tfrac{1}{2}\sigma_{2|0}^2\right)\right] \end{aligned} \tag{15}$$

The difference between (15) and (14) can be decomposed into three components – sorting, additional monitoring, and additional financing – each having a positive contribution to the difference:

$$
\begin{aligned}
&E[V|\text{matched with young}] - E[V|\text{matched with mature}] = \\
&\exp\left(\tfrac{1}{2}\sigma_1^2\right)\Bigg(\underbrace{\left[\exp(\mu_0^H) - \exp(\mu_0^L)\right]}_{Sorting} + \underbrace{\exp\left(\mu_0^H\right)\left[\exp\left(\tfrac{1}{2}\sigma_{2|0}^2\right) - 1\right]}_{Addtional\, monitoring} + \\
&\underbrace{\Phi\left(\frac{\mu_0^H + \sigma_1^2 - T^{H,L}}{\sigma_1}\right)\exp\left(\mu_0^H\right)\left[\exp\left(\tfrac{1}{2}\sigma_{2|1}^2\right) - \exp\left(\tfrac{1}{2}\sigma_{2|0}^2\right)\right]}_{Addtional\, financing}\Bigg). \qquad (16)
\end{aligned}
$$

To illustrate the central finding of this model—the entrepreneurs' sorting mechanism amplifying the effects of the monitoring and financing channels—we plot the difference in expected values with and without a sorting mechanism across various startup-quality distributions. The key takeaway from Figure 3 is that while time matters in a random allocation of startups to mature and young funds, it matters even more when the sorting mechanism is in place.

3 Empirical Analysis

Next, we test our hypotheses and theoretical findings in an empirical setting. This section serves two primary goals: to demonstrate how startups and funds match in equilibrium and to provide evidence for the existence of time-dependent financing and monitoring channels, amplified by startups' selection of VC funds.

3.1 Data

We analyze the universe of VC-backed startups in Israel using a dataset compiled by the IVC Research Center. To extract the names of VC firms and funds, we compare this dataset with information from PitchBook and Crunchbase. Additionally, we hand-collect data on founders' identities, startup ownership, and board seats from the Israeli Registrar of Companies. The complete dataset includes 72,513 investments in 10,861 startups by 14,147 investors between January 1990 and February 2024. These investors include VC funds (31.2% of investments), Angels (17.4%), corporate venture capital (4.5%), private equity funds (1.5%), government agencies (1.2%), and others. We then manually match the IVC data to proprietary data from the Israeli Registrar, yielding the most comprehensive mapping of the Israeli startup-VC investor universe available.

The data includes 24,788 seed-round investments, 16,489 first-round investments, 11,164 second-round investments, 18,000 third-round and later investments, and 2,072 initial public offerings (IPOs) and mergers and acquisitions (M&As). The highest round of funding in our dataset is fifteen.

We narrow our focus to include only first-time investments made by VC firms from funds that have invested in at least two different startups between 2003 and 2023. Funds with only one investment are excluded, as they do not contribute to our analysis and would be absorbed by our fund fixed effects. The dataset begins in 2003, as data on exits—such as M&As and IPOs—are only available from this year onward. After applying these criteria, we obtain 3,633 first-time investments in 2,267 startups made by 416 distinct VC funds, spanning from seed to ninth-round funding. Among these startups, 62 had an IPO, 472 had an M&A, and 9 had both. For our analyses, we treat the first of these two as the exit event. We refer to this as the "investment-level dataset."

To assess how the timing of investments within a fund's lifecycle impacts startup performance, we further refine our dataset. Given that we have a time-invariant dependent variable—a dummy indicating whether the startup experienced a successful exit—our empirical analysis is limited to one observation per startup. Therefore, we focus on seed-round investments made by a single VC fund. This results in a dataset of 1,049 seed investments in 1,049 startups by 205 different VC funds. In this dataset, each entry represents a different startup raising its first institutional capital, meaning all startups are at a very early stage of their lifecycle. Among these startups, 17 had an IPO, and 232 had an M&A. We refer to this dataset as the "startup-level dataset."

Using only investments from a single VC fund enables us to examine the effect of fund age without the confounding influence of multiple investments from funds at different stages. As shown in Table 1, the average fund invests in 8.2 Israeli startups, with an average check size of \$12 million across rounds and \$3.9 million for a single-VC-investor seed round.

3.2 Empirical Strategy

Our main specification uses the "startup-level dataset" to assess the association between startup quality and 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 two startups or more. More specifically, we regress:

$$\begin{aligned} Exit_s = {} & \beta_1 FundAge_s + \beta_2 Ln(DealAmount)_s + \beta_3 PortfolioSize_s \\ & + FundFE + DealYearFE + Inv.CountryFE + IndustryFE + \epsilon_s \end{aligned} \tag{17}$$

where, s indexes startups. $Exit_s$ represents our performance measure, a dummy variable indicating if a startup had an exit through an M&A or an IPO.[3] In our main specification, illustrated in Figure 4, we examine the number of years since a fund's inception, calculated as the difference between the time of investment and the time of the fund's first-ever investment.

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

In our 'startup-level dataset,' we do not control for startups' age because all firms are raising their first seed investment, resulting in minimal variability in this measure. To account for unobserved heterogeneity and capture time trends, country-specific, and industry-specific effects, we include industry, time, and investor-country fixed effects. 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. To ensure the robustness of our results, we test them by excluding these fixed effects and controls; the findings are reported in the appendix. Our standard errors are clustered at the deal-year and investor-country levels.

In our second empirical setting, we aim to confirm our modeling assumption that younger funds are more likely to provide follow-on investments. We first test Assumption 1 of the model and find that VC investments are very sticky. The conditional probability of a follow-on investment being made by an investor who has previously invested is 65% [95% CI: 0.639–0.664]. This result provides confidence in the model's assumption that follow-on investments are made by the same fund.

We then replace our dependent variable, $Exits_s$, in our baseline empirical setting described in Equation 17, with a counter that tracks the number of follow-on investments each startup receives from the same fund.

As the number of follow-on investments changes over time, 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:

$$\begin{aligned} FollowOns_{s,v,r} = {} & \beta_1 FundAge_{s,v,r} + \beta_2 Ln(DealAmount)_{s,r} + \beta_3 StartupAge_{s,r} \\ & + \beta_4 PortfolioSize_{v,r} + RoundFE + FundFE + DealYearFE \\ & + Inv.CountryFE + IndustryFE + \epsilon_{s,v,r} \end{aligned} \tag{18}$$

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

where v stands for a VC fund, r stands for a round of funding, $FollowOns_{s,v,r}$ represents the number of future additional rounds of funding a startup raises from a specific fund, and $StartupAge_{s,r}$ is a startup's age at the time of investment. In contrast to the previous dataset, the startup age varies in this one as we include all funding rounds. Therefore, we 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.

In an alternative approach to this analysis, we include startup fixed effects to examine the funds' lifecycle impact while accounting for the quality of the startup. We include only funds investing in at least two different startups and startups receiving first-time investments from at least two different VC funds.

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

$$\begin{aligned} Exit_s = {} & \beta_1 FundAge_s + \beta_2 Ln(DealAmount)_s + \beta_3 PortfolioSize_s \\ & + \beta_4 Fin.Intensity_j + \beta_5 FunaAge_{s,v} \times Fin.Intensity_j \\ & + FundFE + DealYearFE + Inv.CountryFE + IndustryFE + \epsilon_{s,j} \end{aligned} \tag{19}$$

where $Fin.Intensity_j$ represents our industry-level financial intensity index value for an industry to which startup s belongs. The marginal effect of each additional year is measured by the coefficient of the interaction term $FundAge \times Fin.Intensity$, β_5.

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

$$
\begin{aligned}
Exit_s = {} & \beta_1 FundAge_s + \beta_2 Ln(DealAmount)_s + \beta_3 PortfolioSize_s \\
& + \beta_4 \mathbb{I}\{Specialist_v\} + \beta_5 FundAge_s \times \mathbb{I}\{Specialist_v\} \\
& + FundFE + DealYearFE + Inv.CountryFE + IndustryFE + \epsilon_s
\end{aligned} \tag{20}
$$

where $\mathbb{I}\{Specialist_v\}$ is a dummy variable that equals one if a VC fund invests in two or fewer industries. The marginal effect of an additional year of fund age for specialist funds is captured by the coefficient of the interaction $FundAge \times \mathbb{I}\{Specialist\}$, β_5. The presence of a time-dependent monitoring channel would imply that each additional year with a specialist fund is positively correlated with performance.

Next, we provide evidence for the selection channel and specifically for startups' preference for matching with younger funds. For that, we assess a cross-sectional lifecycle measure. As illustrated in Figure 5, we use our more extensive "investment-level dataset" to estimate market conditions by examining the age of all active funds in a given year and flagging those older than the average active fund for that year. By flagging the ones that are older than the mean, we address the competitiveness of the venture capital market in that year and a startup's preferential matching with respect to fund age. We regress our performance measure against the dummy variable with and without controlling for a fund's age in our more restrictive "startup-level dataset":

$$
\begin{aligned}
Exit_s = {} & \beta_1 \mathbb{I}\{OlderThanMean_{s,t}\} + \beta_2 FundAge_s \\
& + \beta_3 Ln(DealAmount)_s + \beta_4 PortfolioSize \\
& + FundFE + DealYearFE + Inv.CountryFE + IndustryFE + \epsilon_s
\end{aligned} \tag{21}
$$

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

In our final set of empirical analyses, we address three alternative explanations for our baseline results. The first is that funds may engage in 'window dressing' by allocating their most successful startups to younger funds to showcase strong performance to potential investors in subsequent funds. To address this concern, we replicate our baseline analysis using a subsample of standalone funds—that is, VC firms that have raised only one fund. The second alternative explanation is that our results are driven by the VC firm's choice of when to open a new fund. While VC firms likely initiate new funds based on market conditions, they cannot alter a fund's age once it begins investing. To mitigate this potential selection bias, we exclude the first investment made by each fund and rerun our baseline analysis. This approach aims to partially eliminate the influence of a VC firm's decision to start a new fund in response to a specific investment opportunity. The third explanation is that, for some unobservable reasons, the phenomenon may be unique to the Israeli market. To address this concern, we rerun our baseline analyses using a dataset of investments made in the U.S.

3.3 Empirical Results

We present our results for the empirical settings presented in the section above using both the "startup level dataset" and "investment level dataset" when appropriate.

3.3.1 Performance and Fund Age

Our baseline empirical result, presented in Table 2, Column 1, shows a negative correlation between our lifecycle measure "Fund Age" and a startup's exit probability. The likelihood of a startup having an exit decreases by 4.8pp for each additional year that a particular VC fund invests after its inception. This represents approximately 20.5% of the unconditional probability of 23.4% for a startup to have an exit in this subsample. This result demonstrates diminishing returns throughout a fund's lifecycle, where fund age plays an important role in individual investment returns.

We conduct a series of additional tests to validate these findings. In the first set of tests, we rerun our baseline analysis with various controls and fixed effects as reported in Table A.2 in the Appendix. Notably, excluding fund fixed effects reduces the estimated effect size by an order of magnitude—from 4.8pp to 0.47pp. While the direction of the correlation remains negative and statistically significant, the substantial reduction in magnitude underscores the importance of fund quality in the startup-fund matching process. Nevertheless, the fact that the effect remains negative and significant indicates that fund age is important even after accounting for selection based on fund quality.

In the second set of robustness tests, reported in Table A.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. All three approaches yield consistent results, supporting an equilibrium in which higher-quality startups are more likely to sort with younger funds.

3.3.2 The Financing Channel

To assess the impact of a fund's age on the financing channel, we first investigate whether investments made early in the fund's lifecycle result in more follow-on investments by the same fund, as hypothesized in our model. As shown in Table 2 Column 2, we find that each additional year in a fund's age is associated with a 0.28 decrease in the number of follow-on investments, equivalent to a 27% decrease relative to the 1,049 startup-level observations' unconditional mean of 1.04 follow-ons.[4] This result suggests that the age of a fund at the time of investment is negatively correlated with the number of follow-on investments it can potentially offer.

One advantage of using the follow-on variable instead of the exits variable is that it allows us to exploit the richness of the data by analyzing the investment-level dataset. We can examine multiple investments made by different funds in the same startup since the number of follow-ons differs by fund. As reported in Table 3, Column 2, our investment-level regressions produce results similar to those obtained at the startup level. An important difference between the two datasets is that the startups in the investment-level dataset are at various stages and, therefore, at different ages.

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

In an alternative approach, reported in Table 3 Column 3, we include startup fixed effects to account for the quality of a startup in addition to the quality of an investor. In this setting, we compare two or more initial investments from two or more different VC funds in the same company, with the only difference being the age of the fund. We observe that the negative correlation between the fund age and exit probability persists even when comparing investments in the same company by funds of different ages. These results are of a similar magnitude to our previous findings, which do not include startup fixed effects.

To assess the financing channel's intensive margin and to address potential identification concerns in this setting, we regress the interaction between our industry-level financial intensity index and the fund's age as shown in Equation 19. As presented in Table 2 Column

[4]The 1,049 startups in our "startup-level dataset", received a total of 1,091 follow-on investments. Specifically, 294 startups received one follow-on investment; 145 received two; 87 received three; 31 received four; 18 received five; 4 received six; and one startup received eight.

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 4.6% (= coefficient $\times$ std. dev. / unconditional prob. of exit = 0.584 x 0.0184 / 0.234) for every additional year in a fund's age. 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—such as the monitoring channel—we would not expect to see differences based on an industry's financial intensity. Therefore, when holding the 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 plays a role in the correlation between age and exits.

3.3.3 The Monitoring Channel

We identify the monitoring channel by comparing specialist and generalist funds in a similar fashion to our analysis of the financing channel. We assert that an additional year of monitoring is more beneficial to a startup if the investment comes from a specialist fund rather than a generalist fund. A specialist fund focuses on a specific industry or sector, while a generalist fund invests across various sectors and may have a limited ability to effectively add value through monitoring compared to a specialist.

To test for the existence of the monitoring channel, we interact fund age with a dummy variable that equals one when a fund is a specialist, as described in Equation 20. Our findings, presented in Table 2 Column 4, show that an additional specialist year decreases the probability of a successful exit by 0.06 or 27% compared to the sample's unconditional mean.

This result suggests that additional time spent with VC funds is valuable for startups, who benefit from monitoring and mentoring by the VC partners. This added value translates to an increased probability of a successful exit. If mentoring had no value, we would not observe a significant difference in the performance of generalist and specialist VCs when holding time constant.

3.3.4 Startup sorting preferences

In our model, we define a third channel as the preferential sorting channel of startups. This channel posits that all else equal, entrepreneurs who recognize the added value of time would prefer a younger fund, thereby amplifying the economic effects of the financing and monitoring channels. While we lack a clear empirical method to quantify the magnitude of each of the three channels individually, we can demonstrate that our results hold in the cross-section. This implies that investments were more successful when made during periods when the fund was younger than the average active fund. This finding supports a sorting narrative in which higher-quality startups benefit from choosing funds of equal quality that are younger than their competitors at the time of investment. Our hypothesis is that time plays an important role in a VC fund's value proposition.

In our test, shown in Table 2 Column 5, we assess the impact of competition on our equilibrium result and attempt to isolate the startup's preferential sorting channel. To evaluate market conditions at the time of investment, we flag all funds younger than the average age of all active funds each year. Our null hypothesis is that there should be no difference in a startup's performance when the investment is made by a fund that is younger than the other active funds in that year after we control for a fund's age. We find that investments made by funds younger than the average active fund in that year are 8pp more likely to experience a successful exit, equivalent to a 34% increase compared to the unconditional probability of an exit.

3.3.5 Extensions

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

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

Chakraborty and Ewens (2018) shows that VC firms delay write-offs of and reinvestments in lower-quality portfolio companies at existing funds until after the new fund is raised. In contrast to Chakraborty and Ewens (2018), we analyze exits and follow-on funding of portfolio companies during the entire life of VC funds, and not just around fundraising periods. This is important because delaying negative information about startups while fundraising should not change the overall likelihood of a startup exiting successfully or raising follow-on funding.

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

Nevertheless, we test this possibility by limiting our sample to standalone funds. VC firms that manage only a single fund cannot allocate good opportunities found late in the fund's lifecycle into a new and younger fund. Fund age remains negatively correlated with the likelihood of exiting and the number of follow-on rounds, with coefficient estimates similar in magnitude to those in our baseline regressions (Columns 1 and 2 of Table 4).

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 decision to start a new fund in response to a specific investment opportunity. Our results remain robust when excluding funds' first investments, weakening the possibility that this selection phenomenon drives our results (Columns 3 and 4 of Table 4).

A third possible alternative explanation relates to the uniqueness of the Israeli market. The effect of fund age might be unique to Israeli startups due to unknown and unobserved factors. To address this possibility and to test the external validity of our results, we rerun our baseline tests on a sample of VC-backed startups from the United States that we constructed using data from PitchBook. While data from PitchBook are commonly used by papers studying the VC industry (Gompers et al., 2021; Lerner and Nanda, 2023; Yimfor and Garfinkel, 2023, to name a few), these data have several limitations for the context of our study. First, PitchBook does not have the entire universe of VC deals in the US. In contrast, the IVC data contains the near-universe of VC-backed startups in Israel. This is especially important for our mechanism tests. Specifically, having the population of active

VC funds and startup exits allows us to precisely define the "older-than-mean" and "industry financial intensity" measures. Second, we lose 62% of investments by VCs in US startups in the PitchBook data because of missing fund IDs. However, our analysis crucially depends on being able to link investments to VC funds, and not just VC firms, because our identifying variation comes from changes in fund age.

Although the PitchBook data has all these limitations in the context of our study, it still allows us to construct the variables needed for our baseline regressions—namely, fund age, exits, and follow-on investments. We follow the same sample construction steps used for the IVC data. The 'investment-level dataset' includes 99,217 investments in 28,914 startups by 6,681 VC funds, and the 'startup-level dataset' includes 14,626 single-investor seed round investments by 4,683 VC funds, with 32% of startups achieving a successful exit. We find negative and statistically significant correlations between fund age at the time of the initial investment and both the likelihood of exit and follow-on investments, suggesting that our baseline results are not unique to the Israeli market (Columns 5 and 6 of Table 4).

Taken together, these additional analyses reinforce the robustness of our findings, indicating that the negative relationship between fund age and both exit likelihood and follow-on investments is consistent across different contexts and not driven by potential biases or unique characteristics of the Israeli market.

4 Conclusion

This paper develops an equilibrium model and provides empirical evidence highlighting the importance of VC fund age and entrepreneurs' fund selection in the matching process between startups and venture capital funds. Our model attributes the superior performance of startups matched with younger funds to three key channels: additional financing, extended monitoring, and the preferential sorting of higher-quality startups into younger funds. Utilizing a comprehensive dataset of Israeli VC-backed startups, we find empirical support consistent with our theoretical predictions. Our results suggest diminishing returns over time at the fund level, suggesting that a fund's age significantly influences its attractiveness to startups through the provision of professional monitoring and substantial in-the-money options for follow-on investments.

Our analysis is robust across various empirical strategies and datasets, underscoring the generalization of our findings. These results have important implications for the venture capital industry, suggesting that increased flexibility around fund liquidation requirements could enhance fund performance. Extending fund durations, adopting longer follow-on investment horizons, and investing in enhanced monitoring capabilities may provide competitive advantages to VC funds.

Future research could explore whether the financing and monitoring channels act 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. Moreover, investigating potential heterogeneous effects by fund quality could yield valuable insights. While our model assumes homogeneity in fund quality, understanding how variations in quality interact with fund age in the matching process may reveal significant differences in value creation among VC funds.

Our research underscores the critical impact of investment timing within the lifecycle of VC funds on startup success. The findings suggest that early-stage investments benefit from extended monitoring and the potential for follow-on funding, contributing to higher success rates. These insights have practical implications for both venture capitalists and entrepreneurs, emphasizing the strategic importance of timing in investment decisions.

Additionally, our study contributes to the broader literature by offering a nuanced perspective on venture capital funds' lifecycle. By integrating theoretical modeling with empirical analysis, we provide a comprehensive framework for understanding the temporal dynamics of VC investments. Future research could build on our findings by examining how factors such as a VC firm's experience and network, the startup's industry sector, and macroeconomic conditions influence investment timing and outcomes. Another promising avenue for future research would be to compare the temporal dynamics observed in venture capital funds to those in other types of investment funds that operate under less restrictive time horizons.

In conclusion, our study highlights the pivotal role of timing in venture capital investments and suggests that strategic adjustments in the lifecycle and operational practices of VC funds could enhance their performance. By elucidating the temporal considerations in VC investment strategies, this research offers valuable insights for improving the efficacy of venture capital funding in fostering innovation and economic growth.

References

Admati, A.R., Pfleiderer, P., 1994. Robust financial contracting and the role of venture capitalists. The Journal of Finance 49, 371–402.

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

Amor, S.B., Kooli, M., 2020. Do m&a exits have the same effect on venture capital reputation than ipo exits? Journal of Banking & Finance 111, 105704.

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.

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 .

Fu, J.X., Taylor, L.A., 2024. Due Diligence and the Allocation of Venture Capital. 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.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.

Hellmann, T., Thiele, V., 2015. Friends or foes? The interrelationship between angel and venture capital markets. Journal of Financial Economics 115, 639–653.

Hellmann, T., Thiele, V., 2023. Scaling versus Selling Startups: The Role of Foreign Acquirers in Entrepreneurial Ecosystems. Journal of Political Economy Microeconomics .

Hochberg, Y.V., Ljungqvist, A., Lu, Y., 2007. Whom You Know Matters: Venture Capital Networks and Investment Performance. The Journal of Finance 62, 251–301.

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.

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.H., Vishny, R.W., 1991. Window dressing by pension fund managers.

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? Available at SSRN 4912335 .

Malenko, A., Nanda, R., Rhodes-Kropf, M., Sundaresan, S., 2024. Catching Outliers: Committee Voting and the Limits of Consensus when Financing Innovation. Working paper .

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., 2017. Financing risk and innovation. Management Science 63, 901–918.

Phalippou, L., Gottschalg, O., 2009. The Performance of Private Equity Funds. The Review of Financial Studies 22, 1747–1776.

Piacentino, G., 2019. Venture Capital and Capital Allocation. The Journal of Finance 74, 1261–1314.

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

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.

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

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

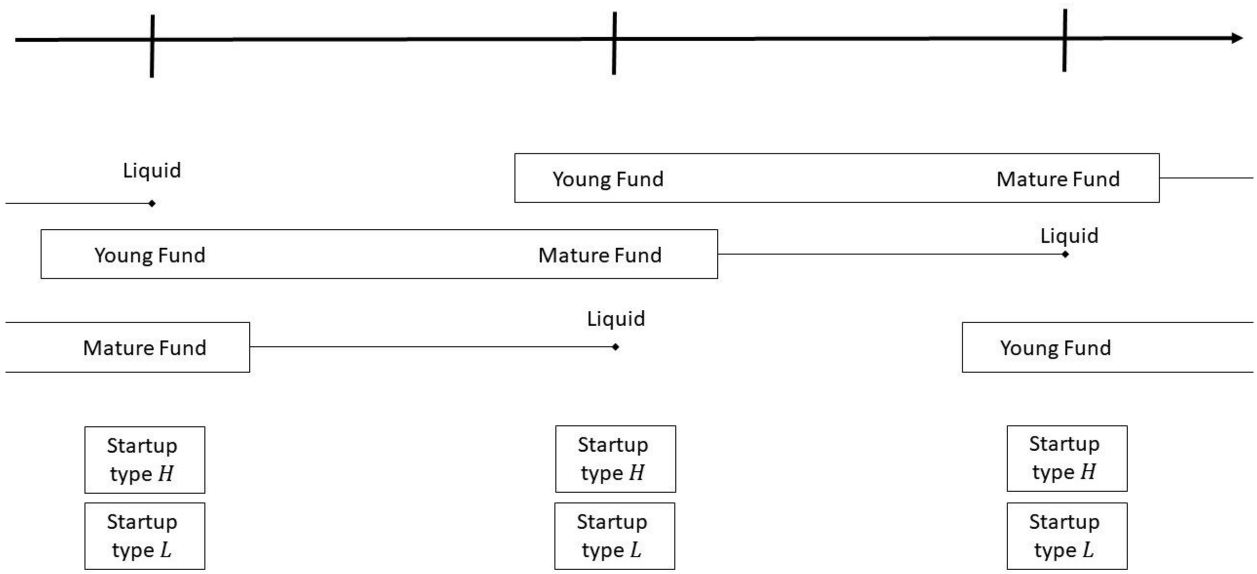

Figure 1. Stock of funds and startups in the model. Each mark on the timeline represents one period. The active status of funds and the entry of new startups are shown below the timeline. "Young Fund" and "Mature Fund" indicate different stages of the fund's life cycle, while "Startup type H" and "Startup type L" represent high-potential and low-potential startup types, respectively.

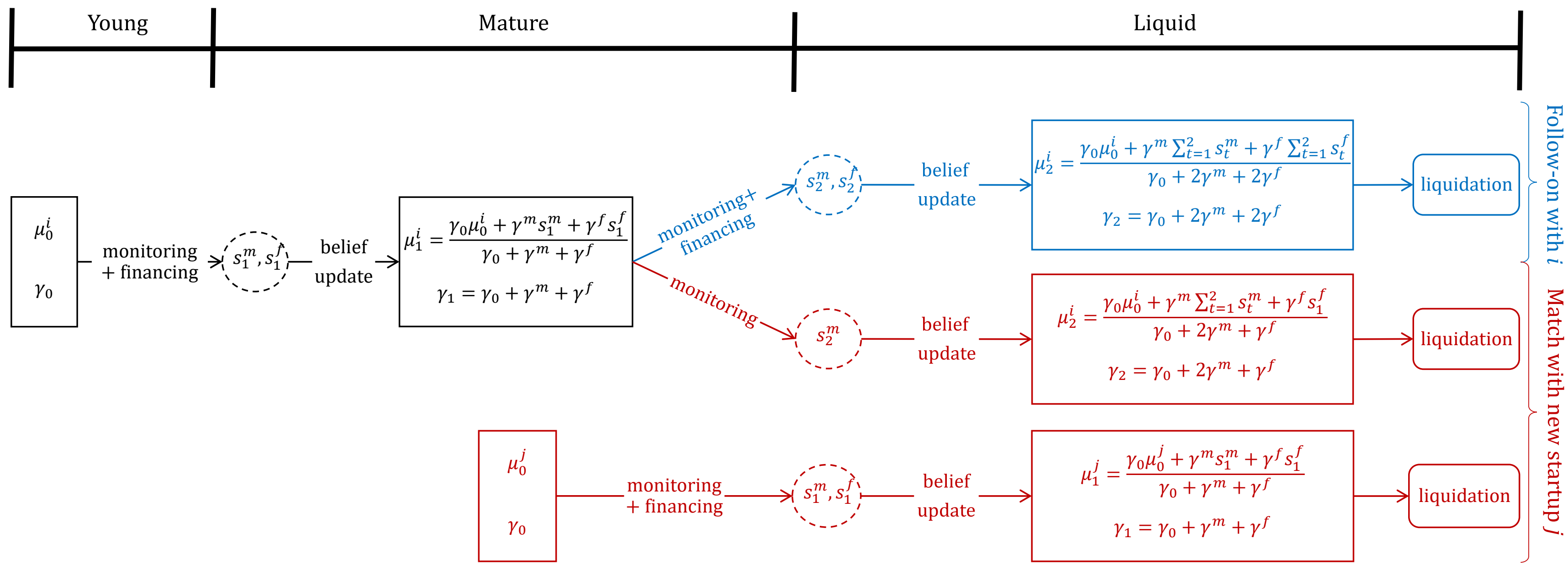

Figure 2. Belief updating throughout the fund's lifecycle. Beliefs about startup quality evolve throughout a fund's lifecycle. Initially, the fund is matched with a startup of type i during its early stages ("Young"). Through financing and monitoring, the fund updates its belief about the startup's quality based on signals received each period. In the blue scenario, the fund and startup i sign a follow-on contract as the fund matures. In the red scenario, no follow-on investment occurs, and the fund is matched with a new startup of type j when it reaches the mature stage. Equations in the diagram reflect the update process, with variables representing initial quality (μ_0^i, μ_0^j), signal-based updates (s_m, s_f), and cumulative precision (γ) values at each stage.

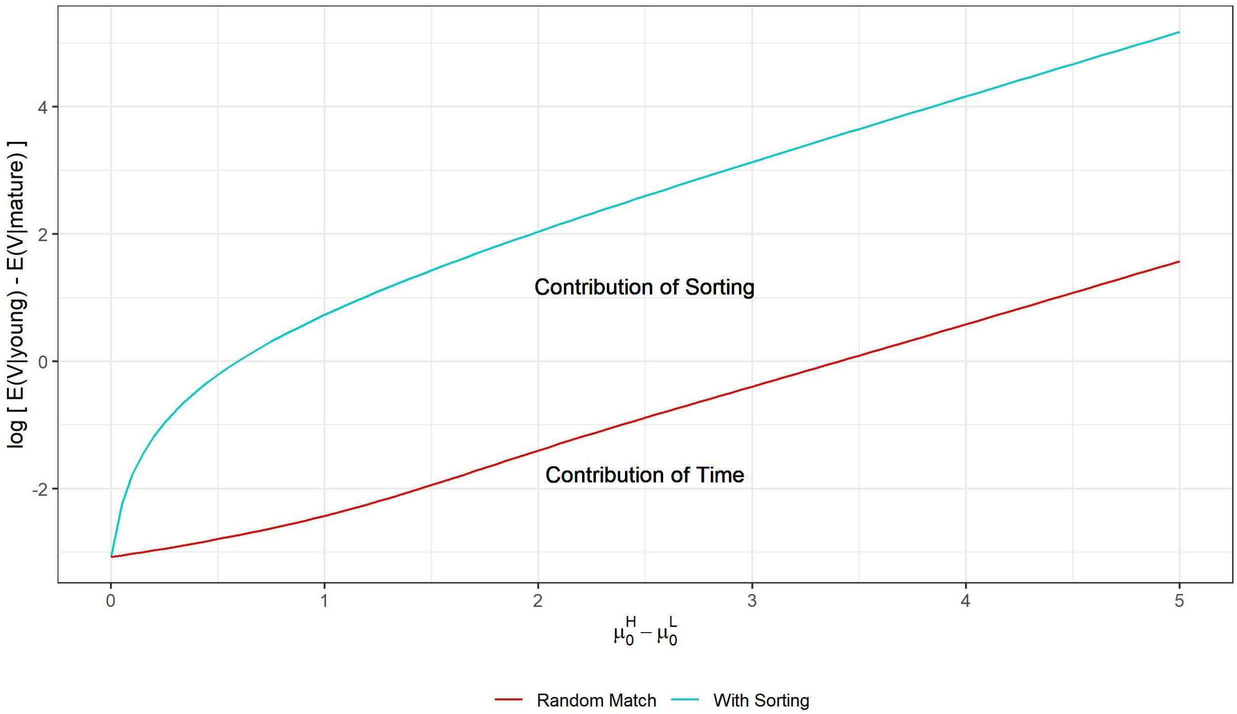

Figure 3. Model simulations with $x = 0.1$, $\gamma_0 = 1$, $\gamma_m = \gamma_f = 0.5$, $\mu_0^L = 0$ and μ_0^H varying from 0 to 5. For each value of μ_0^H we calculate the gap between the expected value of a startup matched with a young fund and a startup matched with a mature fund. The gap is displayed in log terms, once for our baseline model (in blue) with sorting and once for an alternative model in which matching between startups and funds is random (in red).

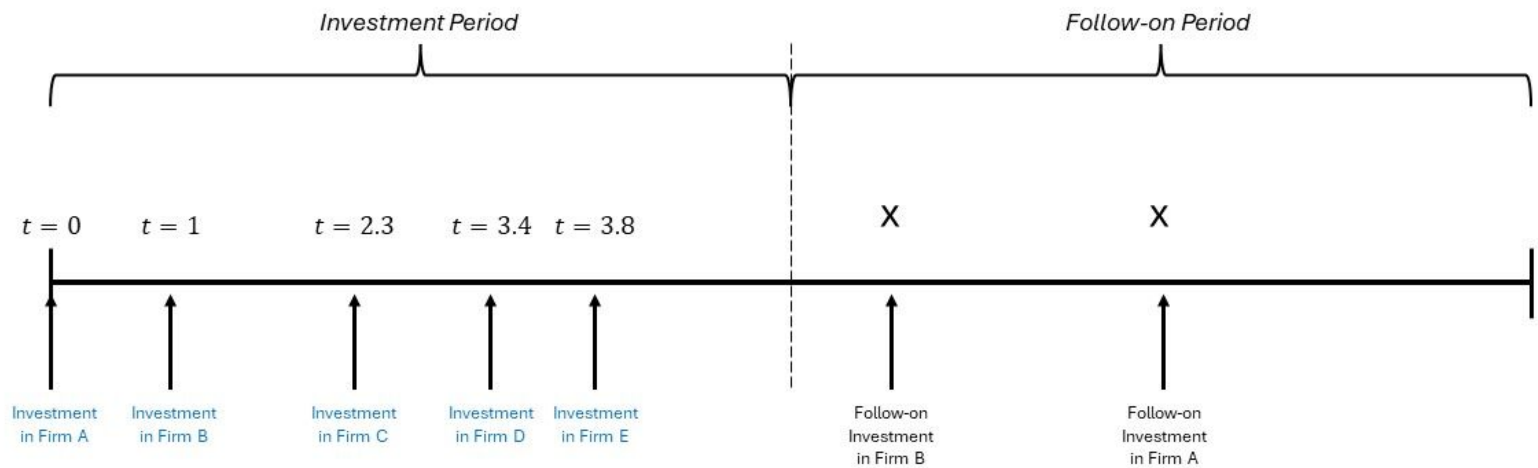

Figure 4. Fund Age. The variable '*Fund Age*' marks the initial investment of each fund as time zero and measures the number of days between that investment and every subsequent investment made by the same fund. These days are then converted into years for analysis, with any follow-on investments excluded from the calculation.

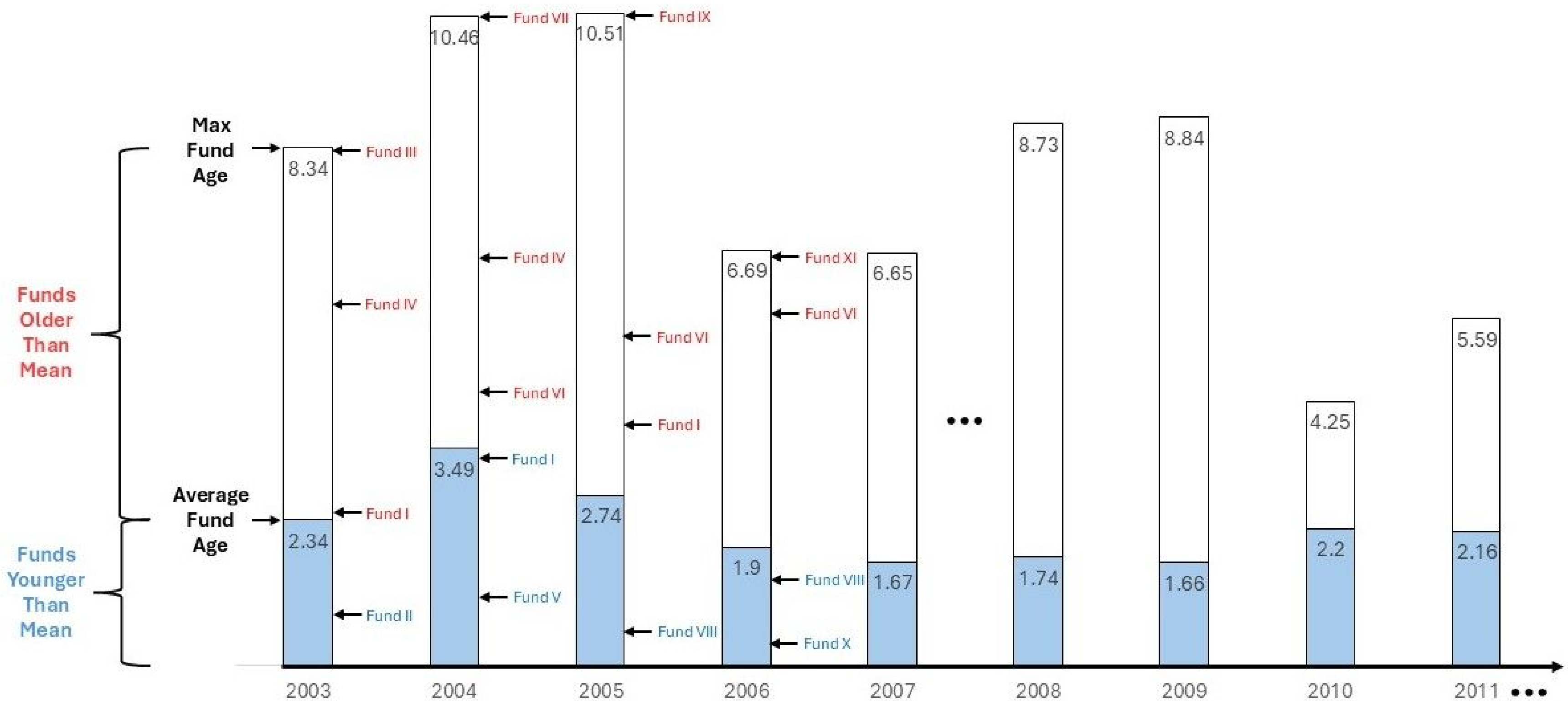

Figure 5. Older than Mean. The variable '*Fund Older than Mean*' is a dummy that flags funds older than the average age of all active funds in a given year. For each year, we identify all active funds, calculate their average age, and classify funds as "old" if they exceed this average. All follow-on investments are excluded from this analysis.

Tables

Table 1. Summary Statistics - IVC

Panel A: Investment Level - All Rounds					
	N	Exits	IPOs	M&As	
Startups	2,267	525	62	472	
		Num. of Startups Per Fund			
	N	Mean	Min	Median	Max
Funds	416	8.20	2	8	31
		Years Since Inception			
	N	Mean	Min	Median	Max
Deals (Exc. follow-ons)	3,633	1.79	0	1.47	14.78
		Investment Amount ($M)			
	N	Mean	Min	Median	Max
Total	3,633	12.0	0.005	5	1300
Seed Round	1,795	5.6	0.005	3	600
First Round	950	9.3	0.02	5	143
Second Round	418	14.9	0.02	10	132
Third Round	236	24.9	0.2	16	250
Fourth Round	119	53.3	0.3	25	1300
Fifth Round	59	50.9	0.1	30	250
Sixth Round	22	56.6	0.755	37	300
Seventh Round	10	51.8	2.5	38	238
Eighth Round	13	59.0	5	25	200
Ninth Round	11	63.0	10	47	320

Panel B: Startup Level - Single Investor, Seed Round Only					
	N	Exits	IPOs	M&As	
Startups	1,049	245	17	232	
		Num. of Startup Per Fund			
	N	Mean	Min	Median	Max
Funds	205	5.12	2	4	25
		Years Since Inception			
	N	Mean	Min	Median	Max
Deals (Exc. follow-ons)	1,049	1.96	0	1.58	15.12
		Num. of Follow-ons			
	N	Mean	Min	Median	Max
	1,091	1.04	0	1	8
		Investment Amount ($M)			
	N	Mean	Min	Median	Max
Seed Round	1,049	3.92	.0.005	1.7	600

Table 2. Baseline results - Fund age as the variable of interest

OLS regression results. The dependent variable in regressions (1) and (3)-(5) 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. *Fund Age* measures the fund's age at the time of investment, *Financial Intensity* is an industry-level inverse exit multiple, *Specialist* is a dummy turning one if the fund is a sector specialist, and *Fund Older than Mean* is a dummy turning one if the fund is older than the average active fund that year. Controls include the logarithm of the total deal amount and the number of portfolio companies in the fund at the time of investment, with fixed effects for deal year, investor country, industry, and fund. The sample includes only seed-stage startups that received investments from a single VC fund, provided the fund had invested in at least two different startups. 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
	Exits	Follow-on	Exits	Exits	Exits
Fund Age	-0.0477***	-0.282***	-0.0184***	-0.0347***	-0.0449***
	(0.00352)	(0.0477)	(0.00136)	(0.00501)	(0.00331)
Fund Age x Financial Intensity			-0.0177**		
			(0.00568)		
Fund Age x Specialist				-0.0634***	
				(0.0102)	
Fund Older than Mean					-0.0787***
					(0.0169)
Num. of Port. Comp.	-0.00471***	0.00454	-0.00565***	-0.00580***	-0.00274**
	(0.00103)	(0.00407)	(0.00113)	(0.00143)	(0.000978)
Ln(Deal Amount)	0.0119	0.120***	0.0118	0.0126	0.0120
	(0.0128)	(0.0247)	(0.0125)	(0.0123)	(0.0123)
Observations	1,049	1,049	1,049	1,049	1,049
R-squared	0.359	0.364	0.359	0.362	0.361
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

Table 3. Follow on investments regressed against years since inception

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

	Follow-on	Follow-on	Follow-on
Fund Age	-0.282***	-0.261***	-0.335***
	(0.0477)	(0.0444)	(0.0240)
Num. of Port. Comp.	0.00454	0.00529**	0.00771***
	(0.00407)	(0.00201)	(0.00139)
Ln(Deal Amount)	0.120***	0.0707***	-0.181***
	(0.0247)	(0.0181)	(0.0441)
Startup Age on Deal Date		-0.0171***	
		(0.00464)	
Sample Level	Startup	Investment	Investment
Observations	1,049	3,633	2,168
R-squared	0.364	0.320	0.922
Deal Year FE	Yes	Yes	Yes
Investor Country FE	Yes	Yes	Yes
Industry FE	Yes	Yes	No
Fund FE	Yes	Yes	Yes
Round FE	No	Yes	No
Startup FE	No	No	Yes

Table 4. Alternative Explanations

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

	Standalone		No First Inv.		PitchBook	
	Exits	Follow-on	Exits	Follow-on	Exits	Follow-on
Fund Age	-0.0578*	-0.417***	-0.0754**	-0.342***	-0.00843***	-0.0521***
	(0.0220)	(0.100)	(0.0233)	(0.0405)	(0.00198)	(0.0106)
Num. of Port. Comp.	-0.00419*	0.0125*	-0.000835	0.0124***	-0.00168***	-0.00584***
	(0.00158)	(0.00459)	(0.00346)	(0.00104)	(0.000406)	(0.000314)
Ln(Deal Amount)	0.00623	0.0363	0.0107	0.729**	0.0269***	-0.00845***
	(0.0108)	(0.0312)	(0.0110)	(0.0139)	(0.000642)	(0.00265)
Startup Age on Deal Date		-0.00373		-0.270***		-0.0258***
		(0.0175)		(0.00263)		(0.00169)
Sample Level	Startup	Investment	Startup	Investment	Startup	Investment
Observations	230	959	927	3,223	10,864	69,440
R-squared	0.430	0.356	0.361	0.327	0.474	0.249
Deal Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Investor Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes	Yes	Yes	Yes
Round FE	No	Yes	No	Yes	No	Yes

Appendix

Table A.1. Theoretical and Empirical Models Notation

Panel A: Theoretical Model

Variable	Notation	Description
True Quality	θ	True quality of the startup
Expected Quality	μ_t	Expected quality of the startup t periods after initial match with a fund
Belief Precision	γ_t	Precision of belief about quality of the startup
Type	H, L	Startup type high and low, respectively
Investment	x	Investment made in a financing round
Signals	s^f, s^m	Signals from financing and monitoring, respectively
Signal Precision	γ^f, γ^m	Precision of the financing and monitoring signals, respectively
Financing Indicator	$\mathbb{I}_t^f$	Equals one if financing was provided in period t
Expected Quality variance	$\sigma^2_{t+1\mid\mathbb{I}_t^f}$	Variance of μ_{t+1} given financing decision in period t
Follow-on Threshold	$T^{i,j}$	A threshold for expected quality above which a follow-on occurs
Risk-Free Rate	R	Gross risk-free rate, assumed to equal 1
Shares	$\lambda(\cdot)$	Ownership share given to investors
Value	$V(\cdot)$	Value of the startup
Entrepreneur's Profit	$U^E(\cdot)$	Entrepreneur's profit from a match with a fund
Gains	$G^E(\cdot), G^F(\cdot)$	Expected gains from a follow-on investment for the entrepreneur and the fund, respectively, above and beyond their outside option

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

A Proofs

A.1 Proof of Proposition 1

Rearranging (8) yields that a fund will make a follow-on investment if and only if:

$$\exp(\mu_1)\left(\lambda(\mu_1)\exp\left(\tfrac{1}{2}\sigma^2_{2|1}\right)+\lambda(\mu^i_0)\left[\exp\left(\tfrac{1}{2}\sigma^2_{2|1}\right)-\exp\left(\tfrac{1}{2}\sigma^2_{2|0}\right)\right]\right)> \lambda(\mu^j_0)\exp\left(\mu^j_0+\tfrac{1}{2}\sigma^2_1\right) \quad (22)$$

Note that the left-hand-side of the above equation is increasing in μ_1:

$$\frac{\partial}{\partial\mu_1}LHS=\exp(\mu_1)\left(\underbrace{[\lambda(\mu_1)+\lambda'(\mu_1)]}_{x^2/(\exp(\mu_1)+x)^2}\exp\left(\tfrac{1}{2}\sigma^2_{2|1}\right)+\lambda(\mu^i_0)\left[\exp\left(\tfrac{1}{2}\sigma^2_{2|1}\right)-\exp\left(\tfrac{1}{2}\sigma^2_{2|0}\right)\right]\right)>0 \quad (23)$$

Thus, there is a threshold $T^F(\mu_0^i, \mu_0^j)$ such that (8) holds if and only if $\mu_1 > T^F$ and T^F is increasing in μ_0^i and μ_0^j.

Condition (9) for the entrepreneur to accept the contract is met if and only if:

$$\lambda(\mu_1) < \left[1 - \lambda(\mu_0^i)\right] \left[1 - \exp\left(\tfrac{1}{2}\sigma_{2|0}^2 - \tfrac{1}{2}\sigma_{2|1}^2\right)\right] \tag{24}$$

Since $\sigma_{2|0}^2 < \sigma_{2|1}^2$, the right-hand-side of the above inequality is positive. Furthermore $\lambda'(\mu_1) < 0$, so there is a threshold $T^E(\mu_0^i)$ such Condition (9) holds if and only if $\mu_1 > T^E$, and T^E is decreasing in μ_0^i.

Denote $T^{i,j} = \max\left\{T^F(\mu_0^i, \mu_0^j), T^E(\mu_0^i)\right\}$ then both agents agree to the follow-on contract if and only if $\mu_1 > T^{i,j}$. Furthermore, $T^{i,j}$ increases with μ_0^j.

□

A.2 Proof of Lemma 3

Consider an entrepreneur matched with a young fund. Let $G^E(\mu_1|\mu_0^i, \mu_0^j)$ denote her expected gain from a follow-on investment above and beyond her outside option of receiving only monitoring (see Equations 11 and 12 in the body of the paper), then:

$$G^E(\mu_1|\mu_0^i, \mu_0^j) \equiv \begin{cases} [1 - \lambda(\mu_0^i) - \lambda(\mu_1)] \exp\left(\mu_1 + \frac{1}{2}\sigma_{2|1}^2\right) - [1 - \lambda(\mu_0^i)] \exp\left(\mu_1 + \frac{1}{2}\sigma_{2|0}^2\right) & \text{if } \mu_1 > T^{i,j} \\ 0 & \text{otherwise} \end{cases} \tag{25}$$

The definition of $T^{i,j}$ implies that $G^E(\mu_1) > 0$ for $\mu_1 > T^{i,j}$ (see Proposition 1). Thus, $E\left[G^E(\mu_1|\mu_0^i, \mu_0^j)\right] > 0$. 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:

$$
\begin{aligned}
&U^E(young|\mu_0^i, \mu_0^j) = \\
&\quad [1-\lambda(\mu_0^i)]E\left[\exp\left(\mu_1 + \tfrac{1}{2}\sigma_{2|0}^2\right)\Big|\mu_1 \le T^{i,j}, \mu_0^i\right]\Pr(\mu_1 \le T^{i,j}) + \\
&\quad E\left([1-\lambda(\mu_0^i)-\lambda(\mu_1)]\exp\left(\mu_1 + \tfrac{1}{2}\sigma_{2|1}^2\right)\Big|\mu_1 > T^{i,j}, \mu_0^i\right)\Pr(\mu_1 > T^{i,j}) = \\
&\quad [1-\lambda(\mu_0^i)]E\left[\exp\left(\mu_1 + \tfrac{1}{2}\sigma_{2|0}^2\right)\Big|\mu_0^i\right] + E\left[G^E(\mu_1|\mu_0^i, \mu_0^j)\right] = \\
&\quad [1-\lambda(\mu_0^i)]\exp\left(\mu_0^i + \tfrac{1}{2}\sigma_1^2 + \tfrac{1}{2}\sigma_{2|0}^2\right) + E\left[G^E(\mu_1|\mu_0^i, \mu_0^j)\right] = \\
&\quad U^E(mature|\mu_0^i)\exp(\tfrac{1}{2}\sigma_{2|0}^2) + \underbrace{E\left[G^E(\mu_1|\mu_0^i, \mu_0^j)\right]}_{C(\mu_0^i, \mu_0^j)}, \qquad (26)
\end{aligned}
$$

where $\exp(\frac{1}{2}\sigma_{2|0}^2) > 1$ captures the value of an additional period of monitoring and $C(\mu_0^i, \mu_0^j) \equiv E\left[G^E(\mu_1|\mu_0^i, \mu_0^j)\right] > 0$ is the follow-on option value.

□

A.3 Proof of Proposition 4

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 quality is expected to be μ_1. According to Proposition 1, a follow-on investment will not take place if $\mu_1 \le T^{i,j}$. In this case, the fund will offer startup i one period of monitoring and will invest x in its outside option - the type-j startup. The expected value of this outside option, given μ_1, is:

$$\lambda(\mu_0^i)\exp\left(\mu_1 + \tfrac{1}{2}\sigma_{2|0}^2\right) + \lambda(\mu_0^j)\exp\left(\mu_0^j + \tfrac{1}{2}\sigma_1^2\right) - x. \qquad (27)$$

However, if $\mu_1 > T^{i,j}$, a follow-on investment will take place and provide the fund with an expected profit of:

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

Let $G^F(\mu_1|\mu_0^i,\mu_0^j)$ denote the fund's expected gain above and beyond its outside option (27), then:

$$G^F(\mu_1|\mu_0^i,\mu_0^j) \equiv$$
$$\begin{cases} [\lambda(\mu_0^i)+\lambda(\mu_1)]\exp\left(\mu_1+\frac{1}{2}\sigma_{2|1}^2\right)-\lambda(\mu_0^i)\exp\left(\mu_1+\frac{1}{2}\sigma_{2|0}^2\right)-\lambda(\mu_0^j)\exp\left(\mu_0^j+\frac{1}{2}\sigma_1^2\right) & \text{if } \mu_1 > T^{i,j} \\ 0 & \text{otherwise} \end{cases} \tag{28}$$

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

$$\begin{aligned}
&\Pr(\mu_1 \le T^{i,j}|\mu_0^i)\left[\lambda(\mu_0^i)E\left(\exp(\mu_1+\tfrac{1}{2}\sigma_{2|0}^2)\middle|\mu_1 \le T^{i,j}\right)+\lambda(\mu_0^j)\exp(\mu_0^j+\tfrac{1}{2}\sigma_1^2)\right]+\\
&\quad\Pr(\mu_1 > T^{i,j}|\mu_0^i)E\left([\lambda(\mu_0^i)+\lambda(\mu_1)]\exp(\mu_1+\tfrac{1}{2}\sigma_{2|1}^2)\middle|\mu_1 > T^{i,j}\right)-2x=\\
&\lambda(\mu_0^i)E\left[\exp\left(\mu_1+\tfrac{1}{2}\sigma_{2|0}^2\right)\middle|\mu_0^i\right]+\lambda(\mu_0^j)\exp\left(\mu_0^j+\tfrac{1}{2}\sigma_1^2\right)+E\left[G^F(\mu_1|\mu_0^i,\mu_0^j)\right]-2x=\\
&\lambda(\mu_0^i)\exp(\mu_0^i)\exp\left(\tfrac{1}{2}\sigma_1^2+\tfrac{1}{2}\sigma_{2|0}^2\right)+\lambda(\mu_0^j)\exp\left(\mu_0^j+\tfrac{1}{2}\sigma_1^2\right)+E\left[G^F(\mu_1|\mu_0^i,\mu_0^j)\right]-2x
\end{aligned} \tag{29}$$

Lemma 6. *The function $\lambda(\mu)\exp(\mu)=\frac{x\exp(\mu)}{x+\exp(\mu)}$ is increasing in μ.*

Lemma 6 implies that the first argument in (29) is increasing in μ_0^i. It remains to show that $F(\mu_0^i)\equiv E\left[G^F(\mu_1|\mu_0^i,\mu_0^j)\right]$ is also increasing in μ_0^i.

Note that

$$F(\mu_0^i)=E\left[G^F(\mu_1|\mu_0^i,\mu_0^j)\right]=E\left[G^F(\sigma_1 z+\mu_0^i|\mu_0^i,\mu_0^j)\middle|z>\frac{T^{i,j}-\mu_0^i}{\sigma_1}\right],$$

where $z\sim N(0,1)$.

Following the Leibniz integral rule:

$$F'(\mu_0^i)=\underbrace{-G^F\left(T^{i,j}\middle|\mu_0^i,\mu_0^j\right)\phi\left(\frac{T^{i,j}-\mu_0^i}{\sigma_1}\right)\left[\frac{\partial T^{i,j}}{\partial\mu_0^i}-1\right]}_{A}+ \underbrace{\int_{\frac{T^{i,j}-\mu_0^i}{\sigma_1}}^{\infty}\frac{\partial}{\partial\mu_0^i}G^F\left(\sigma_1 z+\mu_0^i\middle|\mu_0^i,\mu_0^j\right)\phi(z)\,dz}_{B} \tag{30}$$

As for argument A in Equation (30), there are two possibilities. If $T^{i,j}=T^F(\mu_0^i,\mu_0^j)$ then by definition, $G^F(T^F)=0$ and argument A nullifies. Otherwise, $T^{i,j}=T^E(\mu_0^i)$, in which case $\frac{\partial T^{i,j}}{\partial \mu_0^i} < 0$ (see proof of Proposition 1) and argument A is positive.

The positivity of argument B will follow from showing that $\frac{\partial}{\partial \mu_0^i} G^F \left(\sigma_1 z + \mu_0^i \middle| \mu_0^i, \mu_0^j \right) > 0$ for $z > \frac{T^{i,j} - \mu_0^i}{\sigma_1}$. In that region:

$$
\begin{aligned}
G^F \left(\sigma_1 z + \mu_0^i \middle| \mu_0^i, \mu_0^j \right) = {} & [\lambda(\mu_0^i) + \lambda(\sigma_1 z + \mu_0^i)] \exp \left(\sigma_1 z + \mu_0^i + \tfrac{1}{2}\sigma_{2|1}^2 \right) - \\
& \lambda(\mu_0^i) \exp \left(\sigma_1 z + \mu_0^i + \tfrac{1}{2}\sigma_{2|0}^2 \right) - \lambda(\mu_0^j) \exp \left(\mu_0^j + \tfrac{1}{2}\sigma_1^2 \right) = \\
& \lambda(\mu_0^i) \exp(\mu_0^i) \left[\exp(\sigma_1 z + \tfrac{1}{2}\sigma_{2|1}^2) - \exp(\sigma_1 z + \tfrac{1}{2}\sigma_{2|0}^2) \right] + \\
& \lambda(\sigma_1 z + \mu_0^i) \exp(\sigma_1 z + \mu_0^i) \exp(\tfrac{1}{2}\sigma_{2|1}^2) - \lambda(\mu_0^j) \exp \left(\mu_0^j + \tfrac{1}{2}\sigma_1^2 \right). \quad (31)
\end{aligned}
$$

Lemma 6 implies that $\lambda(\mu_0^i)\exp(\mu_0^i)$ and $\lambda(\sigma_1 z + \mu_0^i)\exp(\sigma_1 z + \mu_0^i)$ are increasing in μ_0^i, so $G^F \left(\sigma_1 z + \mu_0^i \middle| \mu_0^i, \mu_0^j \right)$ is also increasing in μ_0^i.

□

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 had invested in at least two different startups. Standard errors clustered at the deal year and investor country levels are shown in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	Exits	Exits	Exits	Exits	Exits
Fund Age	-0.00802*	-0.00532**	-0.00468**	-0.0675***	-0.0477***
	(0.00387)	(0.00217)	(0.00184)	(0.00850)	(0.00352)
Ln(Deal Amount)	0.0324**	0.0406***	0.0363***	0.0127	0.0119
	(0.0130)	(0.00803)	(0.00796)	(0.0121)	(0.0128)
Num. of Port. Comp.					-0.00471***
					(0.000120)
Observations	1,155	1,153	1,153	1,049	1,049
R-squared	0.110	0.128	0.154	0.357	0.359
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

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 had invested in at least two different startups. Standard errors clustered at the deal year and investor country levels are shown in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	Exits	Exits	Exits	Exits	Exits
Fund Age	-0.0655***	-0.0451*	-0.0516*	-0.636**	-0.566
	(0.0238)	(0.0258)	(0.0283)	(0.308)	(0.351)
Ln(Deal Amount)	0.220***	0.283***	0.274***	0.0653	0.0642
	(0.0828)	(0.0876)	(0.0953)	(0.104)	(0.106)
Num. of Port. Comp.					-0.0142
					(0.0377)
Observations	1,155	1,146	1,146	658	658
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