Asset Sorting in Private Equity*

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Abstract

The compensation of general partners in most private equity firms is linked to the performance of the firm's individual funds rather than its aggregate performance. We argue this compensation structure provides incentives for general partners to arrange assets across funds in a manner that increases fees collected from investors. We refer to this practice as asset sorting and document its prevalence in the venture capital industry over the last forty years. While asset sorting could facilitate specialization, VC firms group investments with correlated payoffs together even when the benefits of specialization appear limited. Furthermore, sorting does not enhance investment performance or reward VC firms for their reputation, pointing to a potential agency conflict in the industry.

JEL classification: G11, G24, M12

Keywords: Agency costs, corporate governance, asset sorting, venture capital, private equity

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Abstract

The compensation of general partners in most private equity firms is linked to the performance of the firm's individual funds rather than its aggregate performance. We argue this compensation structure provides incentives for general partners to arrange assets across funds in a manner that increases fees collected from investors. We refer to this practice as asset sorting and document its prevalence in the venture capital industry over the last forty years. While asset sorting could facilitate specialization, VC firms group investments with correlated payoffs together even when the benefits of specialization appear limited. Furthermore, sorting does not enhance investment performance or reward VC firms for their reputation, pointing to a potential agency conflict in the industry.

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1. Introduction

The compensation of general partners (GPs) in venture capital (VC), leveraged buyout (LBO), and other private equity (PE) firms is typically tied to the performance of individual funds rather than firm's aggregate performance.[1] For example, GPs in private equity firms usually receive a percentage of the profits generated by each fund in their portfolio above a predefined threshold, a practice commonly referred to as *carried interest* or *carry* (see Gompers and Lerner 1999a). We argue that the convexity of fund-based carry provides incentives for GPs to group investments with positively correlated payoffs, thereby reducing within-fund diversification and increasing expected carried interest. We refer to this behavior as *asset sorting* and examine its prevalence and implications in the VC industry over the 1980–2022 period.[2]

Asset sorting can create economic value by facilitating within-fund specialization. Prior research shows that specialization enhances the performance of private equity firms (Cressy et al. 2007; Gompers, Kovner, and Lerner 2009; Brown, Fei, and Robinson 2023; Racculia 2014; Spaenjers and Steiner 2024), and this benefit may extend to individual funds within a firm. We refer to this possibility as *productive* sorting. Fund-based carry, however, creates incentives for GPs to group investments with correlated payoffs together even when such grouping does not create economic value. We refer to this possibility as *agency-based* sorting. Corporate governance research suggests that such wealth transfers are more likely when investors are unaware of the

[1] According to a recent McKinsey report, the PE industry in North America (mainly the US) raised approximately $690 billion in 2021, with the VC and buyout firms alone raising approximately $400 billion. For the same year, buyout and VC firms had approximately $2.5 trillion of assets under management. See McKinsey & Company, "Private Markets Rally to New Heights", McKinsey Global Private Markets Review 2022.

[2] We focus on VCs because they have a relatively simple equity-based capital structure. The asset-sorting incentives analyzed in this paper, however, are expected to apply to other organizations such as buyout firms.

problem and their rights are not fully protected (Jensen and Meckling 1976; Core, Guay, and Larcker 2003).

To examine asset sorting, we focus on investment rounds by VC firms managing at least two active funds at the time of the investment and compare GP compensation under the actual allocation with a counterfactual allocation in which each investment is assigned to another contemporaneously active fund of the same VC firm. Following the literature, we measure performance through investment success, defined as whether a portfolio company ultimately goes public or is acquired (see, e.g., Gompers and Lerner 2000). If VC firms strategically sort assets into portfolios, expected GP compensation should be higher under the actual allocation than under the counterfactual one. We show this to be the case. Based on several specifications, we estimate asset sorting to increase carried interest by 0.6% to 1.2% of invested capital, which amounts to about $200 million to $400 million per year.

Can specialization explain the observed sorting premium? To address this question, we examine fund specialization along two dimensions that have been shown to generate synergies: industry and geographic regions (e.g., Gompers, Kovner, and Lerner 2009; Chen et al. 2010). We find that about 85% of specialization across industries and U.S. states occurs at the VC firm level, while only 15% occurs at the fund level. Although these findings do not rule out fund-level specialization, they suggest that it is unlikely to explain the sorting premium. Further empirical analysis corroborates this result: when we restrict counterfactual allocations to funds investing in the same industry and geographic region as the investing fund, the increase in carried interest attributable to asset sorting remains similar, ranging from 0.5% to 1.1% of invested capital.

We acknowledge that funds may specialize based on unobserved characteristics. Furthermore, the preliminary results cannot rule out the possibility that sorting creates economic value, because our counterfactual analysis keeps investment performance fixed. To design a sharper test for agency-based sorting, we focus on follow-on investments in the same company and examine whether GPs allocate these investments across funds strategically by conditioning on observed fund performance. We find that GPs are more likely to direct follow-on financing rounds of better-performing companies towards better-performing funds, even when these funds have no prior investments in the company. Moreover, investment migration towards better performing funds is well-pronounced even when the new fund is less specialized in the industry and geographic location of the company than the old fund. This result suggests that, as new information arrives, GPs reallocate investments across funds in a manner that increases their total compensation without necessarily increasing specialization.

To further assess the potential benefits of asset sorting, we perform two additional tests. The first test examines whether past asset sorting by VC firms can predict the performance of their new investments. If asset sorting enhances GPs' ability to make better investment decisions, it should be positively related to investment performance. To measure past asset sorting, we use the average difference in estimated carried interest between the actual and counterfactual allocations of all investments of the VC firm over the preceding year. We find that investment performance is not significantly related to asset sorting. The second test examines whether VC firm reputation helps explain asset sorting at the time of each new investment. We again use the difference in estimated carried interest between the actual and counterfactual allocations of each new investment to measure asset sorting and use each VC firm's market share and age to measure reputation at the time of investment. If asset sorting reflects productive effort, we expect it to be more pronounced for reputable VC firms, which have strong reputational incentives to perform well and may collect some of their reputational premium through asset sorting. The generated surplus could thus be shared between the GPs and the LPs. We find that VC reputation is not significantly related to asset sorting, casting further doubt on the productive-sorting hypothesis.

The paper contributes to the literature on corporate governance by identifying a new agency conflict related to the allocation of investments across funds within a single private equity firm.[3] Asset sorting resembles the asset-substitution problem described by Jensen and Meckling (1976), in which an agent holding a call option on firm value could increases their own expected payoff by raising the principal's risk exposure. However, asset sorting is distinct from asset substitution. At its core, asset sorting leads to a direct transfer of value from the principal to the agent.[4] For instance, asset sorting may occur even when the set of investments is fixed, so that overall firm performance and risk remain unchanged. Furthermore, asset sorting may not increase the risk borne by investors if they hold stakes across all funds of the firm. Yet, even in this case, sorting transfers wealth from investors towards the GPs.

The analysis advances our understanding of business practices in the private equity industry. The industry has expanded rapidly over recent decades, raising hundreds of billions of dollars annually and managing trillions in assets. Much of this growth has been driven by capital inflows from public pension plans worldwide (see, e.g., Ivashina and Lerner 2018).[5] It is well documented that private equity firms employ complex distribution rules that range from investor-friendly to GP-friendly (Litvak 2009; Metrick and Yasuda 2010a). We argue that fund-based

[3] Robinson and Sensoy (2013) discuss existing agency conflicts in the PE industry. See Griffin and Kruger (2024) for a recent review of the academic work on forensic finance, including private equity.

[4] Asset sorting may have additional ramifications because it may, for example, distort the investment behavior of agents.

[5] As of the writing of this paper, major private equity firms and regulators are planning to also add private investments to 401(k) plans. See https://www.wsj.com/finance/investing/trump-executive-order-to-help-open-up-401-k-s-to-private-markets-c90c6788?mod=hp_lead_pos6.

carried interest creates incentives for GPs to transfer value from LPs by strategically allocating assets across funds.[6] Alternative contractual arrangements, such as less convex or linear compensation contracts for firms managing multiple funds, could mitigate these incentives while preserving the productive aspects of carried interest. LP interests could be also better protected if they were granted greater discretion over cross-fund allocation decisions.

Finally, our paper contributes to the literature on executive option compensation. The original rationale for convex compensation contracts such as stock options is to encourage productive risk-taking (e.g., Bettis et al. 2010). While option-type pay could be valuable in private equity where investments are inherently risky, it could also lead to unintended consequences. For example, options have been shown to incentivize earnings manipulation (Burns and Kedia 2008; Bennett et al. 2017) and to damage customer relationships when granted at high levels (Liu, Masulis, and Stanfield 2021). Using standard principal–agent arguments, some scholars even argue that the costs of option-type compensation outweigh the benefits (Dittmann and Maug 2007). Our study highlights another potential cost of option-type compensation when pay is linked to the performance of individual subdivisions of a firm rather than the whole firm.

2. A definition of asset sorting and hypotheses development

2.1. Background

Venture capital firms are financial intermediaries between large investors (such as banks, endowments, pension funds, life insurance companies, and wealthy private individuals) and

[6] The adverse selection problem examined in this study is distinct from the one examined in Axelson, Strömberg, and Weisbach (2009). In their model, ex ante financing through funds alleviates adverse selection problems that arise in ex post deal-by-deal financing, in which the GPs have an incentive to finance and invest in all deals, including deals they know to be bad. In our setting, the GPs have an incentive to strategically rearrange investments across funds to increase their carry, including when the set of investments is kept fixed and the GPs do not knowingly undertake bad investments.

private enterprises (Cumming and Johan 2013). Each VC firm is structured as a limited partnership, where the general partners (GPs) raise money from investors, or the limited partners (LPs), and invest the funds in portfolio companies on their behalf. The capital committed by LPs is attached to a particular fund and is usually provided to that fund in the first three to four years of the fund's life.

The capital provided is invested in a portfolio of startups and early-stage companies. It typically takes time, often years, until LPs start receiving money back from the fund's investments. Reneging on a capital commitment already made to a VC fund is costly for the LPs, as they may face high penalties, potential litigation, and severe reputational harm in private equity markets. Limited partner stakes are illiquid because there is practically no secondary market for them. Of import, the contract between the LPs and GPs provides the latter with substantial discretion in terms of when, how much, and in what companies to invest the fund's capital.

The compensation of GPs usually takes the form of a fixed annual fee applied to assets under management and a percentage of the profits generated, both of which are usually contracted at the fund level. The fee charged on the percentage of the profits is known as the "carried interest" (or simply the "carry") and is usually subject to a contracted hurdle rate (Brown, Fei, and Robinson 2023). Examining actual contracts between GPs and LPs, Gompers and Lerner (1999a) and Metrick and Yasuda (2010a) find that the management fee is typically around 2% of assets under management and that carried interest arrangements are concentrated at 20%, with some minor variation.[7]

[7] In addition to fee structure, contracts often include various covenants, such as clawback provisions, that aim at restricting the GPs' ability to expropriate the LPs (Metrick and Yasuda 2010a).

2.2. Definition of asset sorting

We define asset sorting as the strategic allocation of assets to funds in a manner that increases GPs' payoff from carried interest. In general, asset sorting can be achieved by grouping investments with highly correlated payoffs in the same fund while placing investments with less or negatively correlated payoffs in separate funds. Allocating investments in this manner increases expected fund carry because it reduces the chance that potential losses from one investment will offset the carry from potential gains from another investment within the same fund.

In Figure 1, we illustrate the idea of asset sorting using a simulation. The figure examines how asset sorting affects the carried interest to the GP under various degrees of asset sorting. For the figure, we assume there are 3 funds, where each fund contains 10 investments (for more details, see Appendix A). Investments are of 3 types.[8] Investments within the same type are correlated with a correlation coefficient of ρ, where ρ is the same within all types. We assume the correlation between investments of different types is 0. For each simulation, we measure the degree of asset sorting within a fund using the Herfindahl-Hirschman index of its allocation across the three investment types. Afterwards, we average the asset sorting measures across the three funds to obtain a firm-level measure of asset sorting.

[Insert Figure 1 about here]

Examining Figure 1, we see that, as the degree of asset sorting increases from low to medium to high, the carried interest received by the GPs also increases. This result obtains as long as the within-type correlation of investments is greater than 0. We can further see from the figure

[8] The results are similar if we assume there are 2 or 4 types of investments and funds.

that the effect of asset sorting on the carried interest gets more pronounced as the correlation within types increases.

Asset sorting admits two alternative interpretations: specialization and agency. Existing research shows that specialization is widespread in the VC industry, with firms focusing on particular industries (e.g., Gompers, Kovner and Lerner 2009) or geographic regions (e.g., Chen et al. 2010). Moreover, specialization has been linked to superior performance in private equity, including venture capital (Cressy et al. 2007; Gompers, Kovner, and Lerner 2009; Brown, Fei, and Robinson 2023; Racculia 2014; Spaenjers and Steiner 2024). While these studies focus at the level of VC firms, specialization at the level of individual funds may also yield benefits, such as a more efficient allocation of duties and incentives across the GPs. Under this scenario, sorting may reflect a preference for specialization, which could ultimately benefit the LPs. We refer to it as productive sorting.

Given the existing compensation structure in the industry, however, GPs would have an incentive to sort, even when sorting does not create economic value. In this case, sorting leads to a wealth transfer from investors to GPs. We refer to this possibility as agency-based sorting. The corporate governance literature has identified numerous situations in which managers could extract rents from investors (see e.g., Core, Guay, and Larcker 2003).

2.3. Testable hypotheses

Building on the insight that asset sorting should increase carried interest, we first develop a general test of asset sorting. We focus on investment rounds and, for each new investment, we identify all open funds of the VC firm at the time of the investment. We then estimate carried interest under two scenarios. In the first scenario, the new investment is allocated to the fund making the investment (the *actual* scenario). In the second scenario, the new investment is allocated to another contemporaneous fund of the same VC firm (the *counterfactual* scenario). To test for asset sorting, we propose the following hypothesis:

> ***Hypothesis 1 (A general test of asset sorting).*** *If VC firms allocate new investments strategically across funds, then their carried interest should be higher under the actual scenario relative to the counterfactual scenario.*

The above hypothesis remains agnostic about the motivation and specific information guiding GPs' allocation decisions. To design a test for agency-based sorting, we focus on cases where the GPs have information about the performance of both the new investment as well as their active funds. In such settings, a VC firm seeking to maximize carried interest has an incentive to allocate well-performing investments to well-performing funds. A portfolio that is already performing well is likely to generate carried interest, so adding another successful investment increases the expected carry. By contrast, a poorly performing portfolio is more likely to realize an overall loss; allocating a successful investment to such a portfolio would simply offset existing losses, thereby reducing the carried interest.

To distinguish between the agency-based view and the specialization view, we examine the allocation of new rounds of investments in a company where at least one open fund of the VC firm has a prior investment (an *invested* fund) and at least one open fund does not (a *non-invested* fund). The agency-based view predicts that switching to a non-invested fund is more likely when both the company and the non-invested fund are performing well. Explaining fund switching with specialization-based sorting proves more challenging, given that the invested fund has already demonstrated a preference for investing in the company. Taken together, these considerations motivate the following hypothesis:

Hypothesis 2 (A test of agency-based sorting). *If VC firms allocate new investments strategically across funds in a manner that increases their carried interest, then moving new investment rounds away from an invested fund and into a non-invested fund should be more likely when both the company and the non-invested fund are performing well. This behavior should be independent from fund industry and state specialization.*

3. Data and variables

Our data come from the Thomson Reuters's VentureXpert database and contain VC investments in U.S. companies during the period between 1980 and 2022. VentureXpert is one of the two main VC data sources available to researchers; the other is Dow Jones' VentureSource. Both databases have been validated by previous researchers against known financing rounds (see e.g., Kaplan, Strömberg, and Sensoy 2002). VentureXpert began compiling data in 1977 and is more comprehensive than VentureSource in earlier years. The VentureXpert database contains detailed information about the dates of venture financing rounds, the investors, and portfolio companies involved, the estimated amounts invested by each fund, and the ultimate outcome for each portfolio company. The reinterpretation of the Employee Retirement Income Security Act (ERISA) "prudent man" standard in 1979 is widely believed to mark the beginning of the modern VC market (Gompers and Lerner 1999b, Hellmann, Lindsey, and Puri 2008). We therefore start our sample from January 1, 1980.

We use VentureXpert to identify each VC fund making the investment. We exclude funds where VentureXpert indicates that the VC fund is "unspecified" in the name of the fund and funds where the time between the first and last investments is more than 12 years. Our starting sample contains 78,061 investments by VC firms between 1980 and 2022. We use this sample to determine the date of each fund's first and last investments.

Figure 2 plots the number of investments conditional on when the investment is made relative to each fund's first investment. As the figure shows, the majority of investments are made within the first several years after a fund opens. For example, 69,514 investments (or 89.1% of all investments) are made within five years while 75,237 investments (or 96.4% of all investments) are made within seven years of each fund's first investment.

[Insert Figure 2 about here]

Table 1 presents the annual number of investments, total invested amounts, number of VC funds, number of VC firms, and number of portfolio companies in the sample.[9] Examining the table, we note the rapid expansion of the industry since the 1979 ERISA regulatory change. The table also illustrates the well-documented fluctuations due to "hot" and "cold" markets that characterize the VC industry. In our sample, there are 1,815 investments in the average year with annual invested amount at $33.97 billion in 2024 U.S. dollars. In the average year, our sample contains 339 VC firms and 480 funds investing in 1,072 companies.

[Insert Table 1 about here]

An important aspect of our analysis is the presence of VC firms that manage multiple funds at the same time. To examine the importance of multi-fund VC firms, in Figure 3 we plot by year the number of investments and dollar amounts invested by single-fund and multi-fund VC firms. A VC firm is classified as single-fund if no other fund is open at the time of the investment and as multi-fund if at least one other fund is open at the time of the investment. We consider a fund to

[9] To adjust for inflation, all dollar amounts are expressed in 2024 U.S. dollars using the GDP implicit price deflator from the Federal Reserve Bank of St. Louis (https://fred.stlouisfed.org/series/GDPDEF).

be open from the date of its first investment to the date of its last investment, based on our data. In our sample of 78,061 investment, 32,567 investments are made by single-fund VC firms and 45,494 investments are made by multi-fund VC firms. The importance of multi-fund VC firms is evident throughout the entire sample period and is consistent with prior studies (e.g., Metrick and Yasuda 2010b).

Most VC firms tend to have several funds operating in any given year so that multi-fund firms are common in the VC industry. They account for a large fraction of the number of investments and dollar amount invested in the VC industry. In addition, the market share of multi-fund VC firms tends to increase in hot periods and decrease in cold periods, which suggests that, when demand by investors is high, it is relatively easier for an established VC firm to start a new fund than for a new VC firm to enter the market.

[Insert Figure 3 about here]

To construct our main sample, we keep only new investments where the VC firm has at least one other fund that is open at the time of the investment. For some of the analysis, we examine the importance of specialization and further limit the sample to contemporaneous funds that invest (at any time) in the same industry and state as the new investment. We define industries using the Minor Industry Group level based on the industry classifications provided by VentureExpert. Appendix B provides the list of industries and states in our sample. We further require each fund to have at least one prior investment. This condition is necessary for us to measure counterfactual performance and leads to 45,347 investments between 1980 and 2022.

We measure investment future performance using data on whether the company experiences an IPO or an acquisition in the future. Fund expected performance at the time of the new investment is then calculated as the value-weighted average future performance of all investments up to and including the new investment. An investment is classified as successful (success=1) if the company goes public or is acquired in the future; otherwise, an investment is classified as unsuccessful (success=0). To allow companies time to mature, the main sample of multi-fund VC firms used for testing Hypothesis 1 contains 40,079 investments between 1980 and 2017. When we further focus on contemporaneous funds that invest in the same industry and state as the new investment, the sample contains 31,656 observations between 1980 and 2017.

Table 2, Panel A, presents summary statistics for the two samples. Examining the sample with all multi-find VC firms, when making a new investment, the average VC firm in our sample has close to 1.9 other contemporaneous funds. The average fund making the new investment holds 16.1 companies in its portfolio at the time of the investment. Other contemporaneous funds hold a similar number of companies, at 15.6. The average investment is $16.9 million in 2024 U.S. dollars, and around 40% of all investments end with an IPO or an acquisition. Panel A also reports summary statistics for two measures of VC firm reputation: cumulative market share and age since founding (e.g., Gompers 1996; Atanasov et al. 2019). At the time of the average investment, VC firm market share is 0.3% and VC firm age since founding is 13.6 years.

[Insert Table 2 about here]

Panel A of the table also reports summary statistics for 31,656 new investments where the VC firm manages at least two contemporaneous funds that invest in the same industry and state as the new investment. The average VC firm in this sample has 1.6 other contemporaneous funds. At the time of the investment, the average fund making the new investment holds 16.5 companies in its portfolio while other contemporaneous funds hold 17.4 companies. The average investment is $17.2 million in 2024 U.S. dollars, and around 41% of the new investments end with an IPO or an acquisition. At the time of the average investment, VC firm market share is 0.35% and VC firm age since founding is 13.7 years. We use this subsample in Section 6.2, where we examine the relation between asset sorting and VC firm reputation.

4. A general test of asset sorting

Hypothesis 1 predicts that the carried interest should be higher under the actual allocation of new investments relative to a counterfactual scenario, in which a new investment is undertaken by another contemporaneous fund. To estimate the effect of the allocation decision on the carried interest, we make several assumptions about the future value of each fund at the time the new investment is made. Our data provides information about the amount a and timing t of each investment and the fund undertaking the investment. We assume the fund dissolves at time T after the new investment. We also have future information on whether the investment resulted in an IPO, an acquisition, or neither.

Based on this data, we design a hypothetical experiment in which we estimate the future value of each fund (actual or counterfactual) based on its past investments and the new investment, while assuming the fund does not make additional investments in the future. To calculate the hypothetical fund value, we use information about the success x of each investment, where x equals 1 if the company goes public or is acquired in the future and 0 otherwise. We assume investments in successful companies provide a return with a multiple of M, $M > 0$, while investments in unsuccessful companies result in a total loss.

Formally, the hypothetical future value of fund k managed by VC firm j as of time t, net of management fees γ and investor hurdle rate r, is defined as follows:

$$V_{jkt} = \sum_{i=1}^{I}\left[a_{ijkt}x_i M - a_{ijkt}\left(1-\left(1-\gamma\right)^T + \left(1+r\right)^T\right)\right]. \quad (1)$$

We let a_{ijkt} equal the investment amount in company i by fund k and VC firm j up to and including time t. As discussed above, we let x_i equal to 1 if company i goes public or is acquired in the future and 0 otherwise.

To measure the amount attributable to carried interest for each VC firm j at time t, we use the following equation:

$$Y_{jt} = \theta \sum_{k=1}^{K} \max\left[V_{jkt}, 0\right]. \tag{2}$$

In this equation, θ is the carried interest, which we assume is equal across all funds. For the rest of the analysis, we assume that $\gamma = 2\%$ and that $T = 5$ years. As baseline assumptions, we consider $M = 5$, $r = 8\%$, and $\theta = 20\%$.[10] We then study the effect of asset sorting on the carry under several assumptions for M, r, and θ.

For each new investment by a VC firm, we first identify all funds of the VC firm that are open at the time of the investment. We consider a fund to be open from the date of its first investment to the date of its last investment in our data. We then use Equations (1) and (2) to estimate a hypothetical carried interest the VC firm would collect from all open funds under two scenarios: actual and counterfactual. In the actual scenario, the new investment is placed in the actual fund making the investment; we label the estimated carried interest under the actual scenario Y_{jt}^{AC}. In the counterfactual scenario, the new investment is placed in another open fund of the same VC firm; we label the estimated carried interest under the counterfactual scenario Y_{jt}^{CF}. If

[10] We calibrate the baseline assumptions to obtain within-sample annual limited partner return close to the 14% size-weighted median return of VC funds reported in Table 2 of Kaplan and Schoar (2005). A positive hurdle rate is consistent with Brown, Fei, and Robinson (2023).

the VC firm has several other open funds, we sequentially place the new investment in each of these fund and average the estimated carry across all such cases.

To estimate the effect of asset sorting on the carry for VC firm j making an investment at time t, we use the difference in the VC firm's carried interest between the two scenarios:

$$\Delta CARRY_{jt} = Y_{jt}^{AC} - Y_{jt}^{CF}. \tag{3}$$

For ease of interpretation, we express this effect as a percent of the amount of the new investment. Because assets under management (AUM) of a given fund are a cumulative amount of all investments by that fund, the estimated percentage effect of asset sorting on the carry can be interpreted as a percent of total AUM.

Table 3 provides estimates of the effect of asset sorting on carried interest under a range of assumptions about the multiple of successful investments (M), the hurdle rate of limited partners (*r*), and the percent carry to general partners (θ). In Panel A, we use the sample of all 40,079 investments by multi-fund VC firms between 1980 and 2017. We find that the effect of asset sorting on the carry is positive and statistically significant (at the 0.01 level) under the full range of assumptions. For instance, at the baseline assumptions of $M = 5$, $r = 8\%$, and $\theta = 20\%$, asset sorting increases carry by around 0.8% of AUM. Increasing the multiple M to 7 or reducing it to 3 leads to estimates that range from around 0.7% to 1.0% of AUM.

[Insert Table 3 about here]

A higher percent carried interest tends to increase the effect of asset sorting on the carry. For instance, at $M = 5$, the highest incremental carry occurs when the hurdle rate is 4% and when the percent carried interest is 25%, in which case asset sorting increases carry by 1.2% of AUM.

In Panel B of the table, we limit the sample to investments where at least two of the funds managed by the VC firm invest in the same industry and state as the company receiving the new investment. Focusing on these funds allows us to assess the extent to which industry and state specialization may affect asset sorting. Now, at the baseline assumptions of $M = 5$, $r = 8\%$, and $\theta = 20\%$, we find that asset sorting increases carry by around 0.7% of AUM. Increasing the multiple to 7 or reducing it to 3 leads to estimates that range from around 0.6% to 0.8% of AUM. The similarity in estimates between Panels A and B indicates that fund specialization at the level of industry and state cannot explain most of the estimated effect of asset sorting on carried interest.

Most standard VC databases do not disclose the pre- and post-money valuation of all portfolio companies after each round. In addition, the data does not provide information on management fees, carried interest, and investor hurdle rates at the fund level. The only information available is the investment amount in each round, the exit outcome of each portfolio company (IPO, acquisition, or neither), and the VCs participating in each round. While these limitations may introduce noise in our estimates, we do not expect them to bias our findings. Moreover, we ensure our findings are robust to a wide range of assumptions.

The overall findings presented in this section are consistent with the hypothesis that the general partners in VC funds strategically sort assets into funds in order to increase carried interest. The increase in carried interest is statistically and economically significant under several assumptions of the carry percentage, hurdle rates, and investment performance. At the lowest estimate in Table 3, Panel B, of 0.5%, asset sorting increases carry by an aggregate of $170 million in the average year (with aggregate investments of $34.0 billion). At the highest estimate in Panel B of 1.1%, asset sorting increases carry by an aggregate of $374 million in the average year.

5. The importance of specialization and agency

The previous section presents significant evidence of asset sorting in the VC industry. As noted earlier, asset sorting may have both a productive (specialization) and a redistributive (agency) explanation. In this section, we try to distinguish between the specialization- and agency-based explanations. We start by examining the propensity of VC firms to specialize at the fund-level versus the firm-level. We then perform a test for agency-based sorting by focusing on follow-on investments in the same company and examine whether GPs reallocate these investments across funds strategically conditional on fund performance.

5.1. Firm- versus fund-level specialization

A multi-fund VC firm may specialize at two levels. First, specialization may occur at the level of the whole firm. For example, a VC firm may choose to focus its investments within an industry (e.g., Gompers, Kovner, and Lerner 2009) or a geographic region (e.g., Chen et al. 2010) because of unique expertise. Second, the firm may specialize at the level of individual funds. For example, a multi-fund VC firm may make investments in multiple industries or geographic regions while keeping the investments in each fund focused within an industry or a region. Even though within-fund specialization does not enhance expertise, which is determined by the expertise of all GPs, it may lead to optimal allocation of duties and incentives across the GPs.

In this section, we examine the extent of VC specialization at the fund level relative to the firm level. For each year t between 1985 and 2022, we construct a sample of multi-fund VC firms, defined as firms with at least two open funds as of December 31 in that year. For each year t, we use all past investments and count the number of investments n_{klij} within each industry k, state l, firm i, and fund j, where $(k,l,i,j) \in K \times L \times I \times J$. Letting $\mu_{klij} = E(n_{klij})$ be the expected count for cell (k,l,i,j) conditional on the model, we fit two Poisson regression models. The first model includes the main effects of industry, state, firm, and fund, as well as the industry-state interaction:

$$\ln\left(\mu_{klij}\right) = \lambda + \lambda_k^K + \lambda_l^L + \lambda_i^I + \lambda_j^J + \lambda_{kl}^{KL}. \tag{4}$$

The second model extends (4) by adding industry-firm, state-firm, and industry-state-firm interactions:

$$\ln\left(\mu_{klij}\right) = \lambda + \lambda_k^K + \lambda_l^L + \lambda_i^I + \lambda_j^J + \lambda_{kl}^{KL} + \lambda_{ki}^{KI} + \lambda_{li}^{LI} + \lambda_{kli}^{KLI}. \tag{5}$$

We estimate each model for each year t and obtain their respective goodness-of-fit measures: $R_{1,t}^2$ and $R_{2,t}^2$.[11] The share of variation explained by VC firms in a given year t is equal to $\pi_{firm,t} = \left(R_{2t}^2 - R_{1t}^2\right)/\left(1 - R_{1t}^2\right)$. The share of variation explained by VC funds is equal to $\pi_{fund,t} = 1 - \pi_{firm,t}$. The resulting estimates are plotted in Figure 4.

[Insert Figure 4 about here]

Examining the figure, we see that around 85% of VC specialization in industries and geographic regions is explained by specialization at the level of the firm while specialization at the level of the fund accounts for the remaining 15%. In more recent years, the share of specialization explained by individual funds has declined to around 11%. While these findings do not fully rule

[11] To measure the goodness of fit of a Poisson regression model, we use:

$$R^2 = 1 - \frac{\sum_{klij}\left[n_{klij}\log\left(n_{klij}/\mu_{klij}\right) - \left(n_{klij} - \mu_{klij}\right)\right]}{\sum_{klij} n_{klij}\log\left(n_{klij}/\overline{n}_{klij}\right)},$$

where n_{klij} is the frequency count in group (k,l,i,j), $\overline{n}_{klij}$ is the average n_{klij} across all groups, and μ_{klij} is the predicted value of n_{klij} from the estimated model. See Greene (2002, page 742).

out specialization at the level of VC funds, they do show that most specialization occurs at the level of VC firms rather than VC funds. The findings are also consistent with Gompers, Kovner, and Lerner (2009) who find that VC firms exhibit high specialization in particular industries and with Chen et al. (2010) who find that VC firms exhibit high specialization in particular geographic regions.

5.2. Do VC firms allocate follow-on investment rounds to better performing funds?

In this subsection, we test Hypothesis 2, which examines how multi-fund VC firms decide which fund undertakes a new follow-on investment in the same company. When a multi-fund VC firm finances a new round in an existing portfolio company, it faces a choice: the round may be allocated either to a fund that has previously invested in the company (an *invested* fund) or to a fund that has not (a *non-invested* fund). The agency-based view of asset sorting predicts that allocating an investment to a non-invested fund is more likely when both the company and the non-invested fund are observed to be performing well. In contrast, the specialization view of asset sorting does not generate a clear prediction linking reallocations to company or fund performance. The allocation of an investment to a non-invested fund when an invested fund is also open itself is inconsistent with specialization because it is likely to reduce differentiation at the fund level.

To test Hypothesis 2, we construct measures of observed performance for the company receiving the new investment, as well as for the invested and non-invested funds. We measure company performance using the total number of investment rounds the company has received from any VC firm prior to the date of the new investment. This measure is suitable for our setting because VC financing naturally occurs in stages. Each subsequent financing round follows the achievement of a "fundable milestone," which typically supports a higher valuation and signals improvements in company quality. Moreover, this measure can be calculated consistently across companies, allowing the analysis to be based on the entire sample of funds and portfolio companies. To measure fund performance, we use the average number of prior rounds among the companies in a fund's portfolio at the time of the new investment. We measure the invested fund's history with the company using the time since the fund's last investment in the company and the number of prior rounds in the company financed by that fund. We also measure the age of the invested and non-invested funds and the number of companies in their portfolios.

To account for specialization, we construct measures for fund specialization in the industry and the state of the company receiving the new investment. Fund industry specialization is measured as the proportion of the fund's concurrent portfolio companies that are in the same industry as the new investment. Similarly, fund state specialization is measured as the proportion of the fund's concurrent portfolio companies that are in the same state as the new investment.

Summary statistics for this sample are presented in Table 2, Panel B. We observe that around 7% of new investments are placed in a non-invested fund rather than in an invested fund. Therefore, when investing in the same company, VC firms are more likely to allocate an investment in an invested rather than a non-invested fund. The invested fund has provided 2.0 rounds of financing to the same company, where the last round is 1.3 years before the new investment. Invested funds have around 20.0 companies in their portfolio, on average, and are 4.0 years old. Non-invested funds have 13.7 companies in their portfolio and are 4.1 years old. The company receiving the new investment has obtained 3.5 rounds of financing in the past. The average performance of invested and non-invested funds, as measured by the average number of prior rounds of their portfolio companies, is similar at 3.6 and 3.7 rounds. Examining the specialization variables, 33% of the companies in the portfolio of the invested funds are in the same industry and 45% are in the same state as the new investment. For non-invested funds, these percentages are 27% and 40% respectively.

In Table 4, we estimate linear probability models in which the dependent variable equals 1 if the new investment is undertaken by a non-invested fund and 0 if it is undertaken by an invested fund (i.e., a fund switch). The key explanatory variable is an interaction term between the number of prior rounds of the new investment, which is our measure of company performance, and the performance of the non-invested fund. If VC firms allocate well-performing companies to well-performing funds, we expect the coefficient on this interaction to be positive and statistically significant. As additional explanatory variables, in model 1 we include the number of prior rounds of the new investment and non-invested fund performance.

We find that the coefficient of the interaction term between non-invested fund performance and company performance (i.e., # prior rounds of new investment) is equal to 0.31 and is significant at the 0.01 level. The estimated coefficient indicates that the likelihood of a fund switch increases when both the company and the non-invested fund are performing well. Examining the coefficients of the standalone variables, we find the likelihood of allocating the new investment to a non-invested fund decreases with the performance of the invested fund and with the performance of the company receiving the new investment.

[Insert Table 4 about here]

We find similar results in model 2, where we include additional control variables. The coefficient estimate of the interaction term between non-invested fund performance and company performance is now equal to 0.30 and is again significant at the 0.01 level. Examining the rest of the explanatory variables, the likelihood of allocating the new investment to a non-invested fund decreases with invested fund performance, the number of prior rounds in the company by the invested fund, the number of companies in the invested fund, and the age of the non-invested fund. This likelihood increases with the time since the invested fund's last round in the company, the number of companies in the non-invested fund, and the age of the invested fund. The likelihood of switching the fund for follow-on rounds in the same company decreases with invested fund specialization and increases with non-invested fund specialization in the industry and the state of the company. These results are consistent with specialization at the fund level. However, the robust coefficient on the interaction term between non-invested fund performance and company performance suggests that performance-based asset sorting is independent of specialization.

In model 3, as additional control variables we include interaction terms between all explanatory variables and company performance. The coefficient estimate on the interaction term between non-invested fund performance and company performance is again positive, at 0.23, and significant at the 0.01 level.

Overall, the evidence presented in this section supports Hypothesis 2. VC firms tend to switch the fund undertaking follow-on rounds in the same company when both the company and the non-invested fund are performing well. While specialization at the fund level seems to affect the decision to move investments into non-invested funds, it does not subsume the importance of performance. The findings are consistent with the idea that some of the observed asset sorting is agency-based and independent from specialization.

6. Additional tests

6.1. Asset sorting and investment performance

One possible interpretation of asset sorting is that it increases the value of portfolio companies and therefore should be expected in a competitive market. If asset sorting improves specialization or creates stronger incentives for the GPs to monitor the companies in their portfolios, it could create value for investors net of the wealth transfer to the GPs. For example, there is evidence that specialization improves the performance of private equity firms (Cressy et al. 2007; Gompers, Kovner, and Lerner 2009; Brown, Fei, and Robinson 2023; Racculia, 2014; Spaenjers and Steiner 2024).

A closer consideration of the above possibility, however, suggests that any potential benefits of asset sorting are unlikely to offset completely the associated costs for investors. First, rent-seeking activity is likely to crowd out productive effort (Murphy, Shleifer, and Vishny 1993). If the GPs can transfer wealth from the LPs without costly monitoring, they would always choose to do so. Second, even if investments are placed in multiple funds, the GPs' overall portfolio remains diversified across a large and diverse pool of companies, thus reducing overall carry sensitivity to any one specific investment. Lopez-de-Silanes, Phalippou, and Gottschalg (2015) present evidence for diseconomies of scale in the PE industry.[12]

To examine the question of whether asset sorting improves the performance of investments, we estimate regression models in which the dependent variable is the future performance of each new investment. As an explanatory variable of main interest, we use our measure of asset sorting, which compares the carried interest in the actual and counterfactual allocations, averaged at the level of the VC firm over the prior one year.[13] For this table, we assume the hurdle rate is 8%, the

[12] Prior studies have shown that the level of monitoring that GPs provide depends on company characteristics, the degree of moral hazard and agency problems between VCs and entrepreneurs, and the ease of access to a company (Gompers 1995; Bernstein, Giroud, and Townsend 2016). The structuring of investments across funds is unlikely to affect these characteristics, or the outlook of a particular portfolio company.

[13] We find similar results if we measure asset sorting over the prior three years or the prior five years.

value of a successful investment as a multiple of invested amount is 5, and the percent carried interest is 20%.[14] The estimates are presented in Table 5.

[Insert Table 5 about here]

We find that the relation between asset sorting and investment performance is negative and mostly insignificant. The estimated coefficient on the asset sorting variable in model 1 is equal to -6.61 with a *t*-statistic of -1.68, indicating significance at the 0.10 level. While the coefficient on asset sorting remains negative, it is insignificant in models 2 and 3 where we introduce additional control variables. In model 3, for example, we control for VC firm fixed effects, which should capture potential reputation effects on company performance (Sørensen 2007; Nahata 2008) and find an insignificant relation between asset sorting and investment success. Examining the rest of the explanatory variables, we find that in model 2 investment performance increases with past invested amounts but declines with the number of prior investments.

6.2. Asset sorting and VC firm reputation

Is it possible that high-reputation GPs use asset sorting as a means of extracting additional rents for their reputation? For example, Hüther et al. (2020) find that higher reputation GPs achieve higher carried interest by using deal-by-deal carry rather than whole-fund carry. Their findings could be interpreted as reflecting a competitive outcome in which higher reputation GPs are compensated with extra fees for their reputation. Maybe a similar effect exists for asset sorting so that high-reputation GPs use it to extract reputation rents.

To examine this question, we estimate regression models where the dependent variable is an estimate of asset sorting for each new investment and the explanatory variable of interest is VC

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[14] Varying these assumptions does not lead to a positive relation between asset sorting and investment performance.

firm reputation. To measure asset sorting, as in Section 4, we compare the carried interest the VC firm expects to collect from all contemporaneous funds under the actual and counterfactual allocations of the new investment. For the table, we assume the hurdle rate is 8%, the value of a successful investment as a multiple of invested amount is 5, and the carried interest is 20%.[15] As discussed in Section 3, we measure VC firm reputation using two variables: VC firm cumulative market share up to the year of the new investment and VC firm age since founding. The findings are presented in Table 6.

[Insert Table 6 about here]

We do not find a significant relation between VC firm reputation and asset sorting in any of the models. In model 1, the coefficient estimate on VC firm market share equals -0.03 and is not significant at conventional levels. In model 2, the coefficient estimate on VC firm age equals -0.01 and is again statistically insignificant. These findings are inconsistent with the idea that asset sorting represents a return to the reputation capital of VC firms.

7. Conclusion

The compensation of the general partners in many private equity firms is linked to the performance of the individual funds in their portfolio rather than the aggregate performance of the firm. We show this compensation structure, together with the practice of simultaneously managing multiple funds, provides incentives for the general partners to arrange assets across funds in a manner that maximizes the value of their call option-like contracts. Our estimates suggest that asset sorting leads to a significant increase in GP compensation.

[15] Varying these assumptions leads to similar conclusions.

Could our findings be explained by specialization at the level of VC funds within the same VC firm? While this idea has some economic merit, our analysis suggest that fund specialization cannot fully explain the findings of carry-increasing asset sorting. For example, consistent with general observations from prior literature, we find that most VC specialization occurs at the firm rather than at the fund level. In addition, our tests show the likelihood that a VC firm will "switch" an investment from a fund that has already invested in the company (invested fund) to a fund that has never invested in the company (non-invested fund) increases with the performance of the company and with the performance of the non-invested fund. We find that such sorting behavior is independent from fund specialization at the industry and state levels. These findings, while difficult to explain with fund specialization, directly follow from an agency cost explanation of how VC firms allocate investments to funds.

Consistent with agency-based explanation, we also show that asset sorting does not improve investment performance and does not compensate VC firms for high reputation. Finance theory suggests that market participants should not expect compensation for bearing idiosyncratic risk, especially when this risk can be diversified away. Yet, by managing multiple funds, GPs diversify fund-specific risk while effectively collecting compensation for this risk.

Who bears the agency cost of asset sorting? If investors fully understand and internalize the agency costs of asset sorting, then they will demand compensation for it. If investors do not fully internalize the agency costs, then they will bear part of the cost. Our analysis and anecdotal evidence suggest that asset sorting is not well understood and/or internalized by the LPs. The inherent complexity of the private equity industry works against LPs' recognizing asset sorting. Moreover, the governance of some LPs may be poor, which could result in lack of attention to asset sorting. For example, Atanasov et al. (2019) show that public pension funds, a key LP in the private equity industry, are three times more likely to invest in new funds of VCs that have suffered reputational damage than other LPs. As another example, Jackson, Ling, and Naranjo (2023) provide evidence that agency frictions within pension fund LPs influence GPs of private equity commercial real estate funds to artificially boost and smooth interim reported returns.

At the end, we would like to note that the agency cost of asset sorting is likely greater than our estimates indicate. First, our tests treat the number of funds managed by a VC firm as given. If firms sort assets opportunistically, however, the number of funds itself may be strategically inflated. Second, our estimates capture only part of the cost borne by investors. Some of this cost may already be shifted to GPs through restrictive covenants in LP agreements, costly dispute resolutions, or lost business opportunities. Third, GPs may sort along multiple dimensions. For example, they could cherry-pick both the investment and the strategic exit option. Such behavior is consistent with Robinson and Sensoy (2013), who show that GPs strategically time distributions to LPs around the waterfall date, thereby earning immediate carry while limiting the risk that investment values might subsequently decline.

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Appendix A

This appendix describes the simulation used to construct Figure 1. To perform the simulation, we assume there are 3 funds, where each fund contains 10 investments. Each investment takes an initial amount of 1 unit and may succeed (success=1), with a probability of 40%, which matches the average rate of IPOs/acquisitions in our sample. The investment may fail (success=0), with a probability of 60%. Investments are of 3 types. Investments within the same type are correlated with a correlation coefficient ρ, where ρ is the same for each of the 3 types. The correlation between investments of different types is equal to 0.

We start each simulation by setting the value of within-type correlation ρ. We then randomly allocate the 30 investments to three funds, with 10 investments per fund. We sample 10,000 observations of the success of each investment using the distribution described above and calculate 10,000 realizations of the performance of each fund. Fund performance is equal to the average success of all investments in the fund. Based on these 10,000 realizations, we estimate the average carried interest per fund using Equations (1) and (2) of the paper and our baseline assumptions. We assume that management fee is $\gamma = 2\%$, the duration of each investment is $T = 5$ years, multiple of success is $M = 5$, investor hurdle rate is $r = 8\%$, and carried interest is $\theta = 20\%$. We represent the carry collected per fund as a proportion of the total invested amount of 10 per fund.

To measure the degree of asset sorting for each simulation, we calculate the Herfindahl-Hirschman index of investment type within each fund and average it across the 3 funds. Let s_{kq} be the proportion of investments of type q ($q = 1,\ldots,3$) in fund k ($k = 1,\ldots,3$). The Herfindahl-

Hirschman index for each fund k is then equal to $H_k = \sum_{q=1}^{3} s_q^2$ and the degree of asset sorting for each simulation is equal to $H = \frac{1}{3}\sum_{k=1}^{3} H_k$.

We repeat the above steps 1,000 times, which provides us with a joint distribution of the carried interest per fund and the degree of asset sorting under the assumed within-type correlation ρ. We then repeat the whole procedure starting with a different value of ρ. The value of ρ varies from 0.0 to 1.0 by an increment of 0.1.

For the figure, we examine three levels of asset sorting: low, medium, and high. For each choice of ρ, the low degree of asset sorting uses simulations with the lowest Herfindahl-Hirschman index, averaging at 0.34, which corresponds to cases where the number of investments per type are 3, 3, and 4 in each fund. The medium degree of asset sorting uses simulations with the median Herfindahl-Hirschman index, averaging at 0.43, which approximately corresponds to cases where the number of investments per type are 2, 2, and 6. The high degree of asset sorting uses simulations with the highest Herfindahl-Hirschman index, averaging at 0.53, which approximately corresponds to cases where the number of investments per type are 1, 2, and 7.

Appendix B

This appendix provides the list of industries (Table B.1) and states (Table B.2) for the sample of VC 78,061 investments between 1980 and 2022. We define industries at the Minor Industry Group level based on the industry classifications provided by VentureExpert.

Table B.1: Industries

Industry class	Major group	Minor group	Obs.
Information Technology	Communications and Media	Communications and Media	6,772
Information Technology	Communications and Media	Internet Specific	2,831
Information Technology	Computer Related	Computer Hardware	4,520
Information Technology	Computer Related	Computer Software and Services	21,539
Information Technology	Computer Related	Internet Specific	11,103
Information Technology	Semiconductors/Other Electronics	Semiconductors/Other Electronics	5,268
Medical/Health/Life Sci.	Biotechnology	Biotechnology	7,406
Medical/Health/Life Sci.	Medical/Health/Life Sciences	Medical/Health	10,217
Non-High Technology	Non-High Technology	Consumer Related	2,661
Non-High Technology	Non-High Technology	Industrial/Energy	2,817
Non-High Technology	Non-High Technology	Other Products	2,927

Table B.2: States

State	Obs.	State	Obs.	State	Obs.	State	Obs.
AK	2	ID	77	MT	42	PR	20
AL	197	IL	1,588	NC	1,403	RI	196
AR	42	IN	318	ND	6	SC	153
AZ	700	KS	110	NE	83	SD	13
CA	32,760	KY	156	NH	465	TN	823
CO	2,610	LA	120	NJ	1,713	TX	4,251
CT	968	MA	8,591	NM	184	UT	592
DC	303	MD	1,255	NV	102	VA	1,612
DE	116	ME	144	NY	4,319	VT	117
FL	1,246	MI	644	OH	1,109	WA	2,387
GA	1,438	MN	1,169	OK	87	WI	345
HI	47	MO	410	OR	858	WV	30
IA	99	MS	33	PA	2,002	WY	6

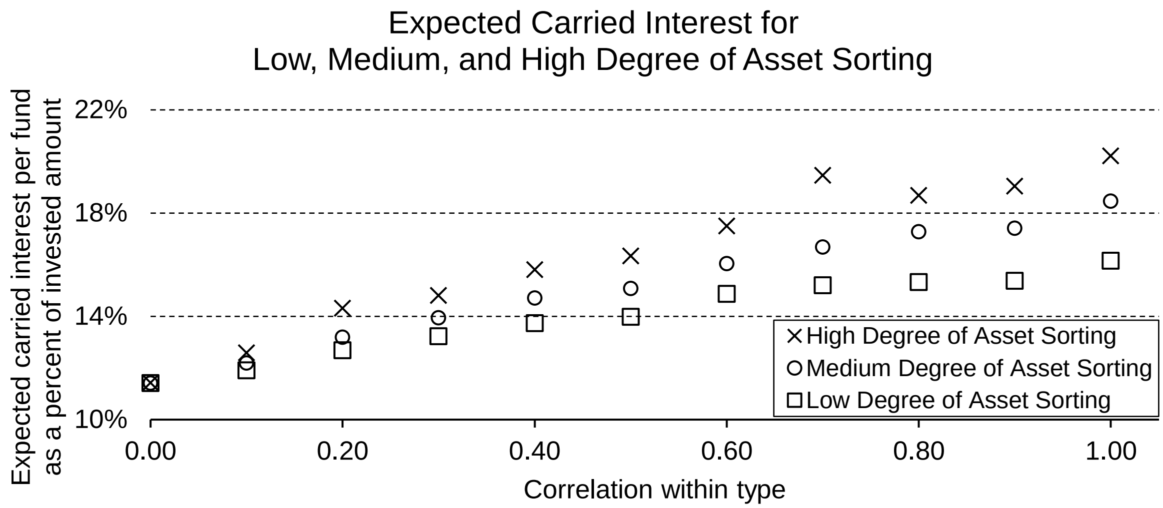


Figure 1. Expected carried interest across simulated portfolios
The figure plots estimates of carried interest per fund as a percentage of invested amount for low, medium, and high degrees of asset sorting. The estimates are obtained based on the simulation described in Appendix A. We assume there are three funds, where each fund contains ten investments. Investments are of three types. Investments within the same type are correlated with a correlation coefficient of ρ, plotted on the *x*-axis. The correlation between investments of different types is set to 0.0. For each simulation, we measure the degree of asset sorting using the Herfindahl-Hirschman index of investment types in each fund, averaged across the three funds. Based on all simulations for a given ρ, squares plot estimates at the lowest degree of asset sorting (averaging 0.34), circles plot estimates at the median degree of asset sorting (averaging 0.43), and crosses plot estimates at the highest degree of asset sorting (averaging 0.53).

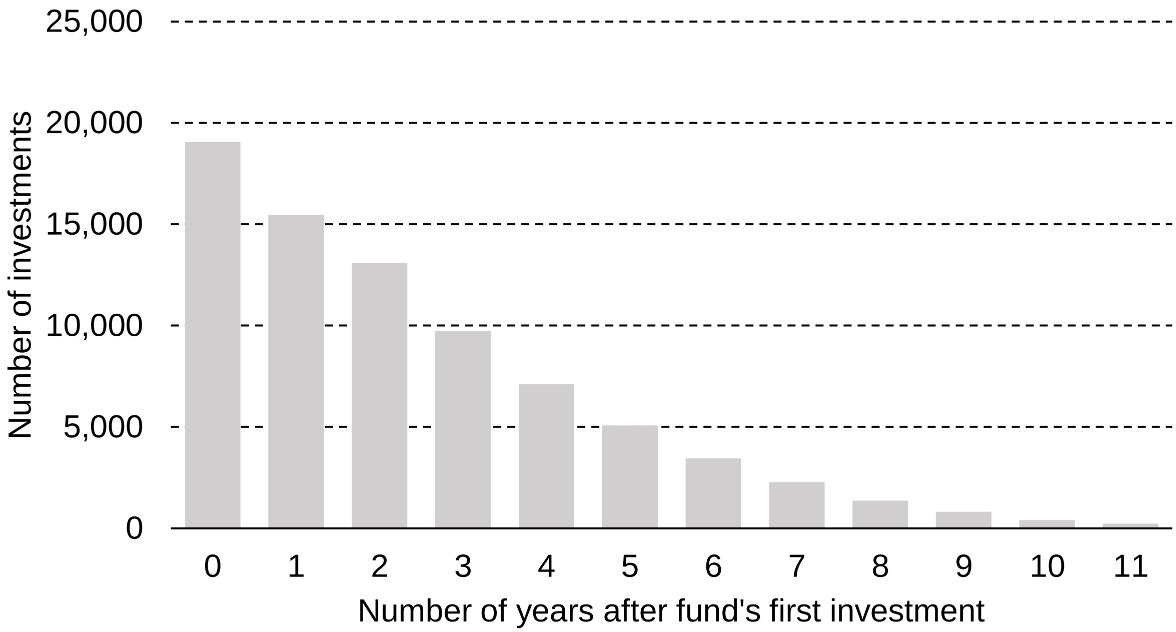
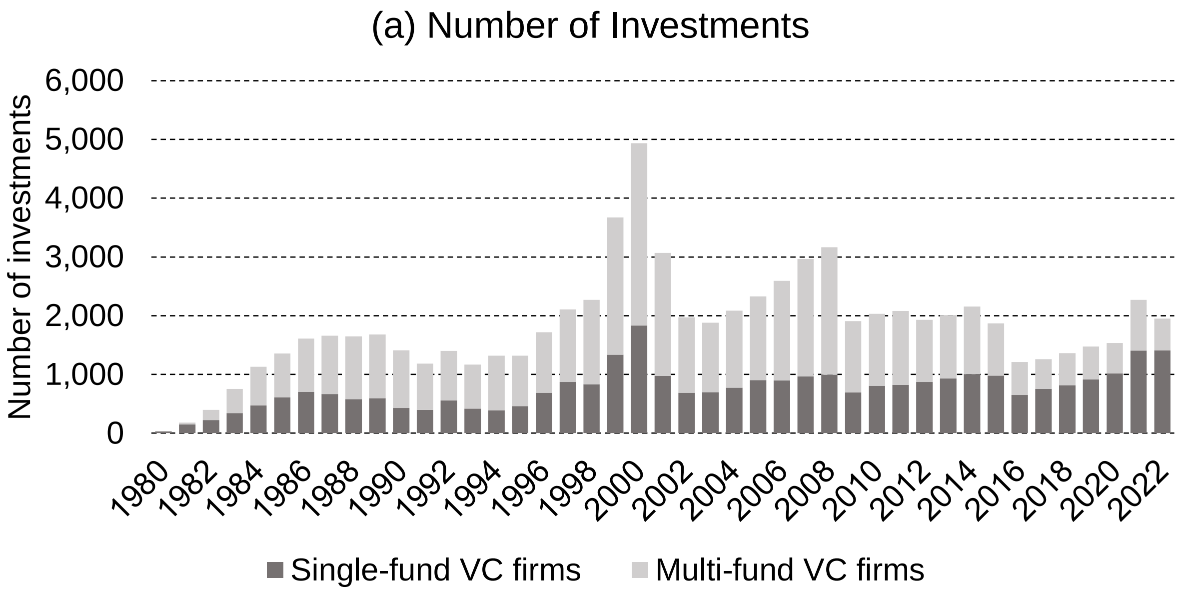


Figure 2. Distribution of fund investments over time

The figure plots the number of investments by VC funds in U.S. companies conditional on when the investment is made relative to each fund's first investment. The sample is obtained from VentureExpert and contains 78,061 investments between 1980 and 2022. The sample excludes funds where the time between the first and last investments is more than 12 years.



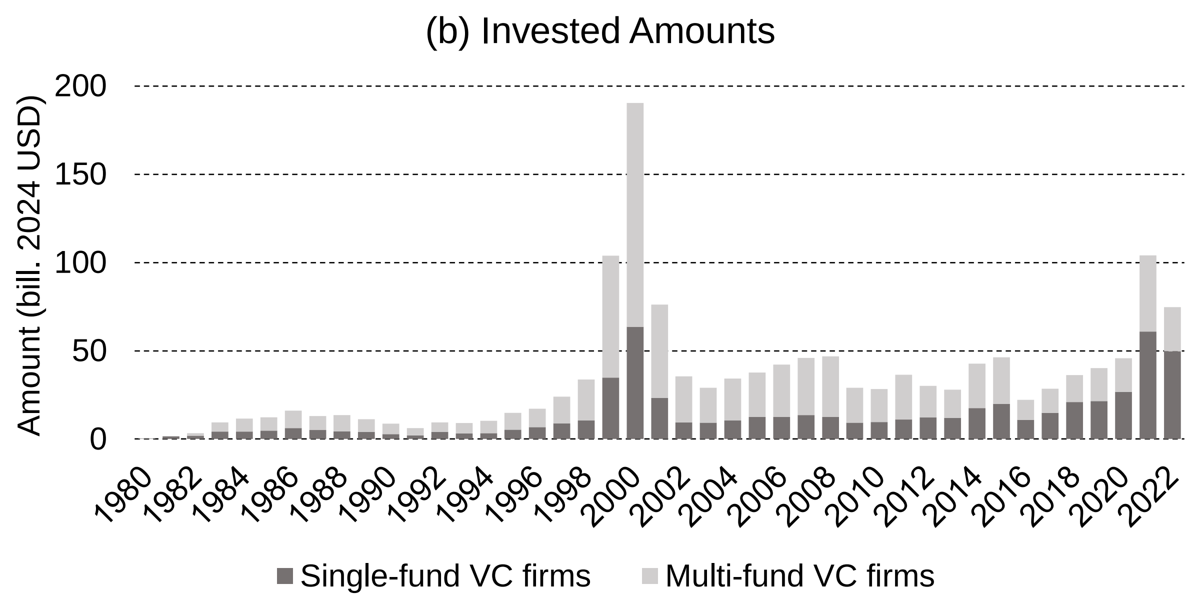


Figure 3. Number of investments across single-fund and multi-find VC firms
The figures plot (a) the number of investments and (b) investment amounts by single-fund VC firms and by multi-fund VC firms each year. The sample comes from VentureExpert and contains 78,061 investments between 1980 and 2022. The sample excludes funds where the time between the first and last investments is more than 12 years. A VC firm is classified as single-fund if no other fund is open at the time of the investment and as multi-fund if at least one other fund is open at the time of the investment. We consider a fund to be open from the date of its first investment to the date of its last investment. Overall, 32,567 investments are made by single-fund VC firms and 45,494 investments are made by multi-fund VC firms.

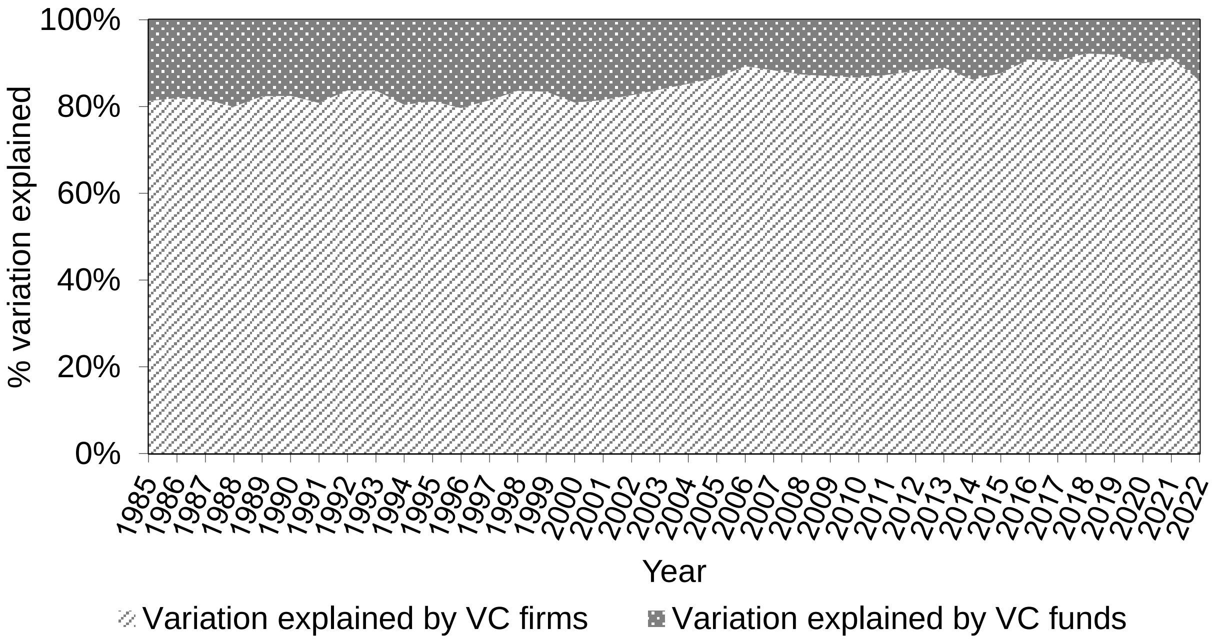


Figure 4. Specialization at the firm vs. fund level

The figure plots the percentage of variation of VC specialization in industries and geographic regions explained by VC firms and VC funds by year based on two Poisson regression models explaining the number of investments n_{klij} within each industry k, state l, firm i, and fund j. Appendix B provides the list of industries and states in our sample. The first model (Equation 4 of the paper) includes the main effects of industry, state, firm, and fund, as well as the industry-state interaction. The second model (Equation 5 of the paper) extends the first model by adding the industry-firm, state-firm, and industry-state-firm interactions. We estimate both models separately for each year. We restrict the sample to VC firms with at least two open funds as of December 31 in year t and use all past investments of the funds. For each year t, we obtain the goodness-of-fit measures, $R^2_{1,t}$ and $R^2_{2,t}$, for each model. The share of variation explained by VC firms in a given year t is equal to $\left(R^2_{2t} - R^2_{1t}\right)/\left(1 - R^2_{1t}\right)$ The share of variation explained by VC funds is equal to one minus the share of variation explained by VC firms.

Table 1
VC market activity by year
The table shows the number of investments, invested amounts, number of VC firms, number of VC funds, and number of companies by year. The sample is obtained from VentureExpert and contains 78,061 investments between 1980 and 2022. The sample excludes funds where the time between the first and last investments is more than 12 years.

Year	# investments	Amount (bill. 2024 USD)	# VC firms	# funds	# companies
1980	34	0.26	17	19	28
1981	179	1.70	53	56	108
1982	397	3.36	79	96	196
1983	754	9.39	117	156	343
1984	1,129	11.51	179	242	507
1985	1,355	12.32	201	272	670
1986	1,611	16.06	204	283	751
1987	1,659	13.04	199	284	817
1988	1,651	13.65	203	309	821
1989	1,683	11.21	204	315	817
1990	1,409	8.78	182	279	658
1991	1,183	6.15	162	235	580
1992	1,400	9.51	180	260	675
1993	1,166	9.08	169	255	595
1994	1,317	10.34	181	265	623
1995	1,322	14.75	194	276	697
1996	1,720	17.26	226	332	985
1997	2,107	23.94	293	413	1,164
1998	2,271	33.65	319	459	1,299
1999	3,674	103.85	413	661	1,996
2000	4,935	190.40	519	832	2,806
2001	3,068	76.15	503	754	1,711
2002	1,972	35.59	448	666	1,142
2003	1,880	29.03	442	622	1,114
2004	2,087	34.33	456	643	1,222
2005	2,328	37.73	498	719	1,350
2006	2,591	42.10	508	772	1,511
2007	2,964	46.04	525	842	1,710
2008	3,167	46.77	537	858	1,796
2009	1,907	29.01	440	646	1,153
2010	2,033	28.36	437	632	1,267
2011	2,081	36.50	421	611	1,243
2012	1,927	30.22	419	585	1,299
2013	2,012	27.99	404	554	1,336
2014	2,158	42.66	436	595	1,484
2015	1,871	46.28	448	610	1,314
2016	1,209	22.17	335	437	943
2017	1,262	28.60	390	477	959
2018	1,361	36.33	435	551	1,031
2019	1,474	40.13	462	580	1,118
2020	1,533	45.72	482	580	1,140
2021	2,268	103.98	591	771	1,636
2022	1,952	74.71	647	821	1,478
Average	1,815	33.97	339	480	1,072

Table 2
Summary statistics
The table reports summary statistics of the variables used in the analysis. Panel A uses a sample of investments between 1980 and 2017 and reports summary statistics of the amount of each new investment (in 2024 U.S. dollars), IPO/acquisition dummy (equals 1 if the company receiving the investment has an IPO or an acquisition in the future, 0 otherwise), number of contemporaneous funds managed by the VC firm at the time of the new investment, number of companies in the portfolio of the fund making the new investment, and number of companies in the portfolio of other contemporaneous funds. The panel also reports the cumulative market share up to year *t* and the age since founding of the VC firm making the new investment. Dollar amounts, VC market share, and VC age are winsorized at the 1st and 99th percentiles. Summary statistics in Panel A are reported for two subsamples. The first subsample includes 40,079 investments where the VC firm manages at least two funds at the time of the new investment. The second subsample includes 31,656 investments where the VC firm manages at least two funds that invest in the same industry and state as the new investment. Appendix B provides the list of industries and states in our sample. We consider a fund to be open from the date of its first investment to the date of its last investment and require all funds to have at least one prior investment. We use all investments of a fund (past and future) to determine whether the fund invests in a given industry or state. Panel B uses 43,416 investments between 1980 and 2022 while restricting the sample to investments where at least one open fund of the VC firm has a prior investment in the company (an *invested* fund) and at least one open fund does not have a prior investment in the company (a *non-invested* fund). The panel reports summary statistics for several variables, all measured using information available at the time of the new investment: an indicator variable equal to 1 if the new investment is allocated to a non-invested fund (0 otherwise), the number of years since the invested fund's last investment in the company, the number of prior rounds in the company by the invested fund, the number of prior rounds in the company by any VC firm up to the date of the new investment, the number of companies in the portfolios of the invested and non-invested funds, the age of the invested and non-invested funds, the performance of the invested and non-invested funds, and specialization of the invested and non-invested funds in the industry and the state of the new investment. Fund performance is measured by the average number of prior rounds of all investments in the fund's portfolio at the time of the new investment. Fund industry (state) specialization is measured as the proportion of all portfolio companies of the fund that are in the same industry (state) as the new investment.

Panel A: Summary statistics of investments, VC firms, and funds

	All multi-fund VC firms (40,079 observations)		VC firms with multiple funds in industry and state of new investment (31,656 observations)	
Variable	Mean	Std. dev.	Mean	Std. dev.
New investment amount (millions, 2024 USD)	16.87	22.51	17.18	22.58
IPO/Acquisition	0.40	0.49	0.41	0.49
# other contemporaneous funds	1.86	1.16	1.62	0.96
# companies in fund making the investment	16.10	12.01	16.48	12.21
# companies in other contemporaneous funds	15.61	12.20	17.36	12.54
VC market share (%)	0.34	0.63	0.36	0.64
VC age (years)	13.63	9.39	13.70	9.56

Table 2 -- continued

Panel B: Summary statistics for fund switching sample (43,416 observations)

Variable	Mean	Std. dev.
New investment is allocated to a non-invested fund	0.07	0.26
Invested fund # years since last investment in company	1.28	1.06
Invested fund # rounds in company	2.02	1.36
Invested fund # companies	20.16	12.99
Non-invested fund # companies	13.73	12.56
Invested fund age (years)	4.04	2.21
Non-invested fund age (years)	4.08	3.00
# prior rounds of new investment	3.53	2.30
Invested fund performance	3.61	1.31
Non-invested fund performance	3.68	1.69
Invested fund specialization in industry	0.33	0.23
Non-invested fund specialization in industry	0.27	0.30
Invested fund specialization in state	0.45	0.31
Non-invested fund specialization in state	0.40	0.37

Table 3
A general test of asset sorting
The table presents estimates (*t*-statistics in parentheses) from tests of asset sorting at the time of each new investment under several different assumptions about the hurdle rate, the value of a successful investment as a multiple of invested amount, and the percent carried interest. We estimate the carried interest the VC firm expects to receive from all funds under two scenarios. In the first scenario, the new investment is placed in the actual fund making the investment. In the second scenario, the new investment is placed in another contemporaneous fund of the same VC firm. We consider other funds to be contemporaneous if they are open (Panel A) and invest in companies in the same industry and state as the new investment (Panel B). Appendix B provides the list of industries and states in our sample. We consider a fund to be open from the date of its first investment to the date of its last investment. If the VC firm manages several other contemporaneous funds, we sequentially place the new investment in each of these funds and average the estimated carried interest across all such cases. Asset sorting is measured as the difference in the VC firm's carried interest between the two scenarios, using all past investments of each fund, expressed as a percentage of the amount of the new investment. To calculate the carried interest at the fund level, we classify each investment as successful if the company goes public or is acquired in the future; otherwise, an investment is classified as unsuccessful. We further assume that (i) unsuccessful investments result in a total loss, (ii) investments last five years, (iii) the general partners charge an annual management fee of 2%, and (iv) the carry is subject to a 100% catch-up provision. The sample for Panel A contains 40,079 investments while the sample for Panel B contains 31,656 investments between 1980 and 2017. Standard errors clustered at the year and VC firm level. *** denotes significance at the 0.01 level.

Panel A: All contemporaneous funds (40,079 observations)

Increase in carried interest (% of investment amount)

Carried interest = 20%				Multiple for successful investments = 5			
Hurdle rate	Multiple for successful investments			Hurdle rate	Carried interest		
	3	5	7		15%	20%	25%
0%	0.80***	0.79***	0.82***	0%	0.59***	0.79***	0.99***
	(6.22)	(4.64)	(4.47)		(4.64)	(4.64)	(4.64)
4%	0.87***	0.91***	0.97***	4%	0.70***	0.91***	1.17***
	(4.20)	(4.93)	(4.81)		(4.96)	(4.93)	(4.92)
8%	0.95***	0.80***	0.72***	8%	0.75***	0.80***	0.91***
	(2.91)	(2.78)	(2.74)		(3.02)	(2.78)	(2.78)

Table 3 -- continued

Panel B: Contemporaneous funds in same industry and state as new investment (31,656 observations)

Increase in carried interest (% of investment amount)

Carried interest = 20%				Multiple for successful investments = 5			
Hurdle rate	Multiple for successful investments			Hurdle rate	Carried interest		
	3	5	7		15%	20%	25%
0%	0.73***	0.69***	0.73***	0%	0.52***	0.69***	0.87***
	(4.77)	(3.48)	(3.45)		(3.48)	(3.48)	(3.48)
4%	0.75***	0.84***	0.83***	4%	0.65***	0.84***	1.06***
	(3.24)	(4.28)	(3.92)		(4.55)	(4.28)	(4.01)
8%	0.82**	0.73***	0.64**	8%	0.62***	0.73***	0.81**
	(2.53)	(2.70)	(1.99)		(2.84)	(2.70)	(2.36)

Table 4

Sorting good companies into good funds: Evidence from follow-on investments

The table reports coefficient estimates (t-statistics in parentheses) from linear probability models examining whether a follow-on investment is undertaken by a fund that does not have prior investments in the same company. We focus on investments where at least two funds of the same VC firm are open at the time of the investment. We further restrict the sample to cases in which at least one open fund of the VC firm has a prior investment in the company (an *invested* fund) and at least one open fund does not have a prior investment in the company (a *non-invested* fund). We consider a fund to be open from the date of its first investment to the date of its last investment. The dependent variable equals 1 if the investment is undertaken by a non-invested fund and 0 if the investment is undertaken by an invested fund. As explanatory variables, model 1 includes the performance of the non-invested fund, the number of prior rounds of the new investment, and an interaction term between these two variables. Fund performance is measured by the average number of prior rounds of all investments in the fund's portfolio at the time of the new investment. As additional explanatory variables, model 2 further includes the performance of the invested fund, the number of years since the last investment in the company by the invested fund, the number of rounds in the company by the invested fund, the number of companies in the invested and non-invested funds, and the ages of the invested and non-invested funds. To examine the importance of specialization, as explanatory variables model 2 also includes fund specialization in the industry and fund specialization in the state of the company receiving the new investment for both the invested and non-invested funds. Fund industry (state) specialization is measured as the proportion of all portfolio companies of the fund at the time of the new investment that are in the same industry (state) as the new investment. Model 3 adds interaction terms of all variables with the number of prior rounds of the new investment as explanatory variables. All models include fixed effects for year, VC firm, and the number of contemporaneous funds. All variables are winsorized at the 1st and 99th percentiles. Standard errors are clustered at the company × round date level. All coefficients are multiplied by 100 for readability. ***, **, * denote significance at the 0.01, 0.05, and 0.10 levels.

Dependent variable equals 1 if an investment is placed in a non-invested fund (0 otherwise)	(1)	(2)	(3)
Non-invested fund performance ×	**0.31*** **	**0.30*** **	**0.23*** **
# prior rounds of new investment	**(7.95)**	**(7.72)**	**(4.59)**
Non-invested fund performance	– 2.71***	– 1.19***	– 0.96***
	(– 15.14)	(– 6.19)	(– 4.37)
# prior rounds of new investment	– 1.23***	– 1.20***	– 1.10***
	(– 7.04)	(– 6.42)	(– 3.20)
Invested fund performance		– 0.78***	– 0.76**
		(– 4.28)	(– 2.42)
Invested fund # years since last investment in company		1.13***	1.01***
		(6.34)	(2.88)
Invested fund # rounds in company		– 0.37***	– 1.08***
		(– 2.66)	(– 3.57)
Invested fund # companies		– 0.05**	– 0.14***
		(– 2.51)	(– 4.87)
Non-invested fund # companies		0.10***	0.16***
		(6.59)	(7.15)

Table 4 -- continued

Dependent variable equals 1 if an investment is placed in a non-invested fund (0 otherwise)	(1)	(2)	(3)
Invested fund age		0.68***	1.52***
		(5.42)	(6.42)
Non-invested fund age		– 1.21***	– 1.58***
		(– 15.64)	(– 12.31)
Invested fund specialization in industry		– 0.46	– 0.42
		(– 0.55)	(– 0.29)
Non-invested fund specialization in industry		3.87***	1.88
		(5.73)	(1.57)
Invested fund specialization in state		– 2.96***	– 3.97***
		(– 3.68)	(– 2.88)
Non-invested fund specialization in state		4.99***	5.37***
		(7.43)	(4.66)
Invested fund performance ×			– 0.03
# prior rounds of new investment			(– 0.47)
Invested fund # years since last investment in company ×			0.02
# prior rounds of new investment			(0.34)
Invested fund # rounds in company ×			0.14***
# prior rounds of new investment			(2.82)
Invested fund # companies ×			0.02***
# prior rounds of new investment			(4.08)
Non-invested fund # companies ×			– 0.02***
# prior rounds of new investment			(– 3.45)
Invested fund age ×			– 0.20***
# prior rounds of new investment			(– 4.36)
Non-invested fund age ×			0.10***
# prior rounds of new investment			(3.57)
Invested fund specialization in industry ×			– 0.01
# prior rounds of new investment			(– 0.04)
Non-invested fund specialization in industry ×			0.56**
# prior rounds of new investment			(2.04)
Invested specialization in state ×			0.27
# prior rounds of new investment			(0.88)
Non-invested specialization in state ×			– 0.10
# prior rounds of new investment			(– 0.38)
Year, VC firm, and # contemporaneous funds fixed effects	Yes	Yes	Yes
Obs.	43,416	43,416	43,416
Adjusted *R*-squared (%)	13.70	15.24	15.37

Table 5
Asset sorting and investment future performance
The table reports coefficient estimates (*t*-statistics in parentheses) from linear regression models examining the relation between asset sorting by VC firms and the future performance of new investments. The dependent variable is investment success, where an investment is classified as successful (success=1) if the company goes public or is acquired in the future; otherwise, an investment is classified as unsuccessful (success=0). As an explanatory variable, model 1 includes an average measure of asset sorting for the VC firm undertaking the new investment over all its investments in the prior one year. To measure asset sorting at the time of each investment, we estimate the carried interest the VC firm expects to collect from all contemporaneous funds under two scenarios. In the first scenario, the new investment is placed in the actual fund making the investment. In the second scenario, the new investment is placed in another contemporaneous fund of the same VC firm. We consider only funds that are open and invest in companies in the same industry and state as the new investment. Appendix B provides the list of industries and states in our sample. We consider a fund to be open from the date of its first investment to the date of its last investment. If the VC firm manages several other contemporaneous funds, we sequentially place the new investment in each of these funds and average the estimated carried interest across all such cases. Asset sorting is then measured as the difference in the VC firm's carried interest between the two scenarios, expressed as a percentage of the new investment amount. To calculate the carried interest at the fund level, we use all past investments of the fund and classify each investment as successful if the company goes public or is acquired in the future; otherwise, an investment is classified as unsuccessful. We assume the hurdle rate is 8%, the value of a successful investment as a multiple of the invested amount is 5, and the carried interest is 20%. We further assume that (i) unsuccessful investments result in a total loss, (ii) investments last five years, and (iii) the general partners charge an annual management fee of 2%. Model 2 adds controls for the total invested amount and number of investments by the VC firm over the prior year. Model 3 further includes VC firm fixed effects. We limit the sample to investments between 1980 and 2017, which allows time for a future exit through an IPO or an acquisition. Average asset sorting by the VC firm over the previous year is available for 40,178 observations, which determines the sample size for this table. Standard errors are clustered at the VC firm level. All coefficients are multiplied by 100 for readability. $^{***, **, *}$ denote significance at the 0.01, 0.05, and 0.10 levels.

Dependent variable: Investment success	(1)	(2)	(3)
VC firm average asset sorting	**– 6.61***	**– 4.39**	**– 3.88**
in prior year	**(– 1.68)**	**(– 1.24)**	**(– 1.13)**
VC firm invested amount in prior year		5.69***	– 0.65
(2024 USD, log)		(8.75)	(– 1.17)
VC firm # investments in prior year		– 0.25***	– 0.04
		(– 4.76)	(– 0.80)
Year fixed effects	Yes	Yes	Yes
VC firm fixed effects	No	No	Yes
Obs.	40,178	40,178	40,178
Adjusted *R*-squared (%)	18.91	19.76	24.25

Table 6
VC firm reputation and asset sorting

The table reports estimates (*t*-statistics in parentheses) from regression models examining the relation between VC firm reputation and asset sorting. As the dependent variable, we use an estimate of asset sorting at the time of each new investment. To measure asset sorting at the time of each investment, we estimate the carried interest the VC firm expects to collect from all contemporaneous funds under two scenarios. In the first scenario, the new investment is placed in the actual fund making the investment. In the second scenario, the new investment is placed in another contemporaneous fund of the same VC firm. We consider only funds that are open and invest in companies in the same industry and state as the new investment. Appendix B provides the list of industries and states in our sample. We consider a fund to be open from the date of its first investment to the date of its last investment. If the VC firm manages several other contemporaneous funds, we sequentially place the new investment in each of these funds and average the estimated carried interest across all such cases. Asset sorting is then measured as the difference in the VC firm's carried interest between the two scenarios, expressed as a percentage of the new investment amount. To calculate the carried interest at the fund level, we use all past investments of the fund and classify each investment as successful if the company goes public or is acquired in the future; otherwise, an investment is classified as unsuccessful. We assume the hurdle rate is 8%, the value of a successful investment as a multiple of invested amount is 5, and the carried interest is 20%. We further assume that (i) unsuccessful investments result in a total loss, (ii) investments last five years, and (iii) the general partners charge an annual management fee of 2%. The sample contains 31,656 investments between 1980 and 2017 with future information about each investment up to and including 2022. As explanatory variables, we use two measures of VC firm reputation. The first measure is the firm's cumulative market share up to year *t* of the new investment (models 1 and 3). The second measure is the age, in years, of the VC firm since its founding (models 2 and 3). All models control for year fixed effects. Standard errors are clustered at the VC firm level. ***, **, * denote significance at the 0.01, 0.05, and 0.10 levels.

Dependent variable: Asset sorting by VC firm at time of new investment (%)

	(1)	(2)	(3)
VC market share (log)	**– 0.03**		**0.01**
	(– 0.26)		**(0.02)**
VC age (years)		**– 0.01**	**– 0.01**
		(– 0.62)	**(– 0.60)**
Year fixed effects	Yes	Yes	Yes
Obs.	31,656	31,656	31,656
Adjusted R-squared (%)	0.27	0.27	0.27