Early indicators of managerial skill and fundraising by venture capital firms

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Abstract

In this paper we show how investors in venture capital funds react to ex-ante signals about managerial skill in venture capital firms. We investigate three leading indicators of low skill that can be deduced from the type of investments the VC firms make: style drift, follow-on investments and investments where the VC firm is not the lead investor in the portfolio company. We find that investments which signal low skill are associated with lower fundraising. We find that skill is moderately stable through time. We also find that signals of skill are more important during bad states of the world.

Keywords

Private equity, signaling, style drift, follow-on investments, lead investor, performance indicator, venture capital

JEL classification

G11, G23, G24

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1. Introduction

This paper is an empirical investigation of how the characteristics of the investments made by a venture capital (VC) firm will generate cross-sectional differences in VC firms' future fundraising. Venture capital is a small but crucial part of the economy. Although VC investments have only totalled about 600 billion over the past 50 years, it is estimated that 21% of the market capitalization and 44% of the R&D expenditures of all publicly traded firms in the United States is at firms that received equity funding from VC firms during their crucial formative stages (Gornall and Strebulaev, 2015). However, not all VC firms are successful. We find that about 42% of VC firms fail to raise a second fund. How do institutional investors choose which VC funds to invest in? There is cross-sectional evidence that more capital is raised by VC firms that are older (Gompers and Lerner, 1998, Kaplan and Schoar, 2005), larger (Kaplan and Schoar, 2005, Balboa and Marti, 2007), have performed better in the past (Cumming, Fleming and Suchard, 2005; Balboa and Marti, 2007; Phalippou, 2010; Crain, 2016; Barber and Yasuda, 2015), are members of their national private equity (PE) association (Balboa and Marti, 2007), provide financial and strategic advice (Cumming, Fleming and Suchard, 2005), and whose compensation is more incentive-based (Cumming, Fleming and Suchard, 2005). Additionally, the amount of time since the firm's last fund was raised has a quadratic impact (Gompers and Lerner, 1998).

However, there has been little research into how the characteristics of a VC firm's investments can impact future fundraising. These characteristics could be important because they are immediately available, easily verifiable, and can be a signal of the skill of the VC firm's managers. In this paper, we focus on three characteristics of investments that may indicate skill: investments that are not style drifts, lead investments, and initial investments. These indicators can be seen as forward-looking measures of expected investment performance. Theoretical models proposed in the literature either focus on investors' learning through past financial performance (Chung, Sensoy, Stern, and Weisbach, 2012) or through unverifiable "soft" information about performance that cannot be measured (Hochberg et al., 2014; Berk and Stanton, 2007). However, most VC firms raise their next fund well before the end of their current fund's life, and information about interim returns are subject to manipulation by the VC firm (Barber and Yasuda, 2015). Thus, neither returns nor "soft" information are both available and verifiable at the time a new fund is raised. We fill this research gap by investigating signals that become publicly available when a VC firm makes investments into portfolio companies, which can serve as performance indicators of the current fund. This is the first paper to assess the impact of leading indicators of skill derived from investments on future fundraising by VC firms. This is also the first paper to investigate lead investments and initial investments as indicators of skill.

To test our hypothesis, we gather a sample of funds raised by VC firms from 1980 to 2014. For each VC firm-year, we measure whether the VC firm successfully raised a new fund, whether it received any capital commitments to its funds, and the size of such commitments. These are our three main dependent variables, and we jointly refer to these as "fundraising activity." For each year, we measure several appropriately lagged indicators of style drifts, lead investments, and initial investments in the VC firm's funds to serve as our signals of skill.

We find that investments which indicate high skill are associated with higher fundraising activity across the board. We find that our indicators of skill are more important indicators of fundraising success when the S&P 500 is going down, recession indicators are high, or when Chicago Fed National Activity Index indicates the economy's growth is low. This is consistent with prior results which show that investment selection and market timing skill varies with the macro environment (Kacperczyk, van Nieuwerburgh, and Veldkamp, 2014).

Finally, we investigate investors' perception of the persistence of VC skill within a VC firm over time. We find that skill is only moderately persistent with a half-life of less than a year, consistent with results obtained for mutual funds by Kacperczyk et al. (2014), who find performance persistence only for horizons up to 6 months. Since we lag our indicators of skill by one period, the effective persistence of skill is slightly longer in VC firms than in mutual funds. This finding agrees with the longer investment cycles in venture capital. Further corroborating this evidence, result for interactions of age or firm size with indicators of skill show no clear pattern. Investors perceive signals of skill in much the same way in old and large firms as in young and small ones.

To test the robustness of our results, we repeat the estimations using only the first five years after the VC firm raises its first fund and find similar results. These results are all robust to several different time lags and definitions for our primary measures of skill and a battery of control variables. Because it is possible that a bad economic state may simultaneously create a lack of supply of suitable investments, as well as force VC firms to drift more often in order to find good-quality investments, we attempt to control for reverse causality. We control for various combinations of year and region dummies and find the same results. In other words, even amongst contemporaneous VC firms in the same region with the same stated investment style, we still find that negative signals of skill lead to lower fundraising.

Our findings contribute to the literature on managerial skill and fundraising in financial intermediaries such as mutual funds (Berk and van Binsbergen, 2015; Berk and Green, 2004; Sirri and Tufano, 1998; Chevalier and Ellison, 1999; Ippolito, 1992), closed-end funds (Berk and Stanton, 2007), and private equity funds (Chung, Sensoy, Stern, and Weisbach, 2012; Phalippou, 2010; Kaplan and Schoar, 2005). This is the first study to identify verifiable, immediately available signals about managerial skill that investors may use when deciding on whether to invest in a particular VC firm's funds and how investment characteristics convey information about future fund performance.

The paper is structured as follows. Section 2 reviews the investment characteristics that we analyze. Section 3 outlines the importance of ex-ante signals of managerial skill in relation to the extant literature and develops our empirical hypotheses. We describe our empirical modelling strategy and the datasets employed in this study in Section 4. Section 5 presents our results, and Section 6 concludes.

2. Characteristics of investment

This section will review the characteristics that we evaluate as proxies for skill. The specific construction of these variables is covered in section 4.2.

The only paper we know of that has investigated the impacts of characteristics of VC investments on fundraising is Crain (2016). He finds that VC funds which perform poorly in their initial investments will subsequently make less risky (i.e., undesirable) investments in an effort to reduce the likelihood that the fund will lose money. He finds evidence that LPs are less likely to invest in VC firms whose returns are highly concentrated in a low number of start-ups, and that this effect is even stronger when the initial fund performance is low. Our paper differs from Crain's because he determines the risk of the VC firm's investments by measuring ex-post the distribution of returns, whereas the characteristics that we investigate are able to be verified ex-ante. This is an important difference because VC firms usually raise subsequent funds before the previous fund's performance is known. Thus, although we do not investigate the investment's riskiness, our paper provides an important piece of supporting evidence for his paper by showing that potential investors utilize information provided by the characteristic of the investment.

2.1. Style drift

An investment fund's "style" is the class of investment in which it invests its clients' funds. In this paper, we define a VC fund's style of investment as the life cycle stages of its investee company at the time of the investment. We distinguish seed stage, early stage, late stage, and balanced stage venture capital as well as buyout investments. Most venture capital funds publicly state their intended style. A "drift" investment is defined as an investment in a startup that is in a different style than the VC fund's stated style (Cumming, Fleming, and Schwienbacher, 2009).

Investors may utilize this information for two purposes: first, they may use it to aid in deciding whether or not to invest in a particular fund given their strategic asset allocation targets. Second, after investing in the fund, investors may use the fund's anticipated style to construct their portfolio's expected risk profile so that their future investment decisions can more accurately maximize their overall portfolio's Sharpe ratio. If a fund were to "drift," that is, make an investment that does not conform to its stated style, this may alter the investor's risk profile in ways that they did not anticipate. Thus, in theory, investors who seek to reduce their portfolio's variance will care about an investment fund's style, and will frown upon a VC firm that deviates from its stated style.

There is evidence that the style of mutual funds matters to investors (Brown and Goetzmann, 1997; Wermers, 2000; Chan, Chen, and Lakonishok, 2002, among others). Huang, Sialm, and Zhang (2011) study risk-shifting behaviour in mutual funds and find that funds that change risk (e.g., by changing their beta or idiosyncratic risk exposure) tend to subsequently perform worse than funds that maintain stable risk levels. They conclude that risk shifting is unlikely to be a signal of superior investment ability. Although mutual funds have many differences compared to private equity, Cumming, Fleming, and Schwienbacher (2009) make a convincing argument that style should also matter to investors in private equity. For practical evidence, they cite the 2008 Global Private Equity Barometer, which finds that 75% of practitioners think that style drift is important, and 84% view style drift as negative. If fund managers are aware of the costs that stage drift imposes on their investors, rational managers will try to limit the incidence of investments outside their stated target stages. In this paper, we will use the terms stage drift and style drift interchangeably.

We hypothesize that style drift is even more important among VC funds than among other types of funds because VC funds are often active managers in their portfolio companies. Venture capitalists are often on the board of directors, and they may add value by providing strategic advice, helping to professionalize firm management, and attracting better resources (Megginson and Weiss (1991); Hellmann and Puri (2000, 2002); Baum and Silverman (2004); Lindsey (2008); Ozmel, Robinson and Stuart (2013)). These activities all require a certain level of skill beyond the ability to screen and select profitable investment targets. For the purposes of this study, skill is defined as the ability to find investments that are ex-ante profitable for that particular VC firm given its possibly unique skillset. We suggest that the VC skill required for a particular startup stage is specialized and is not easily transferable to a different stage. For example, a seed stage startup may need assistance with finding partners to aid in product development, a mid-stage startup may need assistance with sales and marketing, while a late-stage startup may need assistance with preparing for an IPO. While it is possible that a VC firm may possess all of these skillsets, most VC firms are surprisingly small operations. Gorman and Sahlman (1989) report that the mean VC firm has 4.7 partners and 2.6 associates monitoring investments, while Metrick and Yasuda (2010) report that the mean VC fund has 4.81 partners. The small size of VC firms makes it plausible that most VC firms have specialized skillsets, that is, they are better at adding value to a certain type of startup. Thus, our hypothesized fund manager differs from the one discussed by Cumming et al. (2009), who model each manager as possessing a skill level that is the same regardless of the fund style.

If a VC fund invests in a portfolio company in a life cycle stage that is not the fund's focal stage, the fund will be at a disadvantage relative to a fund specialised in this stage. In a Bayesian environment, smart fund managers may recognize their shortcomings and will only invest in startups outside their focus area if the startup has exceptional potential (Cumming et al., 2009). Nevertheless, investors may interpret this stage drift as a negative signal about the fund manager's ability to find profitable investments in its focal stage. Thus, we hypothesize that stage drift is a negative signal about managerial skill, and it will result in a decreased ability for the investor to raise new funds.

2.2. Lead investments

Venture capitalists frequently invest as part of a consortium. Lead venture capitalists spend more time monitoring and advising the startup firm than non-lead VCs (Gorman and Sahlman, 1989; Wright and Lockett, 2003). Therefore, it is reasonable to assume that the talent of the lead VC firm manager contributes more to the success or failure of the startup than the talent of the nonlead VC firm manager. Lead investors often have a more central position in their network of private equity firms (Hochberg, Ljungvist, and Lu, 2007), which may allow them to source more profitable deals and benefit from their peers’ expertise. Investors may thus view a private equity firm that participates in many investments as the lead investor as possessing superior deal sourcing and execution skill.

The reputation of a startup’s lead VC firm has been used in numerous studies (for example, Lin and Smith, 1998; Lee and Wahal, 2004; Ozmel, Trombley, and Yavuz, 2016) as a proxy for the reputation of the startup, but to our knowledge this is the first time that the act of becoming a lead investor has been used to proxy for the reputation of the VC firm itself.

2.3. Follow-on investments

Successful start-ups will often have multiple rounds of VC funding. However, frequently VC firms will not participate in every round of funding. If other VC firms within the funding consortium decide to provide a further round of funding for the startup, there would likely be some pressure to continue to invest in the startup’s success. The decision to opt out of a subsequent round of funding could be an indication of skill, while the decision to opt in could be an indication of laziness. To our knowledge, this is the first use of this variable in the literature.

Investment performance may decrease in subsequent rounds as first-round investors are reluctant to discontinue investing in underperforming portfolio companies for psychological or cognitive reasons or to protect the initial investment. In a study of consecutive investment decisions by VC firms, Guler (2007) finds that contractual arrangements with co-investors penalize VC firms that terminate investments and put pressure on them to continue investing in subsequent rounds. Informal pressure exists through investment norms in the industry that discourage termination, as deviations from the norms are penalized through the syndication network. She further argues that because decisions within a VC firm about which investment to continue are often political and involve horse trading of the “if you don’t veto this, I won’t veto your deal“ kind, follow-on investments may be approved for reasons other than expected investment performance.

Poor subsequent performance may also be caused by artificially high valuations in follow-on rounds. Lerner (1994) suggests that a first-round investor may inflate the portfolio company’s valuation in a subsequent round in order to write up its fund’s net asset value in the hopes of impressing potential investors when raising a new fund. Under an alternative strategy that can result in better performance after a follow-on round, VC investors might use “inside rounds” that involve the startup’s founder to dilute the founder’s interest at an artificially low-valued financing round. However, Broughman and Fried (2012) find little evidence for this hypothesis. Instead, inside follow-on rounds are used as a backstop when new external financing is limited. Non-participation by VC investors in follow-on rounds may thus be seen as an indication that the VC firm has the skill to find more profitable investment options are available elsewhere that justify the negative financial and psychological consequences of investing in the next round.

3. Background on investors' responses to performance signals

What signals about expected fund performance do investors use when deciding whether to make commitments to an investment fund? Prior studies have treated historical fund performance as a signal of managerial skill in VC firms. In addition to these trailing measures of success, some studies employ leading indicators, such as the folume of investments, to predict fundraising. There are no studies, however, that try to incorporate information about the *type* of investments when it becomes available at the time of investment. In this section, we review the existing literature on performance signaling in mutual funds and private equity funds and relate it to the question of why investment characteristics may convey information about future fund performance that is used by investors when deciding whether to invest in a particular VC firm's funds.

3.1. Models of fundraising in mutual funds

Early studies on fund performance focus on signals of realized investment returns in mutual funds. Ippolito (1992) is among the first to study the empirical relationship between mutual fund performance and fund inflows and finds a strong positive relation to historical performance. Kacpercyk et al. (2014) confirm that top-performing mutual funds receive higher inflows. Arguing from a theoretical viewpoint, Berk and Green (2004) develop a learning model for mutual funds in which investors learn about the manager's ability by observing the mutual fund's returns. In their model, signals of managerial skill become more accurate with subsequent observations of returns. They further hypothesize that sensitivity to historical performance is greater in younger mutual funds. Chevalier and Ellison (1997, 1999) find empirical support for this learning model by finding a greater sensitivity of fundraising to historical performance among younger fund managers. Sirri and Tufano (1998) find that investors have a nonlinear reaction to performance information: investors disproportionately buy high performing funds while failing to reduce their exposure to lower performing funds at the same rate. They also provide evidence consistent with the hypothesis that mutual fund flows are affected by factors related to the search costs that consumers must bear. High-fee funds, which they hypothesize spend more on marketing than other funds, exhibit a stronger performance-flow relationship. Because management fees in private equity are high relative to other asset classes, one might expect an even more pronounced relationship between performance and fundraising in the private equity industry.

3.2. How is private equity different from mutual funds?

Lerner et al. (2007) maintain that because “it is generally believed that the private equity market is characterized by greater information asymmetries than public markets, differences among institutions should be most pronounced here.” Information asymmetries among the triangle of general partners, limited partners and potential fund investors are further aggravated by returns that are notoriously difficult to measure due to infrequent transactions at market prices (Phalippou and Gottschalg, 2009). Thus, if signals about the expected performance of a fund are valued by market participants, these signals will have a greater effect in the private equity market than in public markets.

As section 3.1 shows, past financial performance is often used as a signal that investors use in the mutual fund industry. However, in the private equity industry, reliable information about the manager’s past financial performance only becomes available when the manager’s funds sell portfolio companies (Black and Gilson, 1998). The infrequency of this event means that information on past financial performance is only available with either a considerable delay or a considerable amount of noise. Thus, investors in private equity need to rely on other measures of performance. Therefore, alternative signals (i.e., signals other than recent financial performance) should be both more important and easier to detect within PE markets than mutual fund markets.

This shortcoming of PE markets is well-recognized, and it can even cause VC firms who wish to send a reliable signal of their quality sometimes to make decisions that may not be value-maximizing for their current investors. For example, Gompers (1996) shows that young VC firms engage in grandstanding and take portfolio companies public earlier than older VC firms in order to signal investment success to investors when raising new funds. Similarly, young funds invest in riskier buyouts than old funds in order to establish a track record (Ljungqvist, Richardson, and Wolfenzon, 2008).

There is a good reason that fundraising incentives are so important in private equity. Chung, Sensoy, Stern, and Weisbach (2012) study the size of direct pay for performance derived from current carried interest and indirect pay for performance through higher fundraising in better-skilled PE firms in the future. They argue that this indirect pay for performance (obtained by raising larger future funds) represents a substantial fraction of the general partner’s lifetime income. Thus, the potential for future fundraising constitutes an important incentive for the PE firm's managers. In the absence of market prices for portfolio companies, investors need to infer a general partner's ability to generate excess returns from both historical returns and from the general partner's investment behavior. Therefore, we can expect general partners to use a variety of signals to influence investors' perceptions of managerial quality.

3.3. Models of fundraising in venture capital

In this section, we relate how previous studies have approached the problem of signaling in VC investment relationships to the problem of estimating managerial skill. Theoretical models that approach this problem usually assume some kind of learning through unspecified "soft information" (Berk and Stanton, 2007; Hochberg, Ljungqvist, and Vissing-Jørgensen, 2014) or through the fund's financial performance only. A contribution of our paper is an investigation of how the investors' learning process works.

Gompers and Lerner (1998) find that the reputation of individual venture firms drives fundraising. They find that more capital is raised by older and larger VC organizations, as well as by VC firms that hold large equity stakes in companies taken public. In their paper, Gompers and Lerner call for a closer investigation of the generation and impact of reputation in VC markets. For young firms in particular, financial performance is often not suitable as a signal because the first fund's performance is usually not known when the second fund is raised. Balboa and Martí (2007) address this issue by studying how VC firms in developing venture capital markets gain reputation in the absence of past performance information. They find that fund size is related to the volume of investments recorded in the past (although the likelihood of raising a fund is not), the ratio of portfolio companies to investment managers, the percentage of divestments carried out through initial public offerings and trade sales, the membership of the national private equity association, and the size of funds under management. Furthermore, past performance may not be a good indicator for future performance if there is high turnover within the fund's management. Our study supports their finding because leading indicators based on the investments that will ultimately produce the fund's return may give investors a better forecast of future fund returns.

Due to the limited availability of market prices in private equity – and thus a lack of reliable observable returns that could be used to estimate the fund manager's skill – some previous studies have attempted to use other measures to proxy for contemporaneous fund returns. Among these are accounting returns and internal rates of return (IRR) published by the PE firms themselves (Kaplan and Schoar 2005), returns to a “public market equivalent” investment (Kaplan and Schoar 2005), and the final performance of the fund (Phalippou, 2010). These authors have generally found evidence supporting a relationship between performance and future fundraising. Phalippou (2010) finds that by far the best predictor of fund size is the size of the most recent fund. He further argues that as investors learn about fund abilities, they update the optimal fund size. The effect of past performance on fund size is supported by Kaplan and Schoar’s (2005) findings that establish a positive link between the size of the next fund and the current fund’s performance, as measured by it’s cash flow’s public market equivalent, its size, as well as its sequence number. They also document a positive relationship between the likelihood of raising a follow-on fund and past equity returns, past VC industry returns, the current fund’s size, and the current fund’s sequence number. Findings by Chung, Sensoy, Stern, and Weisbach (2012) further corroborate the positive effect of the preceding fund’s IRR and its sequence number on both the likelihood of raising a follow-on fund and the size of this fund relative to the preceding one.

4. Data and method

4.1. Data structure

The data we use in this paper was obtained from the private equity module in Thomson Reuters’ Thomson One database. We observe the fundraising and investment activities of private equity funds for the period 1980 to 2014. The basic unit of analysis is the VC firm-year. Hence, we observe managerial skill at the VC firm level (i.e., the general partner of the fund).

Thomson One measures seven distinct styles of VC funds: seed stage, early stage, late stage VC, balanced stage VC, mezzanine stage, buyouts, and generalist. While generalist PE funds cannot drift by definition, a firm with non-generalist funds may raise a generalist fund that invests in exactly the same stages as the firm’s other funds. The same logic applies to mezzanine funds, which are defined as providing certain types of capital rather than focusing on a particular stage. We keep these funds when measuring our dependent variables because eliminating generalist and mezzanine funds from the fundraising sample might suggest that some firms are less likely to raise a new fund when in fact they raised a generalist fund. The mean number of funds per VC firm in our sample is 12.8 (median 11, minimum 1, maximum 35).

A VC firm enters the dataset when the first fundraising activity occurs. This can be either the first vintage year for this VC firm or the arrival of the first commitments, whichever is observed first. If the first firm-year observation contains only generalist or mezzanine funds, these firm-years are excluded from the sample because stage drift is not possible in these firm-years by definition, which would lead to econometric instability in our models. Because firms may stop raising new funds, we need to define the end of the observation period for each firm. This period is taken to be ten years after the last fund has been raised.[3]

4.2. Primary variables of interest

We investigate three investment characteristics by which investors may signal their quality to potential investors: drift investments, follow-on investments, and lead investments. Note if all three of our signals of skill are valid, our variables for drift and follow-on investments will have a negative relationship with fundraising, while our variables for lead investments will have a positive relationship with fundraising.

For style drift, our primary independent variable of interest is the firm's drift ratio (*Drift ratio*), which is defined as the percentage of the VC firm's investments in the previous year that are drift investments. For robustness, we also test four other measures of drift. We use a dummy variable for whether the VC firm made any drift investments that year (*Drift yes/no*) and the total number of drift investments that year (*Log(drifts+1).* Additionally, relative measures of drift may be relevant because investors in venture capital often follow performance ratings of funds based on their relative position within a cohort of funds in order to seek top-performing VC firms. Therefore, we measure the drift ratio relative to other VC firms in that year (*Drift ratio quantile*), defined as the quantile of the drift ratio relative to all firms in a given year.

Similarly, we construct four measures for follow-on investments and four measures for lead investments. A follow-on investment is defined as the investment's sequence number from the startup firm's perspective (i.e., a dummy variable indicating whether an investment is the firm's initial investment in a portfolio company or whether it is a follow-on investment). Thus, our primary variable for follow-on investments (*Follow-on ratio*) measures the percentage of the VC firm's investments in the previous year that are follow-on investments.

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[3] In unreported robustness tests, we vary the number of years for the cutoff point and find that our main results are substantially the same.

Our primary variable for lead investments (*Lead ratio*) measures the percentage of the VC firm's investments in the previous year that are lead investments. The lead investor is defined as the investor with the largest cumulative investment at the time an investment is made, which follows the definition used by Hochberg et al. (2007). This definition avoids look-ahead bias by not using the lifetime total investment over the entire study period. To obtain this variable, we add all investments by a firm in a company over time and at each round identify the firm with the largest cumulative investment at the investment date. This definition has two advantages. First, taking all investments until the investment date into account results in a higher likelihood to identify the largest (i.e., lead) overall investor in a company, since the biggest investor in a round may not be the firm that originated the deal. Second, Thomson One often only records the total amount invested in a company at a given date without specifying each individual investor's contribution, which makes a round-based lead investor indicator highly unreliable. If there is a tie between two or more investors based on cumulative investment, all of them are treated as lead investors in our analyses.

Table 1 shows the definitions of the variables used in this study. Table 2 provides summary statistics.

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4.3. Control variables

We control for many variables which have previously been found to affect cross-sectional fundraising performance. These include the natural logarithm of the VC firm's age in years (*Log(firm age+1)*) (Gompers and Lerner, 1998; Kaplan and Schoar, 2005), the log of the size of the VC firm's previous funds (*Log(amount raised, cumulative)*) (Kaplan and Schoar, 2005; Balboa and Marti, 2007), the number of years that have passed since the last fund the VC raised (*Years since last fund*), and the square of this number (*Years since last fund squared*) (Gompers and Lerner, 1998). To control for the VC firm's past performance, we include a control variable for the number of successful exits that the VC firm has performed (*Log(exits+1)*) (Cumming, Fleming, and Suchard, 2005; Balboa and Marti, 2007). We use this number rather than the VC firm's self-reported interim performance because the interim returns are notoriously prone to manipulation by the VC fund, particularly when they are in the process of raising a new fund (Barber and Yasuda, 2015). To control for the VC firm's position in its investment cycle, we control for the number of investments the VC firm has placed in portfolio companies in the past year (*Log(investments+1)*) (similar to Balboa and Martí, 2007), and we include a dummy variable for VC firms that made no investments in that year (*No investments*). To control for the differing drift characteristics that may affect mezzanine, buyout, and VC funds, we include controls for the percent of the cumulative amount of capital raised by buyout (*Focus buyout*), mezzanine (*Focus mezzanine*), and VC (*Focus VC*) funds that the firm has raised to date.[4]

Previous papers studying the venture capital industry as a whole find that there are time-varying factors, such as capital gains tax rates, interest rates, and regulatory changes to pension funds, that affect fundraising (Poterba 1989a, 1989b; Gompers and Lerner, 1998; Jeng and Wells, 2000). We account for these by including dummy variables for the year being evaluated. Time dummies will also control for other time-varying effects in the macroeconomic environment that may drive fundraising behavior such as changes in liquidity (Jeng and Wells, 2000; Cumming, Fleming, and Schwienbacher, 2005; Lahr and Mina, 2014), industrial expenditures on research and development (Gompers and Lerner, 1998) or overall economic growth (Gompers and Lerner, 1998).

Because the VC industry is segmented by geography (Chen, Gompers, Kovner, and Lerner, 2010), presumably, VC firms that are in the same location at the same time will face the same investment opportunity set. Therefore, we add an additional set of dummy variables to control for spatial heterogeneity in the four U.S. census regions. There are a small number of firm-years (<1%) in which firms have funds in more than one census region, thus region dummies are not perfectly collinear.

4.4. Modelling strategy

To identify the effect of style drift on fundraising success, our modelling strategy must take into account any potential endogeneity that may be induced by reverse causality or confounding variables.

Although causality from future fundraising to style drift in previous periods seems unlikely, firms may, for one reason or another, decide to cease raising new funds while they are still investing the capital of existing funds. This could remove the incentive to signal their skill and cause the VC firm to be more likely to make investments that signal a lack of skill. The anticipated end of business

[4] These three variables (*Focus buyout, Focus mezzanine,* and *Focus VC*) are not collinear because there are also generalist funds.

activities may thus cause a positive correlation with style drift, but for the correct reason: venture capital firms know that investors would interpret style drift negatively, but they can afford to drift because the firm will stop raising new funds anyway. Thus, theories along this line of thinking support our model of the interaction between the management firm and fund investors.

A potential confounding variable is the unobservable supply of investment opportunities, which may drive both style drift and future fundraising. If future investment opportunities decrease, a firm may reduce its fundraising activities but may also be more likely to drift into non-focus stages, invest as a nonlead firm, or make a follow-on investment in one of its prior portfolio firms due to a lack of suitable new targets. If investment opportunities are correlated across time to a sufficient degree, current style drift may be correlated with future fundraising. Therefore, we need to disentangle signals about managerial skill from signals about future investment opportunities. We control for a range of variables at the firm level, but because of the research question we ask there will be unobserved investment opportunities which may confound our analysis. Since an aspect of managerial skill is to identify profitable targets, and managerial skill is not directly observable, we are unlikely to capture all information about future investment opportunities in our control variables.

We can use time × region dummy variables to remove the effect of unobservable changes in investment opportunities if we assume that investment opportunities are specific to time and region but not to the firm. In other words, firms should not differ in the supply of deals they face, only in their ability to screen this supply, effectively structure deals, divest portfolio companies at a profit and all other skills-related activities of the venture capital cycle. Ideally, there should be many region dummies to accurately reflect changes in the local investment climate. From a statistical point of view, however, there should be as few as possible, because interacting time and region quickly inflates the number of variables in any model, increasing the chance of fitting the errors rather than the underlying economic structure. In order to implement time × region dummies, we define regions as the four main US census regions. The small change in coefficients when comparing models with separate time and region dummies and models with interacted dummies makes us confident that using reasonably sized regions sufficiently accounts for unobserved investment opportunities.

Although we only report results using time x region dummies in tables 3-5, we obtain similar results if we use this specification throughout the paper. We report our main results throughout the paper using time dummies and region dummies independently because of the improved fit of the model according to McFadden R-squared and AIC.

5. Results

5.1. Negative signals about skill reduce likelihood of fundraising

Results for the effect of style drift on the likelihood of raising a new fund are shown in Table 3, Panel A. Style drift has a highly significant negative correlation with whether a firm raises a new fund. This finding is consistent across model specifications using different definitions of style drift with the exception of the cumulative drift ratio, for which the effect is insignificant. A unit change in the drift ratio reduces the likelihood of raising a new fund by 3.2 percent as measured by the average partial effect in model 2 of table 3. The greatest level of significance is attained by the relative drift ratio (*t*-stat = −4.0), followed closely by the drift ratio (*t*-stat = −3.8) and the number of drift investments (*t*-stat = −3.8).

Panel B of Table 3 shows the likelihood of receiving commitments. This may be considered a more accurate measure of fundraising success than the fund's vintage year because it depends less on the firm's choice to begin a new fund and more and more on investors' willingness to commit additional capital to the firm's funds. Results show that style drift is negatively correlated with future commitments raised by the firm. We find the most significant effect among our drift measures for the drift ratio (*t*-stat =−3.9), followed by the relative drift ratio (*t*-stat =−3.7) and the number of drift investments (*t*-stat =−3.5). A unit change in the drift ratio reduces the likelihood of receiving commitments by 3.6 percent as measured by the average partial effect in model 2.

<<<< Insert Table 3 about here >>>>

We next investigate the effects of follow-on and lead investments on fundraising in Tables 4 and 5. Similar to our model for drift investments, we evaluate the likelihood of raising a new fund and the likelihood of receiving commitments.

Follow-on investments negatively predict the likelihood of both new funds and commitments (see Table 4). The best predictor for both outcomes is the percentage of follow-on investments. This is contrary to results presented by Cumming, Fleming, and Suchard (2005) who find that the dollar volume of follow-on investments as a proportion of all existing deals does not affect fundraising from pension funds. In Table 5, we find that having a higher ratio of lead investments is correlated with better fundraising. In these models, the percentage of lead investments is the best predictor for new funds, while the best predictor for new commitments is the quantile of lead investments, followed by the percentage of lead investments.

<<<< Insert Table 4 about here >>>>

<<<< Insert Table 5 about here >>>>

Among our control variables in Table 3, the size of the firm (i.e., past fundraising volume and the number of investments made) is significant as expected. Past performance, as measured by the number of successful exits, also affects the likelihood of raising new funds positively. Our quadratic specification of the number of years since raising the last fund yields the correct signs for the linear and quadratic terms, in contrast to findings by Gompers and Lerner (1998). The quadratic term is negative, as is expected if the probability of raising a new fund is to approach zero in the long run. Since the linear term dominates in the short run, the probability of raising a new fund would first increase over time and then decrease as unsuccessful firms do not attempt to raise a new fund. Control variables predict the likelihood of receiving commitments in a qualitatively similar way to our results for new funds raised. A difference can be seen, however, in the time since the last fund was raised. Although the likelihood of raising new capital still approaches zero for older funds, it starts decreasing right after a new fund was raised rather than increasing first and then decreasing as we found for new funds. In other words, firms may have gaps between their fundraising events, but gaps in new commitments appear to be a negative sign for future fundraising success.

5.2. Negative signals about skill reduce level of fundraising

We investigate the effect of signals of skill on the amount of commitments raised in Table 6. This table shows models for the logarithmic amount of commitments, regressed on the ratio of drift investments and our main set of control variables. We estimate two alternative specifications that allow for sample selection. Maximum likelihood estimation is more efficient if the assumption of bivariate normality holds, while two-step estimation is more robust to misspecification. Identification in both models relies on the functional form of the likelihood function and the inverse Mills ratio.

Panel A shows that style drift not only reduces the likelihood of receiving commitments, it also reduces the amount received conditional on receiving any commitments. We find this effect in both model specifications. Panel B shows that follow-on investments reduce the amount of commitments receives conditional on receiving any commitments. Panel C shows that lead investments increase the amount of commitments conditional on receiving any commitments. These results support our theory that these three measures are all interpreted by investors as signals of a VC firm's skill.

<<<< Insert Table 6 about here >>>>

5.3. Combining multiple signals increases their effect on fundraising

We next investigate whether the effects of style drift are the same for all types of investments or whether additional signals about managerial quality moderate the drift signal. In Table 7, we study how follow-on investments are perceived by investors in relation to style drift. Our hypothesis is that investors will view style drift, follow-on investments and non-lead investments as independent negative signals about the firm's managerial skill. If this is correct, the strongest effect will be found in investments that combine these characteristics.

The variables of interest in Table 7 are interactions of our three skill signals. We interact signals at the investment level (not at the firm level), and identify each investment as a drift or nondrift, follow-on or nonfollow-on, and lead or nonlead investment. The cross product of these dimensions produces eight types of investments. For example, in model 1, the coefficient on *Drift & follow-on & lead inv.* measures the fraction of the total number of investments made by the firm in a year that are at the same time drift, follow-on and lead investments. Similarly, the interaction tested in model 2 uses the fraction of investments that are drift, follow-on, nonlead investments. It is important to note that these interactions are not dummy variables but fractions ranging from zero to one. Hence, the coefficient on these interactions measures the effect of the interaction tested in each model against the excluded baseline fraction of all other types of investments.

Results in Table 7 confirm our expectations. Models testing interactions of signals about skill indicate that the negative correlation of drift investments, follow-on investments and non-lead investments on future fundraising is strongest when all these signals are combined in an investment. Conversely, investors react most positively if a VC firm invests according to its stated stage focus in new portfolio companies and is also the lead investor in a transaction.

<<<< Insert Table 7 about here >>>>

<<<< Insert Table 8 about here >>>>

A natural question to ask is whether all quality signals are judged as equally important by investors. From the VC firm's point of view, knowing which signals investor listen to can improve fundraising performance. From a theoretical perspective, differences in investors' sensitivity to quality signals can shed light on the relative importance of the underlying processes that generate these signals for the ultimate performance of an investment. Lead investors may be better in structuring transactions and providing liquidity to the portfolio company. Initial investments may signal a greater capability of sourcing new deals, while style drift reflects negatively on the firm's ability to find attractive investments in a particular class of potential portfolio firms.

We test the relative importance of signals about skill in Table 8, where we test the three skill measures simultaneously (model 1), a full set of interaction terms of these skill measures (model 2), and all interactions at the investment level (model 3). We have already seen in that non-lead investments reduce the likelihood of raising new funds and receiving new commitments. However, if the ratio of lead investments is included in a model alongside the drift and follow-on ratios, the effect disappears, which suggests that drift and follow-on investments send a stronger signal about managerial quality. Although the effect of lead investments is still negative, it is not significant, which suggests that lead investments frequently occur as initial non-drift investments, both of which signals then dominate the lead investment signal. When we turn to the model with interaction terms at the firm level, we find increased standard errors across all measures of skill, which suggests a substantial degree of correlation among interaction terms. It is thus not possible to say whether there exists any interaction between measures of skill at the firm level. However, this changes when we test all triple interactions between drift, follow-on, and lead investments simultaneously at the investment level. Estimation results for model 3 support the earlier finding about the relatively smaller importance of lead investments: negative effects are strongest for investments that exhibit style drift and are follow-on investments. This negative effect is aggravated by investments that are also non-lead investments as expected, but only by a small insignificant margin. Therefore, the interaction effect of the three signals found at the investment level suggests that signals about the manager's quality are additive, and there is little evidence that these terms are either compliments or substitutes.

5.4. The stability of skill

Investment skill and the perception of managers' skill by investors may be unstable, either over time for all asset managers or within VC firms as they get older. Mutual fund managers, for example, employ different skills in boom periods than in economically less prosperous times. Kacpercyk et al. (2014) find that skilled mutual fund managers outperform by being exceptionally good at stock picking in boom periods and by timing the market in recessions. They show this effect for ex-post measured financial performance. Ex-ante indicators of performance, such as style drift, may exhibit a similar cyclicality or instability. More importantly, it is unclear how investors would react to such signals of skill over time.

<<<< Insert Table 9 about here >>>>

In Panel A of Table 9, We explore the stability of skill within a firm by testing alternative measures of style drift that differ in the length of their "memory". If the skill signaled by style drift is highly stable, investors should take into account all investments made by the firm in all time periods. If skill is unstable, however, investors will only look at the most recent data when deciding about capital allocations. The stability of skill can be formalized in a rational learning model in which the manager's (i.e., general partner's) ability is unknown and must be inferred by market participants. Investors observe investment characteristics and update their assessment of the manager's skill and, depending on this assessment, decide whether and how much to invest in the manager's next fund.

If we assume that the VC firm manager's propensity to drift is moderately stable and thus can be learned, a Bayesian investor may start with an a-priori belief about a new manager's drift ratio. The investor's goal is to learn the manager's propensity to drift, $0 \leq \theta \leq 1$. A natural specification for the investor's belief about θ is a Beta distribution with parameters α and β, which can be interpreted as the number of desirable investments and non-desirable drift investments.[5] The investor then observes the investments made by the firm and updates θ according to the number of style-consistent investments d after observing n investments:

[5] Since $\alpha=\beta=1$ represents a flat prior, an investor in this firm has observed $\alpha-1=0$ drift investments and $\beta-1=0$ non-drift investments.

$$\theta \sim B(\alpha + d, \beta + n - d)$$

If we extract a prediction about the manager's skill by taking the mean of the posterior distribution, then the likelihood that the next investment will be a drift investment is:

$$P(drift) = \frac{\alpha + d}{\alpha + \beta + n}$$

If investors have weak priors, α and β are small and the estimated drift approaches the fraction of drift investments d/n. If investors have reasons to believe that the manager's drift propensity will most likely be large or small, then this can be expressed by choosing α or β large.

The number of drift investments (d) and the total number of investments (n) can be measured over short or long horizons. This depends on an assumption about the stability of the propensity to drift. If drift propensity is constant, we should count all drift investment since the firm's inception. Conversely, if drift propensity is very unstable, the time period for the measurement of drift vs non-drift investments should be short.

One way to investigate the stability of skill is to vary the time horizon used to count drift and non-drift investments and optimize the model's fit depending on this parameter. The drift variable of interest in Table 9, *Drift ratio cumulative*, is constructed from the recursively filtered number of drift investments and total investments made by the VC firm up to the current year for each VC-firm year observation. We use a parameter γ that governs the memory decay. We would expect a large γ for unstable skill and a value close to zero (i.e., a long-memory process) for stable skill.

Results in Table 9 do not support the hypothesis that skill is highly stable, as indicated by the negative effect of a short-memory drift ratio in model 1 (γ=0), which is stronger than the effect for the long-memory drift ratio tested in model 3. To find an estimate of the stability of skill as measured by style drift, we obtain the filter parameter γ by iteratively maximizing the likelihood for model 1 for different values of γ. The result is shown in model 2. The effect of the filtered drift ratio indicates a relatively stable skill. Investors' "memory" decays by about 62% in each period (i.e., they only "remember" about 38% of the VC firm's cumulative investments that were made before the previous period). The average partial effect of this optimized drift ratio with memory is 8.0%. Panels B and C of Table 9 indicate a similar result for our other two signals of skill.

<<<< Insert Table 10 about here >>>>

To explore the stability of investors' perception of skill, we test interactions of style drift with variables indicating macroeconomic conditions. We test each of the variables that are used by Kacperczyk et al. (2014). We find that style drift is punished more in recessions and periods of low economic activity. For example, model 3 shows that when the probability of being in a recession is high, drift investments made in this period are seen particularly negatively by investors. Panels B and C of Table 10 indicate a similar result for our other two signals of skill.

One possible explanation for this finding could be that investors diversify their holdings to protect against downturns. This strategy is jeopardized by VC funds that do not invest according to their stated investment focus and drift into different styles instead because if the investor can not anticipate the type of holdings of the fund, the investor can not effectively mitigate the risks posed by the fund. Another reason may be the difficulty of finding profitable investments in a downturn. When the pool of investible companies dries up, it becomes more difficult for VC firms to find suitable targets within their style focus. Only skilled firms will be able to keep investing according to their investment mandate, thus sending a stronger signal about their skill in economically weak period. Conversely, VC firms may find many exceptionally profitable businesses outside their core focus. Pursuing these opportunities despite a stated investment focus would be rewarded by investors, which then leads to a positive effect of drift on fundraising in economically prosperous period (e.g., the positive coefficient for the S&P500 in model 2 can be interpreted as indicating a positive effect of drift on fundraising in boom periods).

6. Conclusion

Chung, Sensoy, Stern, and Weisbach (2012) show that a substantial portion of a VC fund manager's compensation is derived from demonstrating that they have enough skill to be able to raise future funds. Thus, the fundraising efforts of venture capital funds complete the feedback loop that converts skillful investment selection, successful fund management, and credible performance signals into more investments for the fund's managers, and thus higher earnings for the fund's managers, in the future.

We contribute to the literature by exploring leading indicators of the types of investments undertaken by fund managers. We interpret these indicators as signals about fund managers' skill that LPs may use when making decisions about future capital commitments. In agreement with our hypothesis, we find that investments follow these signals of managerial skill (i.e., the skill of finding and developing profitable portfolio companies). As expected, negative signals about managerial skill reduce the likelihood of raising a new fund, receiving commitments to the firm's funds, and the volume of such commitments.

Style drift, defined as investments in companies that are not in the fund's targeted life cycle stage, has the strongest negative effect on both the likelihood and the level of fundraising success. Follow-on investments and non-lead investments by the firm can also be interpreted as negative signals of skill, and have corresponding negative effects on future fundraising.

When combining multiple signals in a model, the effects of style drift, follow-on investments, and lead investments are largely additive at both the level of the investment and the management firm level. For example, the signal sent by drifting into a different stage adds to the signal sent by making a follow-on investment, such that investments that are simultaneously drift and follow-on investments produce a more negative effect on fundraising. Similar patterns are observed for lead investments.

Finally, we find limited stability of managerial skill in venture capital. This finding is in line with highly unstable skill in the mutual fund industry reported in the literature and highlights that investors cannot rely on their knowledge about a firm's skill for long and constantly need to update their estimate of its skill regardless of the firm's age. Negative signals of skill are punished more strongly in periods of low aggregate economic activity. This finding may be explained by investors being more negatively affected by adverse portfolio allocations due to style drift in downturns and by an amplification of skill signals in these periods due to the shrinking pool of potential investments.

Venture capital is often seen as a driver of innovation and economic growth, and as such a crucial part of the American economy. However, compared to other types of investment vehicles, relatively little is known about how investors choose among venture capital funds due to the paucity of publicly available data. We hope that this paper contributes towards rectifying this problem.

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Table 1. Variable definitions

Variable	Definition
Firm raised a fund	The firm has raised at least one fund in the previous year. The fund year is the vintage year of the fund. Thomson One defines the vintage year as the year of the first drawdown.
Firm received commitments	The firm has received a positive amount of commitments in any of its funds in the previous year. Commitments are identified through each fund's fundraising history.
Drift (yes/no)	Stage drift is defined as deviation of the fund's stated investment focus from the company stage at the time of investment. For an investment not to be considered a drift investment, the fund focus must be match any of the company stages in brackets: Seed stage focus = {Seed Stage, Early Stage} Early stage focus = {Early Stage, Seed, Expansion} Later stage focus = {Later Stage, Expansion} Buyout focus = {Acquisition, Expansion, Public Market} Balanced stage focus = {Seed, Early Stage, Later Stage, Expansion} For example, a fund with stage focus "Early Stage" investing in a company at its expansion stage is not considered stage drift, but the same funding investing in a buyout is.
Drift ratio	The ratio of drift to non-drift investments in a firm-year. See drift definition above.
Log(drifts+1)	Natural logarithm of (number of drift investments in a firm-year plus one)
Drift ratio cumulative	The ratio of all drift investments made by a firm until a given year to the total number of investments until that year based on a flat Bayesian prior. As a formula: (cumulative drift investments +1) / (cumulative total number of investments + 2).
Drift ratio quantile	Quantile of the drift ratio for all firms in a given year (e.g., 1 if a firm has the highest ratio of drift investments among all firms in a given year, 0 if no drift investments have been observed).
Drift ratio up-drifts	Ratio of drift investments that are drifts into later stages in the VC life cycle to the total number of investments defined as follows. Seed stage focus up-drift = investment in {Later Stage, Expansion, Acquisition, Public Market, VC Partnership} Early stage focus = investment in {Later Stage, Acquisition, Public Market, VC Partnership} Later stage focus up-drift = investment in {Acquisition, Public Market, VC Partnership} Buyout focus up-drift = investment in{Public Market, VC Partnership} Balanced stage focus up-drift = investment in {Acquisition, Public Market, VC Partnership}
Drift ratio down-drifts	Ratio of drift investments that are drifts into earlier stages in the VC life cycle to the total number of investments defined as follows. Later stage focus down-drift = investment in {Seed, Early stage} Buyout focus down-drift = investment in{Seed, Early stage, later Stage, Expansion} Down-drift is not possible for seed, early, and balanced stage funds by our definitions of stage drift above (see variable "Drift yes/no").
Follow-on investments (%)	Ratio of follow-on investments in a firm-year to all investments by a firm in that year, lagged by one year. Follow-on investments are investments by a firm in a portfolio company that had already received an investment by the firm and should not be confused with the sequence number of investments irrespective of the firm making the investment, that is, second round or later round investments.
Lead investments (%)	Ratio of lead investments to the total number of investment in a firm-year, lagged by one year. The lead investor is defined at the investment level as the firm with the largest lifetime volume invested in a portfolio company (including the current investment). By this definition, a firm can is considered the lead investors in a syndicated round in which it invested less than other private equity firms if its cumulative investment

	in this portfolio company is larger than any of the other firms' cumulative investments.
Northeast census region	The firm has a fund headquartered in the Northeast census region.
Midwest census region	The firm has a fund headquartered in the Midwest census region.
South census region	The firm has a fund headquartered in the South census region.
West census region	The firm has a fund headquartered in the West census region.
Log(amount raised, cumulative)	Cumulative amount of commitments received by the firm's funds over the lifetime of the firm until the year prior to the observation of dependent variables in USD millions; in logs.
Log(firm age+1)	Firm age is defined as the difference between the year and the founding date of the firm, measured in year. The variable used in our models is the natural logarithm of this firm age plus one.
No investments	A variable indicating whether the firm made no investments in a firm-year.
Log(investments+1)	Natural logarithm of (the number of investments made in the past year by a firm through any of its funds, plus one)
Log(exits+1)	Natural logarithm of (the number of successful exits that are not write-offs in the year prior to the observation of dependent variables, plus one)
Focus buyout	Investment style of the firm, defined as the cumulative amount of capital raised by any of its buyout funds, divided by the total cumulative capital raised
Focus mezzanine	Investment style of the firm, defined as the cumulative amount of capital raised by any of its mezzanine funds, divided by the total cumulative capital raised
Focus VC	Investment style of the firm, defined as the cumulative amount of capital raised by any of its venture capital funds, divided by the total cumulative capital raised

Table 2. Descriptive statistics

This table shows descriptive statistics for the main variables used in our analyses. Median and standard deviation are not shown for dummy variables. N=29714.

Panel A. Main variables

Variable name	Mean	Median	SD	Min.	Max.
Firm raised a fund	0.133			0.000	1.000
Firm received commitments	0.191			0.000	1.000
Drift (yes/no)	0.361			0.000	1.000
Drift ratio	0.152	0.000	0.269	0.000	1.000
Log(drifts+1)	0.466	0.000	0.737	0.000	4.511
Drift ratio cumulative	0.276	0.250	0.163	0.008	0.925
Drift ratio quantile	0.410	0.481	0.330	0.000	1.000
Drift ratio up-drifts	0.108	0.000	0.230	0.000	1.000
Drift ratio down-drifts	0.054	0.000	0.191	0.000	1.000
Follow-on investments (%)	0.302	0.000	0.368	0.000	1.000
Lead investments (%)	0.397	0.333	0.403	0.000	1.000
Syndicated investments (%)	0.495	0.571	0.449	0.000	1.000
Northeast census region	0.411			0.000	1.000
Midwest census region	0.126			0.000	1.000
South census region	0.165			0.000	1.000
West census region	0.308			0.000	1.000
Log(amount raised, cumulative)	4.705	4.653	1.828	0.010	11.155
Log(firm age+1)	2.320	2.398	0.745	0.000	4.718
No investments	0.342			0.000	1.000
Log(investments+1)	1.189	1.099	1.150	0.000	5.572
Log(exits+1)	0.428	0.000	0.621	0.000	4.277
Years since last fund	3.258	2.000	2.937	0.000	10.000
Focus buyout	0.296	0.000	0.443	0.000	1.000
Focus mezzanine	0.021	0.000	0.123	0.000	1.000
Focus VC	0.674	1.000	0.457	0.000	1.000

Panel B. Time distribution of firm-year observations

Year	N	%	Year	N	%
1980	80	0.3	1998	833	2.8
1981	106	0.4	1999	888	3.0
1982	138	0.5	2000	1041	3.5
1983	180	0.6	2001	1204	4.1
1984	230	0.8	2002	1280	4.3
1985	274	0.9	2003	1323	4.5
1986	321	1.1	2004	1354	4.6
1987	362	1.2	2005	1394	4.7
1988	407	1.4	2006	1454	4.9
1989	444	1.5	2007	1503	5.1
1990	501	1.7	2008	1563	5.3
1991	537	1.8	2009	1576	5.3
1992	548	1.8	2010	1533	5.2
1993	571	1.9	2011	1465	4.9
1994	597	2.0	2012	1329	4.5
1995	634	2.1	2013	1302	4.4
1996	685	2.3	2014	1325	4.5
1997	732	2.5			

Table 3. Effect of style drift on the likelihood of new funds and commitments

This table shows Probit models for the likelihood of raising a new fund and receiving new commitments to a fund. The dependent variable in Panel A equals one if a vintage year is recorded in Thomson One for a fund managed by the firm. The dependent variable in Panel B equals one if the firm receives new commitments in any of its funds. Year dummies are for individual years in regressions 1–4 and for three-year periods in regression 5 to retain reasonable cell counts when interacting with census regions. The intercept is not shown. Heteroskedasticity-robust (HC3) standard errors are shown in parentheses. Significance levels: *** p<0.01; ** p<0.05; * p<0.1.

Panel A: Effect of style drift on the likelihood of new funds

	1	2	3	4	5
Drift ratio	-0.165 (0.04) ***				-0.164 (0.04) ***
Drift (yes/no)		-0.065 (0.03) **			
Log(drifts+1)			-0.072 (0.02) ***		
Drift ratio quantile				-0.253 (0.07) ***	
Log(amount raised, cumulative)	0.051 (0.01) ***	0.051 (0.01) ***	0.051 (0.01) ***	0.051 (0.01) ***	0.046 (0.01) ***
Log(firm age+1)	-0.081 (0.02) ***	-0.081 (0.02) ***	-0.081 (0.02) ***	-0.081 (0.02) ***	-0.086 (0.02) ***
No investments	0.067 (0.03) *	0.096 (0.03) ***	0.132 (0.03) ***	-0.050 (0.05)	0.072 (0.03) **
Log(investments+1)	0.224 (0.02) ***	0.239 (0.02) ***	0.266 (0.02) ***	0.225 (0.02) ***	0.228 (0.02) ***
Log(exits+1)	0.107 (0.02) ***	0.105 (0.02) ***	0.111 (0.02) ***	0.107 (0.02) ***	0.124 (0.02) ***
Years since last fund	0.170 (0.01) ***	0.170 (0.01) ***	0.170 (0.01) ***	0.170 (0.01) ***	0.166 (0.01) ***
Years since last fund squared	-2.537 (0.18) ***	-2.540 (0.18) ***	-2.535 (0.18) ***	-2.539 (0.18) ***	-2.475 (0.17) ***
Focus buyout	-0.361 (0.11) ***	-0.355 (0.11) ***	-0.356 (0.11) ***	-0.361 (0.11) ***	-0.354 (0.11) ***
Focus mezzanine	-0.043 (0.13)	-0.039 (0.13)	-0.042 (0.13)	-0.044 (0.13)	-0.038 (0.13)
Focus VC	-0.525 (0.11) ***	-0.520 (0.11) ***	-0.523 (0.11) ***	-0.527 (0.11) ***	-0.527 (0.11) ***
Year effects	Yes	Yes	Yes	Yes	
Region effects	Yes	Yes	Yes	Yes	
Year × region effects					Yes
Observations	29714	29714	29714	29714	29714
McFadden R-squared (adj.)	0.104	0.103	0.104	0.104	0.097
AIC	20850.4	20860.0	20851.5	20851.5	21009.0
Chi-sq. p-value	0.000	0.000	0.000	0.000	0.000
Log-Likelihood	-10375.2	-10380.0	-10375.7	-10375.8	-10433.5

Table 3 (continued)

Panel B: Effect of style drift on the likelihood of new commitments

	1	2	3	4	5
Drift ratio	-0.151 (0.04) ***				-0.150 (0.04) ***
Drift (yes/no)		-0.037 (0.02)			
Log(drifts+1)			-0.062 (0.02) ***		
Drift ratio quantile				-0.227 (0.06) ***	
Log(amount raised, cumulative)	0.016 (0.01) **	0.016 (0.01) **	0.016 (0.01) **	0.016 (0.01) **	0.014 (0.01) *
Log(firm age+1)	-0.040 (0.01) ***	-0.041 (0.01) ***	-0.040 (0.01) ***	-0.040 (0.01) ***	-0.045 (0.01) ***
No investments	-0.038 (0.03)	-0.009 (0.03)	0.019 (0.03)	-0.142 (0.05) ***	-0.036 (0.03)
Log(investments+1)	0.169 (0.01) ***	0.178 (0.02) ***	0.205 (0.02) ***	0.171 (0.01) ***	0.171 (0.01) ***
Log(exits+1)	0.106 (0.02) ***	0.104 (0.02) ***	0.110 (0.02) ***	0.106 (0.02) ***	0.120 (0.02) ***
Years since last fund	-0.149 (0.01) ***	-0.149 (0.01) ***	-0.149 (0.01) ***	-0.149 (0.01) ***	-0.151 (0.01) ***
Years since last fund squared	0.211 (0.14)	0.209 (0.14)	0.212 (0.14)	0.209 (0.14)	0.250 (0.13) *
Focus buyout	-0.331 (0.10) ***	-0.324 (0.10) ***	-0.326 (0.10) ***	-0.331 (0.10) ***	-0.316 (0.10) ***
Focus mezzanine	-0.127 (0.12)	-0.124 (0.12)	-0.125 (0.12)	-0.128 (0.12)	-0.113 (0.12)
Focus VC	-0.553 (0.10) ***	-0.547 (0.10) ***	-0.550 (0.10) ***	-0.554 (0.10) ***	-0.541 (0.11) ***
Year effects	Yes	Yes	Yes	Yes	
Region effects	Yes	Yes	Yes	Yes	
Year × region effects					Yes
Observations	29714	29714	29714	29714	29714
McFadden R-squared (adj.)	0.119	0.119	0.119	0.119	0.114
AIC	25410.8	25424.6	25414.7	25413.0	25564.0
Chi-sq. p-value	0.000	0.000	0.000	0.000	0.000
Log-Likelihood	-12655.4	-12662.3	-12657.3	-12656.5	-12711.0

Table 4. Effect of follow-on investments on the likelihood of new funds and commitments

This table shows Probit models for the likelihood of raising a new fund and receiving new commitments to a fund. The dependent variable in Panel A equals one if a vintage year is recorded in Thomson One for a fund managed by the firm. The dependent variable in Panel B equals one if the firm receives new commitments in any of its funds. Year dummies are for individual years in regressions 1–4 and for three-year periods in regression 5 to retain reasonable cell counts when interacting with census regions. The intercept is not shown. Heteroskedasticity-robust (HC3) standard errors are shown in parentheses. Significance levels: *** p<0.01; ** p<0.05; * p<0.1.

Panel A: Effect of follow-on investments on the likelihood of new funds

	1	2	3	4	5
Follow-on investments (%)	-0.217 (0.04)***				-0.254 (0.04)***
Follow-on inv. (yes/no)		-0.051 (0.03)			
Log(follow-on investments+1)			-0.136 (0.03)***		
Follow-on inv. quantile				-0.255 (0.06)***	
Log(amount raised, cumulative)	0.057 (0.01)***	0.054 (0.01)***	0.056 (0.01)***	0.055 (0.01)***	0.053 (0.01)***
Log(firm age+1)	-0.073 (0.02)***	-0.079 (0.02)***	-0.073 (0.02)***	-0.074 (0.02)***	-0.077 (0.02)***
No investments	0.058 (0.04)*	0.096 (0.04)***	0.198 (0.04)***	-0.014 (0.04)	0.055 (0.03)
Log(investments+1)	0.248 (0.02)***	0.238 (0.02)***	0.360 (0.03)***	0.236 (0.02)***	0.256 (0.02)***
Log(exits+1)	0.104 (0.02)***	0.101 (0.02)***	0.107 (0.02)***	0.104 (0.02)***	0.119 (0.02)***
Years since last fund	0.174 (0.01)***	0.167 (0.01)***	0.173 (0.01)***	0.171 (0.01)***	0.172 (0.01)***
Years since last fund squared	-2.543 (0.18)***	-2.500 (0.18)***	-2.540 (0.18)***	-2.517 (0.18)***	-2.498 (0.16)***
Focus buyout	-0.384 (0.11)***	-0.361 (0.11)***	-0.376 (0.11)***	-0.382 (0.11)***	-0.381 (0.11)***
Focus mezzanine	-0.064 (0.13)	-0.042 (0.13)	-0.061 (0.13)	-0.063 (0.13)	-0.063 (0.13)
Focus VC	-0.509 (0.11)***	-0.514 (0.11)***	-0.508 (0.11)***	-0.517 (0.11)***	-0.508 (0.11)***
Year effects	Yes	Yes	Yes	Yes	
Region effects	Yes	Yes	Yes	Yes	
Year × region effects					Yes
Observations	28962	28962	28962	28962	28962
McFadden R-squared (adj.)	0.104	0.103	0.104	0.104	0.098
AIC	20129.6	20158.6	20132.2	20139.0	20267.2
Chi-sq. p-value	0.000	0.000	0.000	0.000	0.000
Log-Likelihood	-10014.8	-10029.3	-10016.1	-10019.5	-10062.6

Table 4 (continued)
Panel B: Effect of follow-on investments on the likelihood of new commitments

	1	2	3	4	5
Follow-on investments (%)	-0.096 (0.04)***				-0.127 (0.04)***
Follow-on inv. (yes/no)		-0.007 (0.03)			
Log(follow-on investments+1)			-0.053 (0.02)**		
Follow-on inv. quantile				-0.094 (0.05)*	
Log(amount raised, cumulative)	0.019 (0.01)**	0.017 (0.01)**	0.018 (0.01)**	0.018 (0.01)**	0.017 (0.01)**
Log(firm age+1)	-0.037 (0.01)**	-0.040 (0.01)***	-0.037 (0.01)**	-0.038 (0.01)**	-0.040 (0.01)***
No investments	-0.018 (0.03)	0.001 (0.03)	0.037 (0.03)	-0.042 (0.04)	-0.023 (0.03)
Log(investments+1)	0.182 (0.02)***	0.175 (0.02)***	0.224 (0.03)***	0.176 (0.01)***	0.187 (0.01)***
Log(exits+1)	0.108 (0.02)***	0.107 (0.02)***	0.109 (0.02)***	0.108 (0.02)***	0.121 (0.02)***
Years since last fund	-0.150 (0.01)***	-0.153 (0.01)***	-0.151 (0.01)***	-0.151 (0.01)***	-0.151 (0.01)***
Years since last fund squared	0.225 (0.14)	0.246 (0.14)*	0.230 (0.14)*	0.238 (0.14)*	0.252 (0.14)*
Focus buyout	-0.348 (0.11)***	-0.338 (0.11)***	-0.344 (0.11)***	-0.346 (0.11)***	-0.337 (0.10)***
Focus mezzanine	-0.140 (0.12)	-0.129 (0.12)	-0.137 (0.12)	-0.138 (0.12)	-0.131 (0.12)
Focus VC	-0.550 (0.11)***	-0.554 (0.11)***	-0.550 (0.11)***	-0.554 (0.11)***	-0.536 (0.10)***
Year effects	Yes	Yes	Yes	Yes	
Region effects	Yes	Yes	Yes	Yes	
Year × region effects					Yes
Observations	28962	28962	28962	28962	28962
McFadden R-squared (adj.)	0.120	0.120	0.120	0.120	0.115
AIC	24582.0	24589.5	24584.4	24585.9	24722.1
Chi-sq. p-value	0.000	0.000	0.000	0.000	0.000
Log-Likelihood	-12241.0	-12244.7	-12242.2	-12243.0	-12290.1

Table 5. Effect of lead investments on the likelihood of new funds and commitments

This table shows Probit models for the likelihood of raising a new fund and receiving new commitments to a fund. The dependent variable in Panel A equals one if a vintage year is recorded in Thomson One for a fund managed by the firm. The dependent variable in Panel B equals one if the firm receives new commitments in any of its funds. Year dummies are for individual years in regressions 1–4 and for three-year periods in regression 5 to retain reasonable cell counts when interacting with census regions. The intercept is not shown. Heteroskedasticity-robust (HC3) standard errors are shown in parentheses. Significance levels: *** p<0.01; ** p<0.05; * p<0.1.

Panel A: Effect of lead investments on the likelihood of new funds

	1	2	3	4	5
Lead investments (%)	0.131 (0.04)***				0.143 (0.04)***
Lead investments (yes/no)		0.088 (0.04)**			
Log(lead investments+1)			0.081 (0.03)***		
Lead investments quantile				0.140 (0.04)***	
Log(amount raised, cumulative)	0.051 (0.01)***	0.051 (0.01)***	0.051 (0.01)***	0.051 (0.01)***	0.050 (0.01)***
Log(firm age+1)	-0.082 (0.02)***	-0.082 (0.02)***	-0.082 (0.02)***	-0.083 (0.02)***	-0.115 (0.02)***
No investments	0.193 (0.04)***	0.163 (0.04)***	0.086 (0.03)**	0.208 (0.05)***	0.148 (0.04)***
Log(investments+1)	0.226 (0.02)***	0.213 (0.02)***	0.152 (0.03)***	0.234 (0.02)***	0.250 (0.01)***
Log(exits+1)	0.107 (0.02)***	0.105 (0.02)***	0.106 (0.02)***	0.107 (0.02)***	0.116 (0.02)***
Years since last fund	0.170 (0.01)***	0.169 (0.01)***	0.170 (0.01)***	0.170 (0.01)***	
Years since last fund squared	-2.535 (0.18)***	-2.527 (0.18)***	-2.538 (0.18)***	-2.540 (0.18)***	
Focus buyout	-0.362 (0.11)***	-0.353 (0.11)***	-0.358 (0.11)***	-0.363 (0.11)***	-0.424 (0.11)***
Focus mezzanine	-0.036 (0.13)	-0.036 (0.13)	-0.037 (0.13)	-0.036 (0.13)	-0.092 (0.13)
Focus VC	-0.503 (0.11)***	-0.511 (0.11)***	-0.508 (0.11)***	-0.501 (0.11)***	-0.606 (0.11)***
Year effects	Yes	Yes	Yes	Yes	
Region effects	Yes	Yes	Yes	Yes	
Year × region effects					Yes
Observations	29714	29714	29714	29714	29714
McFadden R-squared (adj.)	0.104	0.103	0.104	0.104	0.083
AIC	20854.3	20861.6	20857.4	20854.5	21334.1
Chi-sq. p-value	0.000	0.000	0.000	0.000	0.000
Log-Likelihood	-10377.1	-10380.8	-10378.7	-10377.3	-10598.0

Table 5 (continued)
Panel B: Effect of lead investments on the likelihood of new commitments

	1	2	3	4	5
Lead investments (%)	0.072 (0.03)**				0.138 (0.03)***
Lead investments (yes/no)		0.040 (0.04)			
Log(lead investments+1)			0.056 (0.03)**		
Lead investments quantile				0.100 (0.04)***	
Log(amount raised, cumulative)	0.019 (0.01)**	0.017 (0.01)**	0.018 (0.01)**	0.018 (0.01)**	0.017 (0.01)**
Log(firm age+1)	-0.037 (0.01)**	-0.040 (0.01)***	-0.037 (0.01)**	-0.038 (0.01)**	-0.040 (0.01)***
No investments	-0.018 (0.03)	0.001 (0.03)	0.037 (0.03)	-0.042 (0.04)	-0.023 (0.03)
Log(investments+1)	0.182 (0.02)***	0.175 (0.02)***	0.224 (0.03)***	0.176 (0.01)***	0.187 (0.01)***
Log(exits+1)	0.108 (0.02)***	0.107 (0.02)***	0.109 (0.02)***	0.108 (0.02)***	0.121 (0.02)***
Years since last fund	-0.150 (0.01)***	-0.153 (0.01)***	-0.151 (0.01)***	-0.151 (0.01)***	-0.151 (0.01)***
Years since last fund squared	0.225 (0.14)	0.246 (0.14)*	0.230 (0.14)*	0.238 (0.14)*	0.252 (0.14)*
Focus buyout	-0.348 (0.11)***	-0.338 (0.11)***	-0.344 (0.11)***	-0.346 (0.11)***	-0.337 (0.10)***
Focus mezzanine	-0.140 (0.12)	-0.129 (0.12)	-0.137 (0.12)	-0.138 (0.12)	-0.131 (0.12)
Focus VC	-0.550 (0.11)***	-0.554 (0.11)***	-0.550 (0.11)***	-0.554 (0.11)***	-0.536 (0.10)***
Year effects	Yes	Yes	Yes	Yes	
Region effects	Yes	Yes	Yes	Yes	
Year × region effects					Yes
Observations	29714	29714	29714	29714	29714
McFadden R-squared (adj.)	0.119	0.119	0.119	0.119	0.076
AIC	25422.5	25425.7	25422.0	25420.0	26644.2
Chi-sq. p-value	0.000	0.000	0.000	0.000	0.000
Log-Likelihood	-12661.3	-12662.8	-12661.0	-12660.0	-13253.1

Table 6. Effect of style drift on amount committed

The dependent variable in these models is the natural logarithm of the amount committed to a firm's funds in a given year. The selection equation estimates the likelihood of observing any commitments, while the outcome equations estimate the amount committed to the firm. All models include year and region fixed effects. Standard errors are shown in parentheses. Significance levels: *** p<0.01; ** p<0.05; * p<0.1.

	Maximum-likelihood estimation		Two-step estimation	
	Selection eq.	Outcome eq.	Selection eq.	Outcome eq.
Panel A: Drift ratio				
Drift ratio	-0.151 (0.04)***	-0.289 (0.08)***	-0.151 (0.04)***	-0.671 (0.19)***
Log(amount raised, cumulative)	0.016 (0.01)**	0.602 (0.01)***	0.016 (0.01)**	0.644 (0.03)***
Log(firm age+1)	-0.040 (0.01)***	-0.165 (0.03)***	-0.040 (0.01)***	-0.272 (0.06)***
No investments	-0.037 (0.03)	0.068 (0.06)	-0.038 (0.03)	-0.065 (0.11)
Log(investments+1)	0.169 (0.01)***	0.165 (0.03)***	0.169 (0.01)***	0.580 (0.16)***
Log(exits+1)	0.107 (0.02)***	0.032 (0.03)	0.106 (0.02)***	0.280 (0.11)**
Years since last fund	-0.149 (0.01)***	0.317 (0.03)***	-0.149 (0.01)***	-0.036 (0.14)
Years since last fund squared	0.209 (0.14)	-3.589 (0.33)***	0.211 (0.14)	-3.601 (0.45)***
Focus buyout	-0.332 (0.10)***	-0.050 (0.19)	-0.331 (0.10)***	-0.887 (0.45)*
Focus mezzanine	-0.127 (0.12)	-0.162 (0.22)	-0.127 (0.12)	-0.477 (0.41)
Focus VC	-0.553 (0.10)***	-0.801 (0.20)***	-0.553 (0.10)***	-2.196 (0.62)***
Standard deviation of errors		1.336 (0.02)***		
Error correlation		0.145 (0.10)		
Inverse Mills ratio				3.561 (1.24)***
Observations	29714		29714	
Of which observed	5629		5629	
Log-Likelihood	-22229.1			
R-squared (adj.)			0.511	
Panel B: Follow-on ratio				
Follow-on ratio	-0.096 (0.04)***	-0.523 (0.07)***	-0.096 (0.04)***	-0.730 (0.14)***
Log(amount raised, cumulative)	0.019 (0.01)**	0.611 (0.01)***	0.019 (0.01)**	0.655 (0.03)***
Log(firm age+1)	-0.037 (0.01)**	-0.136 (0.03)***	-0.037 (0.01)**	-0.226 (0.06)***
No investments	-0.018 (0.03)	0.042 (0.06)	-0.018 (0.03)	-0.033 (0.10)
Log(investments+1)	0.183 (0.01)***	0.225 (0.03)***	0.182 (0.01)***	0.629 (0.17)***
Log(exits+1)	0.109 (0.02)***	0.029 (0.04)	0.108 (0.02)***	0.256 (0.11)**
Years since last fund	-0.150 (0.01)***	0.321 (0.03)***	-0.150 (0.01)***	-0.003 (0.14)
Years since last fund squared	0.223 (0.14)	-3.566 (0.33)***	0.225 (0.14)	-3.546 (0.44)***
Focus buyout	-0.349 (0.10)***	-0.127 (0.19)	-0.348 (0.10)***	-0.923 (0.45)**
Focus mezzanine	-0.140 (0.12)	-0.242 (0.22)	-0.140 (0.12)	-0.555 (0.39)
Focus VC	-0.551 (0.10)***	-0.798 (0.20)***	-0.550 (0.10)***	-2.058 (0.60)***
Standard deviation of errors		1.332 (0.02)***		
Error correlation		0.145 (0.11)		
Inverse Mills ratio				3.251 (1.22)***
Observations	28962		28962	
Of which observed	5422		5422	
Log-Likelihood	-21445.6			
R-squared (adj.)			0.5131	
Panel C: Lead ratio				
Lead ratio	0.072 (0.03)**	0.301 (0.07)***	0.072 (0.03)**	0.480 (0.13)***
Log(amount raised, cumulative)	0.016 (0.01)**	0.603 (0.01)***	0.016 (0.01)**	0.647 (0.03)***
Log(firm age+1)	-0.041 (0.01)***	-0.168 (0.03)***	-0.041 (0.01)***	-0.280 (0.06)***
No investments	0.045 (0.04)	0.336 (0.08)***	0.044 (0.04)	0.409 (0.13)***
Log(investments+1)	0.170 (0.01)***	0.168 (0.03)***	0.170 (0.01)***	0.594 (0.17)***
Log(exits+1)	0.105 (0.02)***	0.033 (0.03)	0.105 (0.02)***	0.282 (0.11)**
Years since last fund	-0.149 (0.01)***	0.312 (0.03)***	-0.150 (0.01)***	-0.049 (0.14)

Years since last fund squared	0.212	(0.14)	-3.520	(0.33)***	0.214	(0.14)	-3.533	(0.46)***
Focus buyout	-0.328	(0.10)***	-0.055	(0.19)	-0.328	(0.10)***	-0.900	(0.46)**
Focus mezzanine	-0.122	(0.12)	-0.139	(0.22)	-0.122	(0.12)	-0.449	(0.41)
Focus VC	-0.538	(0.10)***	-0.746	(0.20)***	-0.538	(0.10)***	-2.130	(0.62)***
Standard deviation of errors			1.335	(0.02)***				
Error correlation			0.145	(0.10)				
Inverse Mills ratio							3.631	(1.26)***
Observations	29714				29714			
Of which observed	5629				5629			
Log-Likelihood	-22232.3							
R-squared (adj.)					0.5119			

Table 7. Interactions of drift, follow-on and lead investments

This table shows Probit models for the likelihood of investors making commitments to funds managed by the firm. The dependent variable equals one if commitments are made to any of the firm's funds in a given year. The main variables of interest interact three signals of managerial skill by measuring the fractions of investments in each category. For example, "Drift & follow-on & lead inv." is the fraction of investment in the previous year that are drift, follow-on and lead investments. Heteroskedasticity-robust (HC3) standard errors are shown in parentheses. Significance levels: *** p<0.01; ** p<0.05; * p<0.1.

	1	2	3	4
Drift & follow-on & lead inv.	-0.239 (0.08) ***			
Drift & follow-on & no lead inv.		-0.288 (0.08) ***		
Drift & no follow-on & lead inv.			-0.025 (0.06)	
Drift & no follow-on & no lead inv.				-0.091 (0.08)
Log(amount raised, cumulative)	0.017 (0.01) **	0.016 (0.01) **	0.016 (0.01) **	0.016 (0.01) **
Log(firm age+1)	-0.039 (0.01) ***	-0.039 (0.01) ***	-0.040 (0.01) ***	-0.040 (0.01) ***
No investments	-0.012 (0.03)	-0.014 (0.03)	-0.009 (0.03)	-0.010 (0.03)
Log(investments+1)	0.172 (0.01) ***	0.172 (0.01) ***	0.168 (0.01) ***	0.168 (0.01) ***
Log(exits+1)	0.105 (0.02) ***	0.106 (0.02) ***	0.103 (0.02) ***	0.103 (0.02) ***
Years since last fund	-0.148 (0.01) ***	-0.148 (0.01) ***	-0.150 (0.01) ***	-0.150 (0.01) ***
Years since last fund squared	0.200 (0.14)	0.206 (0.14)	0.207 (0.14)	0.208 (0.14)
Focus buyout	-0.346 (0.10) ***	-0.335 (0.10) ***	-0.336 (0.10) ***	-0.336 (0.10) ***
Focus mezzanine	-0.148 (0.12)	-0.133 (0.12)	-0.136 (0.12)	-0.135 (0.12)
Focus VC	-0.568 (0.11) ***	-0.554 (0.11) ***	-0.561 (0.11) ***	-0.560 (0.11) ***
Year and region effects	Yes	Yes	Yes	Yes
Observations	29604	29604	29604	29604
McFadden R-squared (adj.)	0.119	0.119	0.119	0.119
AIC	25311.8	25308.7	25321.2	25320.3
Chi-sq. p-value	0.000	0.000	0.000	0.000
Log-Likelihood	-12605.9	-12604.3	-12610.6	-12610.2

	5	6	7	8
No drift & follow-on & lead inv.	0.021 (0.05)			
No drift & follow-on & no lead inv.		-0.012 (0.05)		
No drift & no follow-on & lead inv.			0.114 (0.04)***	
No drift & no follow-on & no lead inv.				0.007 (0.05)
Log(amount raised, cumulative)	0.016 (0.01)**	0.016 (0.01)**	0.017 (0.01)**	0.016 (0.01)**
Log(firm age+1)	-0.040 (0.01)***	-0.040 (0.01)***	-0.037 (0.01)**	-0.040 (0.01)***
No investments	-0.004 (0.03)	-0.007 (0.03)	0.047 (0.03)	-0.005 (0.03)
Log(investments+1)	0.168 (0.01)***	0.169 (0.01)***	0.175 (0.01)***	0.169 (0.01)***
Log(exits+1)	0.103 (0.02)***	0.103 (0.02)***	0.105 (0.02)***	0.103 (0.02)***
Years since last fund	-0.150 (0.01)***	-0.149 (0.01)***	-0.147 (0.01)***	-0.150 (0.01)***
Years since last fund squared	0.210 (0.14)	0.206 (0.14)	0.189 (0.14)	0.206 (0.14)
Focus buyout	-0.335 (0.10)***	-0.336 (0.10)***	-0.353 (0.10)***	-0.335 (0.10)***
Focus mezzanine	-0.136 (0.12)	-0.137 (0.12)	-0.145 (0.12)	-0.137 (0.12)
Focus VC	-0.560 (0.11)***	-0.560 (0.11)***	-0.555 (0.11)***	-0.561 (0.11)***
Year and region effects	Yes	Yes	Yes	Yes
Observations	29604	29604	29604	29604
McFadden R-squared (adj.)	0.119	0.119	0.119	0.119
AIC	25321.2	25321.4	25310.5	25321.4
Chi-sq. p-value	0.000	0.000	0.000	0.000
Log-Likelihood	-12610.6	-12610.7	-12605.2	-12610.7

Table 8. Simultaneous tests for interactions of skill signals

This table shows probit models for the likelihood of investors making commitments to funds managed by the firm. The dependent variable equals one if commitments are made to any of the firm's funds in a given year. The main variables of interest interact three signals of managerial skill by measuring the fractions of investments in each category. For example, "Drift & follow-on & lead inv." is the fraction of investment in the previous year that are drift, follow-on and lead investments. The omitted category in model 2 is the fraction of no-drift, no-follow-on and lead investments, which is the category with the largest positive coefficient if included separately. Heteroskedasticity-robust (HC3) standard errors are shown in parentheses. Significance levels: *** p<0.01; ** p<0.05; * p<0.1.

	1			2			3		
Drift ratio	-0.129	(0.04)	***	-0.108	(0.11)				
Follow-on investments (%)	-0.079	(0.04)	**	-0.060	(0.08)				
Lead investments (%)	0.052	(0.04)		0.045	(0.06)				
Drift investments × Follow-on inv.				-0.101	(0.17)				
Drift investments × Lead inv.				0.017	(0.13)				
Follow-on inv. × Lead inv.				-0.003	(0.10)				
Drift inv. × Follow-on inv. × Lead inv.				0.047	(0.23)				
Drift & follow-on & lead inv.							-0.268	(0.09)	***
Drift & follow-on & no lead inv.							-0.315	(0.09)	***
Drift & no follow-on & lead inv.							-0.083	(0.06)	
Drift & no follow-on & no lead inv.							-0.139	(0.09)	
No drift & follow-on & lead inv.							-0.061	(0.05)	
No drift & follow-on & no lead inv.							-0.090	(0.06)	
No drift & no follow-on & no lead inv.							-0.070	(0.05)	
Log(amount raised, cumulative)	0.018	(0.01)	**	0.017	(0.01)	**	0.016	(0.01)	**
Log(firm age+1)	-0.037	(0.01)	**	-0.037	(0.01)	**	-0.037	(0.01)	**
No investments	-0.007	(0.04)		-0.006	(0.05)		-0.061	(0.04)	*
Log(investments+1)	0.182	(0.02)	***	0.181	(0.02)	***	0.178	(0.01)	***
Log(exits+1)	0.112	(0.02)	***	0.113	(0.02)	***	0.109	(0.02)	***
Years since last fund	-0.149	(0.01)	***	-0.149	(0.01)	***	-0.145	(0.01)	***
Years since last fund squared	0.228	(0.14)	*	0.231	(0.14)	*	0.190	(0.14)	
Focus buyout	-0.357	(0.11)	***	-0.356	(0.11)	***	-0.357	(0.10)	***
Focus mezzanine	-0.137	(0.12)		-0.136	(0.12)		-0.146	(0.12)	
Focus VC	-0.551	(0.11)	***	-0.550	(0.11)	***	-0.557	(0.11)	***
Year and region effects	Yes			Yes			Yes		
Observations	28962			28962			29604		
McFadden R-squared (adj.)	0.120			0.120			0.119		
AIC	24572.2			24572.2			25306.8		
Chi-sq. p-value	0.000			0.000			0.000		
Log-Likelihood	-12234.1			-12234.1			-12597.4		

Table 9. Stability of skill within firms

This table shows Probit models for the likelihood of investors making commitments to funds managed by the firm. The dependent variable equals one if commitments are made to any of the firm's funds in a given year. The variable "Drift ratio cumulative" is constructed from the recursively filtered number of drift investments and total investments.

$$d_{smooth,t} = d_t + \gamma d_{smooth,t-1},\ n_{smooth,t} = n_t + \gamma n_{smooth,t-1}$$

where d is the number of drift investments, n is the total number of investments, and γ is a decay parameter. We set d_{smooth}=0 and n_{smooth}=0 at the beginning of the sample period for each firm. The cumulative drift ratio is then defined as

$$Drift_t = \frac{d_{smooth,t} + 1}{n_{smooth,t} + 2},$$

which approaches a non-informative prior if no new investments are made by the firm. Cumulative ratios are constructed for follow-on and lead investments in the same way. Models 2, 4, and 6 use the decay parameter that maximizes the likelihood within this class of models. Sample sizes are smaller for models testing follow-on investments (models 3 and 4) compared with our main models because missing values in the follow-on indicator affect all future observations in the filtered time series of the number of follow-on investments. Heteroskedasticity-robust (HC3) standard errors are shown in parentheses. Significance levels: *** p<0.01; ** p<0.05; * p<0.1.

	Drift				Follow-on				Lead			
	(1)		(2)		(3)		(4)		(5)		(6)	
	γ = 0		γ = 0.384		γ = 0		γ = 0.650		γ = 0		γ = 0.694	
Drift ratio cumulative	-0.263	(0.06)***	-0.338	(0.07)***								
Follow-on ratio cumulative					-0.202	(0.06)***	-0.329	(0.07)***				
Lead ratio cumulative									0.129	(0.06)**	0.236	(0.06)***
Log(amount raised, cumulative)	0.016	(0.01)**	0.015	(0.01)**	0.015	(0.01)*	0.018	(0.01)**	0.016	(0.01)**	0.016	(0.01)**
Log(firm age+1)	-0.040	(0.01)***	-0.041	(0.01)***	-0.031	(0.02)**	-0.027	(0.02)*	-0.041	(0.01)***	-0.043	(0.01)***
No investments	0.015	(0.03)	0.024	(0.03)	0.040	(0.03)	0.056	(0.03)*	0.004	(0.03)	0.009	(0.03)
Log(investments+1)	0.153	(0.01)***	0.154	(0.01)***	0.191	(0.02)***	0.196	(0.02)***	0.168	(0.01)***	0.169	(0.01)***
Log(exits+1)	0.109	(0.02)***	0.108	(0.02)***	0.112	(0.02)***	0.115	(0.02)***	0.106	(0.02)***	0.110	(0.02)***
Years since last fund	-0.149	(0.01)***	-0.151	(0.01)***	-0.144	(0.01)***	-0.146	(0.01)***	-0.150	(0.01)***	-0.151	(0.01)***
Years since last fund squared	0.212	(0.14)	0.239	(0.14)*	0.129	(0.14)	0.175	(0.14)	0.214	(0.14)	0.236	(0.14)*
Focus buyout	-0.329	(0.10)***	-0.341	(0.10)***	-0.387	(0.11)***	-0.406	(0.11)***	-0.328	(0.10)***	-0.344	(0.10)***
Focus mezzanine	-0.126	(0.12)	-0.132	(0.12)	-0.233	(0.13)*	-0.250	(0.13)*	-0.123	(0.12)	-0.125	(0.12)
Focus VC	-0.552	(0.10)***	-0.565	(0.10)***	-0.592	(0.11)***	-0.587	(0.11)***	-0.538	(0.10)***	-0.530	(0.10)***
Year effects	Yes		Yes		Yes		Yes		Yes		Yes	
Region effects	Yes		Yes		Yes		Yes		Yes		Yes	
Observations	29714		29714		27197		27197		29714		29714	
McFadden R-squared (adj.)	0.119		0.120		0.120		0.120		0.119		0.119	
AIC	25409.7		25399.6		22809.4		22795.9		25421.9		25409.8	
Chi-sq. p-value	0.000		0.000		0.000		0.000		0.000		0.000	
Log-Likelihood	-12654.9		-12649.8		-11354.7		-11347.9		-12660.9		-12654.9	

Table 10. Time and macroeconomic effects on sensitivity to skill

This table shows Probit models for the likelihood of receiving new commitments in any of the firm's funds. The drift ratio is interacted with time (whether the dependent variables is observed after the year 2000) and macroeconomic variables indicating the business climate (S&P500 returns, U.S. recession probability, Chicago Fed National Activity Index (CFNAI), real annual GDP growth, all lagged by one year). For each year, the recession probability is the average of monthly recession probabilities for the U.S. (obtained from https://research.stlouisfed.org/fred2/series/RECPROUSM156N) and CFNAI is the average of monthly CFNAI readings. Standard errors clustered by year are shown in parentheses. Significance levels: *** p<0.01; ** p<0.05; * p<0.1.

	1	2	3	4	5
Drift ratio	-0.032 (0.07)	-0.190 (0.04) ***	-0.120 (0.05) **	-0.135 (0.05) ***	-0.228 (0.06) ***
Drift ratio × Year>2000	-0.174 (0.09) **				
Drift ratio × S&P500 return		0.432 (0.20) **			
Drift ratio × Recession probability			-0.330 (0.14) **		
Drift ratio × CFNAI				0.102 (0.05) *	
Drift ratio × GDP growth					3.296 (2.06)
Log(amount raised, cumulative)	0.016 (0.01) **	0.016 (0.01) **	0.016 (0.01) **	0.016 (0.01) **	0.016 (0.01) **
Log(firm age+1)	-0.041 (0.02) **	-0.040 (0.02) **	-0.040 (0.02) **	-0.040 (0.02) **	-0.040 (0.02) **
No investments	-0.035 (0.03)	-0.036 (0.03)	-0.037 (0.03)	-0.037 (0.03)	-0.036 (0.03)
Log(investments+1)	0.169 (0.02) ***	0.170 (0.02) ***	0.170 (0.02) ***	0.169 (0.02) ***	0.169 (0.02) ***
Log(exits+1)	0.106 (0.02) ***	0.106 (0.02) ***	0.106 (0.02) ***	0.106 (0.02) ***	0.106 (0.02) ***
Years since last fund	-0.148 (0.02) ***	-0.148 (0.02) ***	-0.149 (0.02) ***	-0.149 (0.02) ***	-0.148 (0.02) ***
Years since last fund squared	0.204 (0.25)	0.206 (0.25)	0.210 (0.25)	0.209 (0.25)	0.208 (0.25)
Focus buyout	-0.329 (0.12) ***	-0.331 (0.12) ***	-0.333 (0.12) ***	-0.333 (0.12) ***	-0.332 (0.12) ***
Focus mezzanine	-0.125 (0.13)	-0.127 (0.13)	-0.129 (0.13)	-0.128 (0.13)	-0.127 (0.13)
Focus VC	-0.549 (0.12) ***	-0.553 (0.12) ***	-0.555 (0.12) ***	-0.554 (0.12) ***	-0.552 (0.12) ***
Year and region effects	Yes	Yes	Yes	Yes	Yes
Observations	29714	29714	29714	29714	29714
McFadden R-squared (adj.)	0.119	0.119	0.119	0.119	0.119
AIC	25407.5	25408.4	25409.0	25409.2	25409.7
Chi-sq. p-value	0.000	0.000	0.000	0.000	0.000
Log-Likelihood	-12652.8	-12653.2	-12653.5	-12653.6	-12653.9