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How to cite:

Lahr, Henry and Trombley, Timothy E. (2020). Early indicators of fundraising success by venture capital firms. *Journal of Corporate Finance*, 65, article no. 101672.

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Version: Accepted Manuscript

Link(s) to article on publisher's website:

<http://dx.doi.org/doi:10.1016/j.jcorpfin.2020.101672>

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Early indicators of fundraising success by venture capital firms

Accepted manuscript

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June 2020

Abstract

We show how a venture capital firm's fundraising is affected by its investment choices. We investigate three leading indicators that are calculated from the types of investments the venture capital firms make: style drift investments, follow-on investments, and investments in which the venture capital firm is not the lead investor in the portfolio company. We find that these investment characteristics are associated with lower fundraising. Characteristics and the reaction of fundraising to characteristics are both moderately stable through time. We also find some evidence that information about investment characteristics is more important for fundraising during bad states of the world and that ex-ante characteristics are related to eventual exit outcomes and financial performance.

Keywords

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

JEL classification

G11, G23, G24

We are grateful for comments from Douglas Cumming, Babak Lotfaliei, Adam Winegar, Deniz Yavuz, conference participants at the 2017 Paris Financial Management Conference, the 2016 Financial Management Association Meeting, the 2016 California Corporate Finance Conference, the 2016 British Accounting and Finance Association's meeting and seminar participants at Concordia University, Illinois State University, San Diego State University, and The Open University. This paper was made possible in part by a grant from San Diego State University. All errors and omissions are our own.

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1 Introduction

This paper is an empirical investigation of how the characteristics of the investments made by venture capital (VC) firms will generate cross-sectional differences in fundraising by VC firms.

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 are 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 36% of the VC firms in our sample that are at least 10 years old have failed 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 Martí, 2007), have performed better in the past (Cumming, Fleming, and Suchard, 2005; Balboa and Martí, 2007; Phalippou, 2010; Barber and Yasuda, 2017; Crain, 2018), are members of their national private equity (PE) association (Balboa and Martí, 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 the VC firm's investments impact fundraising. Indeed, the only paper we are aware of that has done this is by Crain (2018), who uses the ex-post distribution of returns within a VC fund's portfolio firms to show that VC firms whose funds change their risk levels over time have lower fundraising.

Theoretical models of fundraising that have been proposed in the literature focus on investors' learning either through past financial performance (Chung, Sensoy, Stern, and Weisbach, 2012) or through unmeasurable "soft" information about performance (Berk and Stanton, 2007; Hochberg, Ljungqvist, and Vissing-Jørgensen, 2014). However, most VC firms raise their next fund well before the end of their current

fund's life, and information about interim returns, while potentially informative, is subject to manipulation by the VC firm (Barber and Yasuda, 2017). Thus, neither returns nor “soft” information are both available and verifiable at the time a new fund is raised, and it is useful to search for other explanations of fundraising success.

We fill this research gap by investigating three immediately verifiable³ characteristics of the VC firm's investments in portfolio companies that we show lead to lower fundraising activity: investments that are style drifts, non-lead investments, and follow-on (as opposed to initial) investments. These verifiable characteristics can be seen as choice variables for VC firms that are important to limited partners (LPs) independent of their effect on the risk and return combination of the VC fund. Style drifts are undesirable because institutional investors' (i.e. potential LPs) internal risk models are more reliable if the VC fund stays in the investment style that the VC fund promised in its prospectus (Cumming, Fleming, and Schwienbacher, 2009). Non-lead investments are undesirable because they do not provide the institutional investor with as much information about the portfolio firms (Ozmel, Trombley, and Yavuz, 2019), and hence the institutional investor has less information to inform its other investments in the industry (Chattopadhyay, McConnell, Trombley, and Yavuz, 2020). Follow-on investments can be a measure of VC reputation. It is reputationally costly within the VC community to refuse to participate in follow-on rounds (Guler, 2007), so only high-reputation VC firms can afford to avoid these often overpriced (Lerner, 1994) investments. This is the first paper to assess the impact of verifiable, immediately available indicators of VC managerial investment actions on fundraising activity for the VC firm.

It is important to note that this is not a paper about a VC firm manager's skill. While it is possible that these three investment characteristics are correlated with skill (particularly for follow-on investments), the theoretical reason why each characteristic should matter to VC fund managers is independent of skill.

³ Investment characteristics are immediately available in the sense that this information about the GP's most recent investments is available and verifiable at the time of the fund investor's decision and does not change over time. Reported financial performance at the fund level, on the other hand, is discretionary to a degree, may initially not contain much information, and may be biased.

To test the effects of investment characteristics on fundraising, 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 measures of style drifts, follow-on investments, and non-lead investments by the VC firm’s funds.

We find that investment characteristics that LPs perceive negatively are associated with lower fundraising activity across the board. The economic effect on next-year fundraising for the style drift, follow-on and non-lead investment ratios are between 2% and 10% for a unit change in the ratio. We also find evidence that investment characteristics are more important indicators of fundraising success in bad states of the world. We find this for a broad range of economic indicators such as policy uncertainty, IPO volume, nonfarm payroll growth, consumer sentiment, and the Chicago Fed National Activity Index. If our characteristics are viewed as containing information that is useful to investors, then this is consistent with previous findings that investors make more use of information when making their investment choices during bad economic times (Loh and Stulz, 2018) and that returns are more sensitive to information during bad economic times (Rapach, Strauss, and Zhou, 2010; Henkel, Martin, and Nardari, 2011; Dangl and Halling, 2012; Garcia, 2013; Cen, Wei, and Yang, 2016; Loh and Stulz, 2018). Further, uncertain economic times lead to reduced investments by corporations (Baker, Bloom, and Davis, 2016), particularly for more irreversible investments (Gulen and Ion, 2015), such as a limited partner’s investment in a VC fund. If drift, follow-on, and non-lead investments are viewed as undesirable characteristics, this is also consistent with a flight to quality in bad economic times (Bernanke, Gertler, and Gilchrist, 1996).

We investigate the stability of the characteristics within a VC firm over time and the usefulness of past data on characteristics in determining current fundraising. We find that the optimal (using maximum likelihood estimation) value for the decay (γ) of the usefulness of each variable in predicting fundraising activity is 0.408 for drift, 0.743 for follow-on, and 0.711 for non-lead (a value of zero would indicate that past data is

irrelevant, while a value of 1 would indicate that past data is just as important as current data). These are consistent with a moderately stable characteristic, and with investors taking this moderate stability into account when choosing among VC firms. In short, past data on investment characteristics is useful to predict fund flows, but it is not quite as useful as more recent data. This contrasts with results obtained for mutual funds by Kacperczyk, van Nieuwerburgh, and Veldkamp (2014), who find performance persistence only for horizons up to 6 months. This finding agrees with the evidence for performance persistence in venture capital (Kaplan and Schoar 2005; Hochberg, Ljungqvist, and Lu, 2007; Hochberg, Ljungqvist, and Vissing-Jørgensen, 2014), which is more generally accepted than the evidence for performance persistence in mutual funds (for a review of performance persistence in mutual funds, see Cuthbertson, Nitzsche, and O'Sullivan, 2016). Further corroborating this evidence, results for interactions of age or firm size with VC characteristics show no clear pattern. The reaction of fundraising to information about these characteristics is roughly the same for old and large VC firms as it is in young and small ones.

Finally, we test whether investment characteristics can predict investment performance. We find evidence that follow-on and style drift investments are associated with worse exit outcomes. Both investment characteristics also predict the financial performance of the VC firm. Thus, it is plausible that investment characteristics may be useful to investors as predictors of future investment performance that has not yet been observed when information about investments becomes available.

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. We also repeat the estimations excluding any observations that are more than five years after the fund raises its final fund. We find similar results in both cases. These results are all robust to several different time lags and definitions for our primary variables, as well as to controlling for a battery of control variables. Because it is possible that a bad economic state may simultaneously reduce the likelihood of raising a new fund, as well as affect VC firms' investment characteristics, we attempt to control for reverse causality. We control for various combinations of year, region, and style 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 VC firms whose investments have undesirable characteristics will have lower fundraising activity.

In addition to the above literature about fundraising in private equity, our findings contribute to the literature on the determinants of fundraising by financial intermediaries such as mutual funds (Ippolito, 1992; Chevalier and Ellison, 1999; Sirri and Tufano, 1998; Berk and Green, 2004), closed-end funds (Berk and Stanton, 2007), and crowdfunding (Ahlers, Cumming, Günther, and Schweizer, 2015). This is the first study to identify verifiable, immediately available information that investors may use when deciding on whether to invest in a particular VC firm's funds and how investment characteristics convey information to a VC firm's investors.

2 Determinants of fundraising

What characteristics do investors investigate when deciding whether to make commitments to an investment fund? In this section, we review the existing literature on fundraising in mutual funds and private equity funds and relate it to the question of why investment characteristics may convey information that is used by investors when deciding whether to invest in a particular VC firm's funds.

Fundraising incentives are important in private equity. Chung, Sensory, Stern, and Weisbach (2012) study the size of both direct pay for performance derived from current carried interest and indirect pay for performance through higher fundraising by better PE firms in the future. They argue that 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.

2.1 Verifiability of information about past performance in venture capital

Some theoretical models of fundraising in private equity assume that PE investors learn through unspecified "soft information" (Berk and Stanton, 2007; Hochberg, Ljungqvist, and Vissing-Jørgensen, 2014). There are two distinct types of soft information in VC investing. The first, which is "soft" the sense described by

Hochberg et al. (2014), is information that is observable by LPs currently invested in the fund but not easily transferred through the LPs' internal chain of command. This information does not necessarily need to be verified. If the LP has a sufficiently small chain of command (in the spirit of Berger, Miller, Petersen, Rajan, and Stein, 2005) or grants sufficient autonomy to its decision makers, then existing LPs can observe the information directly through their interaction with the VC firm and use it to make investment decisions. A second type of soft information is information that cannot be credibly communicated to potential investors because of asymmetric information problems (e.g., growth opportunities of portfolio companies). This information is thus not available to investors *ex ante* and may only be inferred *ex post* with a substantial delay. Such soft information is (by definition) unmeasurable and unverifiable for the LP investors, and it may only be available to those who are already insiders. It is thus useful to search for other explanations of fundraising success.

Past financial performance can be verifiable in some cases. In the mutual fund industry, for example, past financial performance has been found to be important to fundraising because it is often used by investors as a proxy for expected future performance.⁴ In the private equity industry, however, 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, which causes returns to be notoriously difficult to measure (Phalippou and Gottschalg, 2009). Therefore, alternative measures that are verifiable (e.g., investment characteristics) should be more important within PE markets than mutual fund markets.

Due to the limited availability of market prices in private equity, some 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

⁴ See Ippolito (1992), Chevalier and Ellison (1997, 1999), Sirri and Tufano (1998), and Berk and Green (2004).

equivalent” investment (Kaplan and Schoar 2005), and the final performance of the fund (Phalippou, 2010). In addition, Barber and Yasuda (2017) use VC funds’ self-reported performance, even though they find that it is subject to manipulation when the VC firm is seeking to raise a new fund. These authors have generally found evidence supporting a relationship between performance and future fundraising.

2.2 Empirical findings of determinants of VC fundraising

As we discussed in the previous section, the contemporaneous performance of VC funds is unverifiable. 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 to sometimes make decisions that may not be value maximizing for their current investors. For example, Gompers (1996) shows that young VC firms engage in “grandstanding” by taking portfolio companies public earlier than older VC firms in order to signal success to investors when raising new funds. Similarly, young buyout funds invest in riskier buyouts than old funds in order to establish a track record (Ljungqvist, Richardson, and Wolfenzon, 2008).⁵

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. 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 both the likelihood of raising a fund and fund size are related to the ratio of portfolio companies to investment managers, the percentage of divestments carried out through IPOs and trade sales, membership in the national private equity association, and the size of funds under management. Further, fund size is related to the volume of investments recorded in the past (although the likelihood of raising a fund is not).

⁵ However, Ljungqvist et al. (2008) do not evaluate the fundraising outcomes of this strategy.

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 a firm's 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 size, sequence number, and performance as measured by its cash flow's public market equivalent. 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.

The only paper we know of that has investigated the impacts of a VC's choice of investments on fundraising is by Crain (2018). He finds that VC funds that 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 startups, 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 the ex-post 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 evidence that potential investors do, indeed, utilize information provided by the investment choices that VC firms make.

In summary, some studies have used trailing measures of success to predict fundraising. Other studies employ leading indicators, such as the size of past funds or information about the VC firm itself. However,

there are no studies about VC fundraising that try to incorporate information about the *characteristics* of the VC firm's investments that is available at the time the LP is considering investing in the VC firm.

3 Three characteristics of VC investments

This section reviews the investment characteristics that we hypothesize to have an impact on investors' decisions. The specific construction of these variables is covered in section 4.2.

3.1 Style drift

An investment fund's "style" is the class of investment in which it invests its clients' funds. For example, a mutual fund can invest in growth stocks or value stocks. In this paper, we define a VC fund's style of investment as the life cycle stage 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, an investor may use the fund's anticipated style to construct its portfolio's expected risk profile so that future investment decisions can more accurately maximize the 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 the investor 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 good proxy for superior investment ability. Although findings from the mutual fund industry are not always applicable 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.

Cumming et al. (2009) suggest that in a Bayesian environment, smart fund managers may recognize the negative effect of style drifts on the accuracy of their investors' risk calculations and will only invest in startups outside their focus area if the startup has exceptional potential. Supporting this theory, they find evidence that style drift investments perform better. However, their result would only be expected if investors do actually avoid investing in VC firms that style drift. Thus, we hypothesize that style drift is negatively correlated with future fundraising activity.

3.2 Non-lead investments

Venture capitalists frequently invest as part of a consortium in which one VC firm takes a lead role. There are two reasons why an investor may be more interested in investing in lead VCs. First, lead VCs have more information about the startup firms than non-lead VCs (Wright and Lockett, 2003; Ozmel, Trombley, and Yavuz, 2019). As one VC told us, part of a lead VC's role is to "shortcut the due diligence process" for non-lead VCs. As a result of this central role, the lead VC is more likely to play an active role in the startup (Megginson and Weiss, 1991) and is more likely to have a seat on the board of directors and be active in recruiting senior managers (Bottazzi, Da Rin, and Hellman, 2008). After the investment, lead VCs make more frequent and longer visits to the startup's headquarters (Gorman and Sahlman, 1989; Elango, Fried, Hisrich, and Polonchek, 1995), and they are more likely to have information about debt repayment schedules, order books, and planned capital expenditures (Wright and Lockett, 2003). This increased information is important because anecdotal evidence from interviews with VCs indicates that some LPs

invest in venture capital specifically for the purpose of obtaining information. They intend to use this information to make more informed investments in public markets (as one VC put it, his investors want to “see what’s coming”). This is confirmed empirically by Chattopadhyay, McConnell, Trombley, and Yavuz, (2020).

About 48% of the startups in the VentureXpert database only have investments from one VC firm. From the VC firm’s perspective, 82% of investments made by VCs in our sample are made in syndicates with other VCs. Thus, a substantial fraction of our lead VC observations are deals with a single VC firm as an investor. It is possible that being a lead VC amongst a consortium may result in a different level of information gathering than being the only VC to invest in a startup. Indeed, 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. This advantage of benefiting from peer expertise is less likely to be present for a VC that invests on its own. However, when we investigate these two phenomena (nonsyndicated investments, and investments as a non-lead investor in a syndicate of VCs) individually, the results were very similar for both groups (results are unreported). Therefore, it is entirely possible that investors do not view them as separate phenomena. For this reason, and for the sake of simplicity, we report results for the more inclusive definition of all lead investments. We hypothesize that non-lead investments are negatively correlated with future fundraising activity.

The reputation of a startup’s lead VC firm has been used in numerous studies (e.g., Lin and Smith, 1998; Lee and Wahal, 2004; Ozmel, Trombley, and Yavuz, 2019) as a proxy for the reputation of the startup, but to our knowledge this is the first time that the choice to be a lead investor has been used as a characteristic that describes the VC firm itself.

3.3 Follow-on investments

Successful startups will often have multiple rounds of VC funding. However, VC firms frequently will not participate in every round of funding. Investment performance may decrease in subsequent rounds as first-round investors may be reluctant to discontinue investing in underperforming portfolio companies for

psychological or cognitive reasons (Guler, 2007) 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 is also exerted 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.

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. Artificially high valuations in follow-on rounds can mechanically cause poor performance for investments in follow-on rounds. 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.

It is highly likely that VC managers who discontinue investing in a startup are aware of the potential for the loss of future partners that Guler (2007) discusses. Highly reputable managers who have less need for partners’ goodwill will suffer less if they avoid investing in overvalued follow-on rounds of investment in a startup. Thus, avoiding follow-on investments could be a credible proxy for reputation because only high reputation VCs can afford to make the sacrifice of reputational capital that is required to avoid these (on average) bad follow-on investments.

In conclusion, we hypothesize that follow-on investments are negatively correlated with future fundraising activity. To our knowledge, this is the first use of this variable in the literature in the context of VC fundraising.

4 Data and method

4.1 Data structure

The data we use in this paper is from Thomson Reuters' Thomson One database (VentureXpert). We observe the fundraising and investment activities of private equity funds located in the United States between 1980 and 2014. Because most of our independent variables are lagged by one period, the observation period for dependent variables is 1981 to 2014. The unit of analysis is the VC firm-year. Hence, we observe investments at the VC firm level (i.e., the general partner of the fund). The dataset used for estimation contains 31,225 firm-year observations.

Our dependent variables are measures of the VC firm's fundraising activity. To account for main events in a fund's lifecycle, we observe whether the firm sets up a new fund, whether the firm receives new commitments to any of its funds, and the amount of new commitments. While the decision to launch a new fund reflects the initial stage of the fundraising process, commitments by limited partners may be considered a more accurate measure of the timing 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 on investors' willingness to commit additional capital to the firm's funds.

VentureXpert measures seven distinct styles of funds with an equity component: seed stage VC, early stage VC, late stage VC, balanced stage VC, mezzanine stage, buyouts, and generalist.⁶ Although mezzanine, buyouts, and generalist funds are not strictly VC funds, we keep these funds because a significant minority of PE firms that raise VC funds also raise these other types of funds, and eliminating these from the fundraising sample might suggest that some firms are less likely to raise a new fund when in fact they raised a generalist, buyout, or mezzanine fund. In order to increase the accuracy of our control variables, we also

⁶ VentureXpert uses different categories for its fundraising database and its investments database, but it is easy to match the categories. To maintain consistency with the literature, we omit fund stages that are fund-of-funds, real estate, and energy funds. For more details, see Table 1.

include PE firms that never raised a VC fund (about 28% of firms in our sample). The mean number of funds per VC firm in our sample is 12.8 (median 11, minimum 1, maximum 35).

A firm enters the dataset when its 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 fundraising activity has been observed (either a fund has been raised or capital has been committed to an existing fund).⁷

4.2 Construction of primary variables of interest

We investigate three investment characteristics that may be perceived negatively by a VC firm's potential limited partners: drift investments, follow-on investments, and non-lead investments. If these indicators are valid, they will have a negative 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. Generalist and mezzanine funds are excluded when measuring drift because they cannot drift by definition. For robustness, we also test four other measures of drift. We use the total number of drift investments that year ($\text{Log}(\text{drifts}+1)$) and a dummy variable for whether the VC firm made any drift investments that year (*Drift yes/no*). Additionally, relative measures of drift may be relevant because investors in venture capital may seek out top-performing VC firms by evaluating their relative position within a cohort of funds.⁸ Therefore we measure the drift ratio

⁷ In unreported robustness tests, we vary the number of years for the cutoff point and find that our main results are substantially the same.

⁸ See "Is Being 'Top Quartile' Any Good?" by Larry Cheng, (Fortune, June 29th, 2011). Similarly, Hunter, Kandel, Kandel, and Wermers (2014) investigate mutual fund performance by fund quartile.

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 non-lead investments. A follow-on investment is defined as an investment by a VC firm in a portfolio company that had previously received an investment from the same VC firm (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.

Our primary variable for non-lead investments (*Non-lead ratio*) measures the percentage of the VC firm's investments in the previous year that are non-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 allows the lead VC to change over time (Cumming and Dai, 2013). To obtain this variable, we add all investments by each firm in a startup and at each round identify the firm with the largest cumulative investment as of 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, VentureXpert 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.

To test the robustness of our definition of lead investments, we define the lead investor in a given round as the investor with the largest equity investment in this round. Depending on whether ties are allowed, this leads to two definitions: If multiple investors provide the largest but equal amount, they are treated as 1) non-lead investors or 2) lead investors. Results show that the sharper lead investor definition (1) produces

results nearly identical to those using the lifetime definition, while definition (2) does not generally give statistically significant effects.

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

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<<<< Insert Table 2 about here >>>>

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 ($\text{Log}(\text{firm age}+1)$) (Gompers and Lerner, 1998; Kaplan and Schoar, 2005), the log of the size of the VC firm's previous funds ($\text{Log}(\text{amount raised, cumulative})$) (Kaplan and Schoar, 2005; Balboa and Martí, 2007), the number of years that have passed since the last fund the VC raised ($\text{Years since last fund}$), and the square of this number ($\text{Years since last fund squared}$) (Gompers and Lerner, 1998). To control for the VC firm's past performance, we use the interim net internal rate of return (IRR) of the VC firm's most recent fund, which we obtain from Preqin, following Hochberg et al. (2014).⁹ We also include the number of successful exits that the VC firm has performed ($\text{Log}(\text{exits}+1)$) (Cumming, Fleming, and Suchard, 2005; Balboa and Martí, 2007).¹⁰ We include this number 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, 2017). To control for

⁹ The exclusion of IRR in our models has no material effect on our coefficients of interest (i.e., style drift, follow-on, and non-lead investments). We also confirm this in separate unreported regressions using only the sample of firm-years for which IRR is available.

¹⁰ We test the robustness of this measure by calculating the number of successful exits for the firm's most recent fund(s) and the lifetime number of successful exits by the firm. The former, when included as a control variable instead of the firm's successful exits in the past year, produces qualitatively identical results. The lifetime number, on the other hand, is generally not significant. We further investigate the optimal number of time period over which successful exits should be measured in Section 5.4.

the VC firm's position in its investment cycle, we include the number of investments the VC firm has placed in portfolio companies in the past year ($\text{Log}(\text{investments}+1)$) (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 possibility that fundraising environments may differ among mezzanine, buyout, and VC funds, we include variables for the percentage 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.¹¹

Previous papers find that there are time-varying factors, such as capital gains tax rates, interest rates, and regulatory changes to pension funds, that affect total fundraising in the whole VC industry (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.

A potential confounding variable is the unobservable supply of investment opportunities, which may drive both investment characteristics 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 non-lead firm, or make a follow-on investment due to a lack of suitable new targets. If investment

¹¹ These three variables (*Focus buyout*, *Focus mezzanine*, and *Focus VC*) are not collinear because there are also generalist funds.

opportunities are correlated across time to a sufficient degree, current investment characteristics may be correlated with future fundraising. Therefore, the econometric design needs to disentangle investment characteristics 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 may be unobserved investment opportunities that confound our analysis.

We can use time $\times$ 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 investing in the same region at the same time should not differ in the supply of potential deals they face. 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. Similarly, we can also use time $\times$ region $\times$ focus dummies if we assume that investment opportunities are specific to time, region, and investment focus. This is what we report in regression 5 of tables 3–5. We define regions as the four main US census regions. We find only a small change in coefficients when comparing models with interacted dummies to models with separate time dummies, region dummies, and focus percentages. This makes us confident that using reasonably sized regions sufficiently accounts for unobserved investment opportunities. We also achieve similar results if we use time $\times$ region dummies (unreported). We report our main results throughout the paper using time dummies, region dummies, and focus coefficients independently because of the improved fit of the model. Note that because fixed-effects probit models are generally inconsistent, we do not use firm-level fixed effects but opt for standard errors clustered by firm instead. This also prevents the loss of observations for firms with only a single fundraising observation. Results are robust to clustering standard errors by year.

5 Results

5.1 Style drift, follow-on, and non-lead investments reduce likelihood of fundraising

Results for the effect of style drift on the likelihood of the firm receiving new commitments to one of its funds are shown in Table 3, Panel A. Results show that style drift is negatively correlated with commitments raised by the firm, and the result is statistically significant for 3 of the 4 measures of style drift. The coefficient on *Drift ratio* has a z -statistic of -3.39 . The average partial effect is a -3.0% change in the likelihood of receiving new commitments in the following year for a unit increase in the drift ratio.

Panel B of Table 3 shows the likelihood of starting a new fund. 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. The coefficient on *Drift ratio* has a z -statistic of -3.31 and an average partial effect of -2.6% .

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

We next investigate the effects of follow-on and non-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 are negatively correlated with the likelihood of both new funds and commitments (see Table 4). The z -statistic for the coefficient on *Follow-on ratio* is -3.29 for new commitments and -5.23 for new funds, with average partial effects of -2.8% and -4.2% , respectively. All measures of follow-on investments are significantly negative, except the follow-on dummy variable. 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 non-lead investments are correlated with lower fundraising activity. The z -statistic for the

coefficient on *Non-lead ratio* is -2.12 for new commitments and -2.71 for new funds, while average partial effects are -1.7% and -2.0% , respectively, for a unit increase in the non-lead ratio. All measures of non-lead investments are significantly negative at either the 5% or the 1% significance level.

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

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

Among our control variables in Tables 3–5, the size of the firm (i.e., past fundraising volume and the number of investments made) and its past performance (i.e., number of successful exits) are positive and significant as expected. The negative coefficient on *Focus VC* indicates that VC funds are less likely than other types of funds to raise a follow-on fund.

All of these tests are robust to controlling for $\text{Year} \times \text{Region}$ or $\text{Year} \times \text{Region} \times \text{Focus}$ dummy variables. Because our model attempts to explain the timing of investor behavior rather than the timing of the VC's decision to start a new fund, in the interest of saving space we will only report results for new commitments in Tables 6–10.

In unreported results, we test regional differences within the U.S. We do this two ways: we run models separately by census region, and we test regional differences more directly through interaction terms in models using the full sample. The effect of drift ratio on the likelihood of obtaining new commitments to a GP's fund (analogous to model 1 in Table 3) is significant in the West region ($p < 0.01$) and weakly significant in the Northeast ($p < 0.1$). Follow-on ratio is significant in the West ($p < 0.05$) and the Northeast ($p < 0.01$). Non-lead ratio is significant in the South ($p < 0.05$) and weakly significant in the Northeast ($p < 0.1$). However, the effects should be interpreted carefully, as significant results for the West and Northeast regions may be due to the size of the subsample, which is largest for these two regions. In regressions in which we interact census regions with style drift, follow-on and non-lead investments, we find that the sign

of the interaction term is always negative but is only statistically significant for 3 of the 12 interaction terms. However, none of the differences between interaction terms are significant.

Investment characteristics may affect fundraising differently throughout a VC firm's lifetime, especially if investors use this information for their portfolio allocation decisions when other information about a VC firm's performance is not yet available. To test this lifetime effect, we use a dummy variable that indicates whether a firm has raised a maximum of one fund so far and interact this dummy with our three investment characteristics – drift ratio, follow-on ratio, and non-lead ratio. Results of these regressions (available from the authors) suggest that new commitments are more sensitive to follow-on investments when the VC firm has not raised a second fund yet. This finding supports the view that investment characteristics are important antecedents of fundraising when other performance information is not available. However, the results for the characteristics themselves remain highly significant even when including an interaction term. This indicates that career concerns are likely not the only driving factor in the importance of investment characteristics.

5.2 Style drift, follow-on, and non-lead investments reduce the size of fundraising

We investigate the effect of the characteristics of investments made by VC firms 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. All models include year and region dummy variables.

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 received

conditional on receiving any commitments. Panel C shows that non-lead investments decrease the amount of commitments conditional on receiving any commitments. All six coefficients of interest in Table 6 are statistically significant at the 1% or 5% level. These results suggest that style drift, follow-on and non-lead investments are all undesirable to investors.

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

5.3 Characteristics have an additive effect on fundraising

Our three investment characteristics are not mutually exclusive. Indeed, every investment made by a VC firm can be characterized as one of 8 types using the two possible outcomes for each of our three investment characteristics ($2 \times 2 \times 2 = 8$). In this section, we investigate whether investment characteristics are complements, substitutes, or independent measures of VC firm characteristics.

An additional motivation for this analysis is that it is possible that follow-on investments and drift investments may be mechanically correlated. This is because startups that become more successful and require an additional investment may “graduate” to a more advanced stage. We find that *Drift ratio* and *Follow-on ratio* are 36% correlated, *Drift ratio* and *Non-lead ratio* are 30% correlated, and *Non-lead ratio* and *Follow-on ratio* are 46% correlated.

In Table 7 we combine characteristics at the investment level (not at the VC firm level), and identify each investment as drift or non-drift, follow-on or non-follow-on, and lead or non-lead. 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 that year that are simultaneously drift, follow-on, and lead investments. Similarly, the interaction tested in model 2 uses the fraction of investments that are drift, follow-on, non-lead investments. The eight variables of interest are fractions ranging from zero to one. Hence, the coefficient of interest in each regression measures the effect of the combination of investment characteristics being tested against the excluded baseline fraction of the other seven possible combinations of investment characteristics.

Results are shown in Table 7. In nearly every case, there is a decrease in the coefficient if any one of the three characteristics is switched from a hypothesized positive to a hypothesized negative characteristic. The sole exception is that drift/follow-on/lead investments are slightly more negative than drift/follow-on/non-lead investments. Investors react most positively if a VC firm invests as the lead investor in a new portfolio company that is in the same stage as the VC firm's stated stage focus.

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

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

A natural question to ask is which investment characteristics are the most important predictors of fundraising. From the VC firm's point of view, knowing which characteristics investors care about may improve fundraising performance. From a theoretical perspective, differences in investors' sensitivity to this information can shed light on the relative importance of the underlying processes that lead to fund managers choosing to make these sorts of investments. We test the relative importance of our three investment characteristics in Table 8. Model 1 shows that when all three variables are evaluated simultaneously at the VC firm level, they all remain significantly negatively correlated with raising new funds. The drift ratio has the highest coefficient and level of statistical significance, and the non-lead ratio has the lowest coefficient and level of statistical significance. Model 2 evaluates a full set of interaction terms at the VC firm level. The results show increased standard errors across all three characteristics, which suggests a substantial degree of correlation among interaction terms. It is thus not possible to say for certain whether there exists any interaction between characteristics at the VC firm level, but the results suggest that our three investment characteristics are neither complements nor substitutes.¹² Model 3 tests all triple

¹² In unreported regressions, we include each interaction term separately and find that none of them are ever statistically significant.

combinations 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.

Altogether, the results in Tables 7 and 8 suggest that the fundraising implications of these three investment characteristics are additive. There is little evidence that these characteristics are either complements or substitutes.

5.4 The stability of VC firms' investment characteristics

A VC firm's investment characteristics and the desirability of investment characteristics to investors may both 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 bust periods. Kacperczyk et al. (2014) find that mutual fund managers who perform well do so by being exceptionally good at stock picking in good times and by timing the market in bad times. They show this effect for ex-post measured financial performance. Ex-ante investment characteristics, such as style drift, may exhibit a similar cyclicity or instability in a Bayesian world. More importantly, it is unclear how investors would react to such characteristics over time.

We find that all three of our investment characteristics are somewhat persistent over time. The correlations of the current value of *Drift ratio* with the value of *Drift ratio* for the same VC firm in the previous period, 2 periods prior, and 3 periods prior are 0.379, 0.310, and 0.264, respectively. The same correlations for *Follow-on ratio* are 0.494, 0.428, and 0.351. The same correlations for *Non-lead ratio* are 0.548, 0.470, and 0.411. We would not expect a 100% correlation because there is a relatively low number of investments in portfolio firms in an average period (mean = 6.1). This causes the set of possible data values to be discontinuous and lowers the correlation ratio for lagged values.

If a VC manager's propensity to style drift is highly stable, investors should take into account all investments made by the firm in all time periods in order to more precisely measure the manager's drift

propensity. However, if the propensity to drift is unstable or if drift differs in importance to investors depending on the state of the world, investors will only look at the most recent data when deciding about capital allocations. The stability of the usefulness of investment characteristics as decision criteria in a fundraising context can be formalized in a rational learning model in which the manager's (i.e., general partner's) underlying type, such as the propensity to drift, is unknown and must be inferred by market participants. Investors observe investment characteristics and update their assessment of the manager's type 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 (non-drift) investments and non-desirable (drift) investments. The investor then observes the investments made by the firm and updates θ according to the number of non-drift investments d after observing n investments:¹³

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

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

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

If investors have weak priors, α and β are small and the estimated drift propensity 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

¹³ Since $\alpha=\beta=1$ represents a flat prior, an investor in a firm with a flat prior has observed $\alpha-1=0$ drift investments and $\beta-1=0$ non-drift investments.

(*d*) and the total number of investments (*n*) can be measured over either short or long horizons. The choice depends on an assumption about the stability of the propensity to drift. If drift propensity is constant over time, 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.

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

One way to investigate the stability of the VC firm's investment characteristics 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 (this can be thought of as similar to a moving average that uses all past observations but with exponentially decreasing weight on older observations). We use a parameter γ that governs the memory decay. We would expect γ to be near zero for unstable VC firm characteristics and a value close to one (i.e., a long-memory process) for stable behavior that retains its importance over time.

Results in Table 9 show a moderate stability of our three investment characteristics. The likelihood of our models is maximized for decay parameters between 0.399 and 0.732. To find an estimate of the stability of 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 propensity to drift. Investors' "memory" decays by about 60% each year (i.e., they only "remember" about 40% of the VC firm's cumulative investments that were made before the previous year). The average partial effect of this optimized drift ratio with memory is -7.2% . In other words, when the decay ratio (γ) is optimized (which we find to be $\gamma=0.399$), a unit increase in the drift ratio reduces the likelihood of future fundraising by 7.2% . In combination with results from our earlier analyses in Tables 3–5, this provides an

estimate of the probable range of the economic effect (i.e., between 3.0% and 7.2% for a unit change in the drift ratio).

Models 5 and 7 of Table 9 indicate a stronger persistence for our other two indicators. Investors' "memory" decays by about 27% (i.e., $1 - 0.732$) per period for *Follow-on ratio* and 33% (i.e., $1 - 0.674$) per period for *Non-lead ratio*. It makes sense that past values of these two variables should have a stronger effect on present fundraising than *Drift ratio* because *Follow-on ratio* and *Lead ratio* are more persistent over time than *Drift ratio* for an individual VC firm. Average partial effects of a unit change in the proportion of follow-on and non-lead investments on the likelihood of receiving new commitments in the following year are -9.6% and -5.2%.

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

To explore the stability of investors' perception of investment characteristics, we test interactions of each characteristic with variables indicating macroeconomic conditions. In public equity markets, stocks have been found to react more strongly in bad economic times than in good economic times to news (Garcia, 2013), macro variables (Rapach, Strauss, and Zhou, 2010; Henkel, Martin, and Nardari, 2011; Dangl and Halling, 2012), and information from stock analysts (Cen, Wei, and Yang, 2016; Loh and Stulz, 2018). Additionally, uncertain economic times lead to reduced investments by corporations (Baker, Bloom, and Davis, 2016), particularly for less reversible investments (Gulen and Ion, 2015) that are characteristic of a limited partner's commitment to a VC fund.

We test a variety of variables that proxy for economic conditions. We test the Chicago Fed National Activity Index, which Kacperczyk et al. (2014) use to test mutual fund managers' skills in different market conditions. We test political policy uncertainty, which has been shown to be a leading indicator of reduced investment by publicly traded firms (Baker, Bloom, and Davis, 2016). Policy uncertainty is also negatively

correlated with venture capital investment and the likelihood of successful exits for a VC fund's portfolio firms (Tian and Ye, 2017). Baker, Bloom, and Davis, (2016) find that the University of Michigan consumer sentiment also "has value for predicting future output and employment movements," so we test this as well. We test IPO volume because the annual volume of IPOs is related to VC investment decisions through liquidity risk (Cumming, Fleming, and Schwienbacher, 2005), so it is possible that IPO volume is also related to LP investment decisions. We also test one other variable that can proxy for economic conditions for startup firms: the growth rate of US nonfarm payrolls. In robustness tests, we test other similar measures, as well as different methods of translating the monthly data points to annual tests, and obtain similar results.

Panel A of Table 10 indicates that style drift is punished significantly more during periods of low IPO volume, low consumer sentiment, and low payroll growth. Panel B of Table 10 indicates that follow-on investments are punished significantly more during periods of high policy uncertainty, low IPO volume, low economic (CFNAI) activity, low consumer sentiment, and low payroll growth. Panel C of Table 10 indicates that non-lead investments are punished significantly more during periods of high policy uncertainty, low IPO volume, low consumer sentiment, and low payroll growth. The sign of the coefficient of the interaction term is consistent across all 15 regressions in Table 10, and 12 of the regressions are statistically significant. Altogether, there is some evidence that investment characteristics are more important during bad states of the world. This is consistent with Kacperczyk et al. (2014), who find that the ability of investors (in this case, LPs) to pick stocks declines during bad macroeconomic conditions.

One possible explanation for the increased importance of style drift in bad times could be that investors diversify their holdings for the purpose of protecting 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 characteristics of holdings of the fund, the investor cannot effectively mitigate the risks posed by the fund. A possible explanation for the increased importance of follow-on investments in bad times may be that the pool of good investments dries up more for low-reputation VC firms in bad times. Thus, the cost to reputation of making follow-on investments may be

more expensive for low reputation VCs in bad times than it is in good times, making it less likely that they'll be willing to forego an overpriced follow-on round. A possible explanation for the increased importance of non-lead investments during bad times could be that the information that LPs gain from lead VC firms becomes more important to the LPs during bad economic times.

5.5 Do investment characteristics predict performance?

In the previous sections, we have established that fundraising by VC firms is negatively associated with drift, follow-on, and non-lead investments. In other words, information available at the time of investment seems to be used by limited partners to make capital allocation decisions. But why do limited partners care about investment characteristics? The previous literature outlined in sections 2 and 3 documents many possible non-performance reasons that investors may care about investment characteristics, including portfolio risk targeting, LPs' acquisition of information about the startup firm, or learning about the VC firm's reputation as viewed by other VC firms. However, performance should not be dismissed as a possible cause for our findings. It is possible that limited partners could use ex-ante investment characteristics as a proxy for investment performance, whether by itself or in combination with any of the other reasons documented in the literature.

We are able to test the link between investment characteristics and performance both at the VC firm level and for individual investments. However, we do this with the caveat that we are not able to distinguish between alternate stories for why investment characteristics may affect future performance.

<<<< Insert Table 11 about here >>>>

5.5.1 Exit outcomes

Because VCs are usually not permanent investors in a firm, each startup will eventually be exited in one of three ways: IPO, acquisition, or write-off. IPOs are generally the most lucrative exit type, acquisitions are generally considered successful but less lucrative, and write-offs indicate unsuccessful investments. We use the eventual exit type of the startup as an indicator for investment performance and test whether it is related

to investment characteristics at the time of investment. While exit type is not a perfect substitute for financial performance, we are not aware of any publicly available dataset that contains both financial outcomes at the investment level and VC firm names which would allow us to match investment returns to our dataset of investment characteristics. Investments are obtained from Thomson Reuters' private equity investments as in our main analyses above, while exits are obtained from Thomson Reuters' VC-backed exits database. We merge these databases by VC firm name and startup company name. Because fund names are often not specified, and it is not possible in cases where multiple investments were made to determine whether any particular investment by a firm's funds is associated with any particular exit event, we assume that all of a VC firm's investments in a portfolio firm are exited whenever an exit event for this portfolio company and VC firm occurs. Our dataset contains 79,150 exit observations.

In Table 11, models 1 and 2 model test successful exits (defined as IPO or acquisition) as the dependent variable. Models 3 and 4 are multinomial logit models which measure IPOs and 3 types of acquisitions, with write-offs as the baseline. All four models indicate that drift investments and follow-on investments are associated with worse investment outcomes. In an earlier study, Cumming, Fleming, and Schwienbacher (2009) find that drift investments increase the likelihood of IPOs relative to observing any other exit outcome (i.e., acquisition or write-off). Their analysis is different in using a binary contrast rather than a multinomial model. When we test a binary indicator for IPO exits against all other exits, the effect for style drift is insignificant, both for the full sample and a sample for their sample period (i.e., 1985–2003).¹⁴

The results for non-lead investments are more nuanced. Non-lead investments decrease the likelihood of secondary and trade sales but increase the likelihood of IPOs. A possible explanation for why the IPO outcomes for non-lead investments do not match IPO outcomes for drift and follow-on investments is that

¹⁴ There are many possible explanations for the difference between our findings and those of Cumming et al. (2009): First, our dataset also includes recession periods. As shown in Table 10, investment characteristics interact with the macroeconomic environment. Second, our model specification is different and includes a larger set of control variables. For example, we include year dummies for investments and the stage focus of the fund. There are likely many other explanations that may be fertile grounds for future research.

lead VCs often voluntarily wait to sell their stake until many years after the IPO (Lin and Smith, 1998). This means the IPO would not be recorded as the exit event for many lead VC firms.

Our results are robust to various alternative specifications. For example, we obtain qualitatively identical results if we omit control variables from our models. To conserve space, we do not show these results and control variables in Table 11. As a further robustness test, we exclude investments with a short time to exit and again find similar results.

<<<< Insert Table 12 about here >>>>

5.5.2 Fund performance

Table 12 shows results of models that explore the relationship between investment characteristics and the performance outcomes of the VC firm. Following Hochberg et al. (2014), we measure performance as the interim net IRR of the most recent fund by vintage year as recorded by Preqin. If there are multiple funds in the most recent vintage year, we weight performance by fund size. In our main set of models for IRRs, we use a dynamic panel setting to account for serial correlation in IRRs that can be attributed to realized performance of portfolio investments within a fund and serial correlation in subsequent funds as documented in the performance persistence literature (Kaplan and Schoar, 2005; Phalippou and Gottschalg, 2009; Harris, Jenkinson, and Kaplan, 2014).

The results indicate a negative relationship between performance and appropriately lagged investment characteristics that are associated with lower fundraising. When testing all three investment characteristics simultaneously in model 1, we find statistically significant negative performance effects for style drift and follow-on investments. The coefficient for non-lead investments is insignificant. Robustness tests using a simple pooled-sample OLS model (in model 2) and dynamic panel models testing investment characteristics individually (models 3–5) support these results.

In sum, we find evidence that investment characteristics may be predictors of investment outcomes. However, we would like to stress that it is beyond the scope of this paper to formally test reasons for this observed relationship. The focus of this paper is primarily on the effects of VC firms' investment characteristics on LPs' investment decisions. Further research is needed to isolate the precise economic nature of these relationships.

6 Conclusion

We explore how VC firms' investment choices are verifiable leading indicators that affect fundraising activity. We find that potential investors (limited partners) consider the characteristics of a VC firm's investments when making investment decisions. They avoid VC funds that make undesirable investment choices such as style-drift, follow-on and non-lead investments. These investment characteristics are hard information that is immediately available and verifiable by any potential investor. VC firms whose investments have undesirable characteristics have a lower likelihood of raising a new fund, lower likelihood of receiving commitments to the firm's funds, and lower volume of such commitments.

We find that investors' reaction to a VC firm's investment characteristics are moderately stable over time. However, negative investment characteristics are punished more strongly when macroeconomic indicators indicate poorer conditions for VC investments. This finding indicates that the VC firm's investment characteristics are more important in bad times, which agrees with an extensive literature on the increased importance of information during bad economic times.

When combining multiple investment characteristics simultaneously in a model, the effects of style drifts, follow-on investments, and non-lead investments are largely additive at both the level of the investment and the management firm level. For example, an investment that is simultaneously a drift and follow-on investment produces a more negative effect on fundraising than an investment that is follow-on and non-drift. However, the effect is strictly additive, as the interaction terms are not significant predictors of fundraising activity.

In conclusion, we believe that this paper suggests that investors seek verifiable information, even in relationship-heavy fields such as VC investing. We provide some initial evidence that the information content of investment characteristics may involve investment performance. However, the exact nature of the information content contained in investment characteristics is unclear. We leave this investigation to future research.

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Table 1. Variable definitions

Variable	Definition
Firm raised a fund	The firm has raised at least one fund in a given year. The fund year is the vintage year of the fund. VentureXpert 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 a given year. Commitments are identified through each fund's fundraising history in VentureXpert.
Drift ratio	The ratio of drift to non-drift investments in the previous firm-year. Stage drift is defined as deviation from the fund's stated investment focus of the company stage at the time of investment. VentureXpert lists 7 fund stages that we consider in its fundraising database and 8 company stages (Company Stage 2) in its investments database. We aim to avoid Type I errors when identifying drift investments. For an investment to not be considered a drift investment, the fund focus must be match any of the company stages in brackets: Seed stage focus = {Seed, Early Stage} Early stage focus = {Early Stage, Seed, Expansion} Later stage focus = {Expansion, Later Stage} Buyout focus = {Acquisition, Expansion, Public Market} Balanced stage focus = {Seed, Early Stage, Expansion, Later Stage} Funds with Mezzanine stage focus and Generalist stage focus cannot drift by definition. Therefore, investments made by funds with a Mezzanine or Generalist style are excluded when measuring drift.
Drift (yes/no)	A dummy variable=1 if the firm has made a style drift investment in the previous year
Log(drifts+1)	Natural logarithm of (number of drift investments in the previous firm-year, plus one)
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 cumulative	The ratio of all drift investments made by a firm until the previous 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).
Follow-on ratio	Ratio of follow-on investments in the previous firm-year to all investments by a firm in that 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 (i.e., second round or later round investments).
Follow-on inv. (yes/no)	A dummy variable=1 if the firm has made a follow-on investment in the previous year
Log(follow-on investments+1)	Natural logarithm of (number of follow-on investments in the previous firm-year, plus one)
Follow-on inv. quantile	Quantile of the follow-on ratio for all firms in a given year (e.g., 1 if a firm has the highest ratio of follow-on investments among all firms in a given year, 0 if no follow-on investments have been observed).
Non-lead investments	Ratio of non-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 is considered the lead investor 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.

Non-lead investments (yes/no)	A dummy variable=1 if the firm has made a non-lead investment in the previous year
Log(non-lead investments+1)	Natural logarithm of (number of non-lead investments in the previous firm-year, plus one)
Non-lead investments quantile	Quantile of the non-lead ratio for all firms in a given year (e.g., 1 if a firm has the highest ratio of non-lead investments among all firms in a given year, 0 if no non-lead investments have been observed).
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)	Natural log of the 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
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 dummy variable=1 if 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)
IRR of most recent fund	Net internal rate of return (IRR) of the VC firm's most recent fund for which IRR is observed, as reported by Preqin. If there is more than one most recent fund, the IRR is weighted by fund size.
IRR not available	If there is no most recent fund with observable net IRR, this dummy variable equals one and is zero otherwise.
Years since last fund	Number of years since the last fund was raised by the firm (i.e., the difference between the current year and the year in which the last fund was raised, in years). For our regressions, this variable is split into 12 dummy variables that indicate the number of years since the last fund for years 0-10 and whether more than 10 years have passed.
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=31,225.

Panel A: Main variables					
Variable name	Mean	Median	SD	Min.	Max.
Firm raised a fund	0.132			0.000	1.000
Firm received commitments	0.188			0.000	1.000
Drift ratio	0.159	0.000	0.272	0.000	1.000
Drift (yes/no)	0.375			0.000	1.000
Log(drifts+1)	0.489	0.000	0.753	0.000	4.500
Drift ratio quantile	0.411	0.463	0.329	0.000	1.000
Drift ratio cumulative	0.278	0.250	0.163	0.008	0.925
Follow-on ratio	0.310	0.000	0.370	0.000	1.000
Follow-on inv. (yes/no)	0.480			0.000	1.000
Log(follow-on investments+1)	0.810	0.000	1.043	0.000	5.226
Follow-on inv. quantile	0.387	0.353	0.342	0.000	1.000
Non-lead ratio	0.273	0.000	0.346	0.000	1.000
Non-lead investments (yes/no)	0.465			0.000	1.000
Log(non-lead investments+1)	0.737	0.000	0.966	0.000	5.283
Non-lead investments quantile	0.384	0.370	0.335	0.000	1.000
Northeast census region	0.407			0.000	1.000
Midwest census region	0.128			0.000	1.000
South census region	0.166			0.000	1.000
West census region	0.309			0.000	1.000
Log(amount raised, cumulative)	4.711	4.663	1.817	0.010	11.155
Log(firm age+1)	2.329	2.398	0.744	0.000	4.718
No investments	0.334			0.000	1.000
Log(investments+1)	1.211	1.099	1.153	0.000	5.572
Log(exits+1)	0.409	0.000	0.613	0.000	4.277
IRR of most recent fund(s)	0.080	0.050	0.257	-1.000	5.156
IRR not available	0.851			0.000	1.000
Years since last fund	3.360	3.000	3.088	0.000	24.000
Focus buyout	0.300	0.000	0.444	0.000	1.000
Focus mezzanine	0.021	0.000	0.122	0.000	1.000
Focus VC	0.670	1.000	0.458	0.000	1.000
Panel B: Time distribution of firm-year observations					
Year	N	%	Year	N	%
1980	81	0.3	1998	865	2.8
1981	107	0.3	1999	933	3.0
1982	140	0.4	2000	1089	3.5
1983	182	0.6	2001	1261	4.0
1984	231	0.7	2002	1336	4.3
1985	276	0.9	2003	1381	4.4
1986	323	1.0	2004	1412	4.5
1987	367	1.2	2005	1458	4.7
1988	415	1.3	2006	1527	4.9
1989	451	1.4	2007	1577	5.1
1990	512	1.6	2008	1647	5.3
1991	552	1.8	2009	1671	5.4
1992	561	1.8	2010	1642	5.3
1993	588	1.9	2011	1589	5.1
1994	616	2.0	2012	1459	4.7
1995	659	2.1	2013	1417	4.5
1996	710	2.3	2014	1428	4.6
1997	762	2.4			

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. Observations are at the firm-year level. The dependent variable in Panel A equals one if a vintage year is recorded in VentureXpert 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. Regions are U.S. census regions. Focus dummies in model 5 are obtained from the *focus* variables and equal to one if the firm has invested any amount in a given focus stage. Regression 5 has fewer observations because some observations need to be dropped due to collinearity with the large number of dummy variables. The intercept is included but not shown. Standard errors are clustered by VC firm and 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 commitments

	1	2	3	4	5
Drift ratio	-0.126(0.037)***				-0.110(0.038)***
Drift (yes/no)		-0.014(0.024)			
Log(drifts+1)			-0.049(0.017)***		
Drift ratio quantile				-0.180(0.058)***	
Log(amount raised, cumulative)	-0.003(0.009)	-0.002(0.009)	-0.003(0.009)	-0.003(0.009)	-0.012(0.009)
Log(firm age+1)	-0.047(0.016)***	-0.049(0.016)***	-0.048(0.016)***	-0.047(0.016)***	-0.062(0.016)***
No investments	-0.055(0.032)*	-0.029(0.031)	-0.007(0.032)	-0.134(0.047)***	-0.043(0.033)
Log(investments+1)	0.194(0.016)***	0.196(0.017)***	0.223(0.019)***	0.195(0.016)***	0.206(0.016)***
Log(exits+1)	0.086(0.019)***	0.086(0.019)***	0.088(0.020)***	0.086(0.019)***	0.088(0.019)***
IRR of most recent fund(s)	0.346(0.129)***	0.352(0.130)***	0.344(0.130)***	0.348(0.130)***	0.350(0.111)***
IRR not available	-0.074(0.032)**	-0.074(0.032)**	-0.075(0.032)**	-0.073(0.032)**	-0.062(0.031)**
Focus buyout	-0.344(0.102)***	-0.336(0.101)***	-0.340(0.101)***	-0.343(0.102)***	
Focus mezzanine	-0.089(0.133)	-0.087(0.133)	-0.088(0.133)	-0.090(0.133)	
Focus VC	-0.609(0.103)***	-0.604(0.103)***	-0.606(0.103)***	-0.609(0.103)***	
Years-since-last-fund dummies	Yes	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes	
Region dummies	Yes	Yes	Yes	Yes	
Year × region × focus dummies					Yes
Observations	31225	31225	31225	31225	31066
McFadden R-squared (adj.)	0.125	0.125	0.125	0.125	0.113
AIC	26426.5	26438.1	26430.1	26428.6	26715.7
Chi-sq. p-value	0.000	0.000	0.000	0.000	0.000
Log-Likelihood	-13152.2	-13158.0	-13154.0	-13153.3	-12779.8

Continued on next page

Table 3 (continued)**Panel B: Effect of style drift on the likelihood of new funds**

	1	2	3	4	5
Drift ratio	-0.140 (0.042)***				-0.116 (0.043)***
Drift (yes/no)		-0.046 (0.026)*			
Log(drifts+1)			-0.059 (0.018)***		
Drift ratio quantile				-0.206 (0.064)***	
Log(amount raised, cumulative)	0.035 (0.011)***	0.035 (0.011)***	0.035 (0.011)***	0.035 (0.011)***	0.024 (0.011)**
Log(firm age+1)	-0.094 (0.019)***	-0.095 (0.019)***	-0.094 (0.019)***	-0.094 (0.019)***	-0.116 (0.019)***
No investments	0.053 (0.036)	0.079 (0.035)**	0.109 (0.036)***	-0.038 (0.052)	0.073 (0.037)**
Log(investments+1)	0.241 (0.018)***	0.252 (0.019)***	0.277 (0.021)***	0.243 (0.018)***	0.257 (0.018)***
Log(exits+1)	0.094 (0.021)***	0.094 (0.021)***	0.097 (0.021)***	0.095 (0.021)***	0.091 (0.020)***
IRR of most recent fund(s)	0.578 (0.144)***	0.580 (0.144)***	0.575 (0.144)***	0.580 (0.144)***	0.582 (0.124)***
IRR not available	-0.027 (0.035)	-0.026 (0.035)	-0.028 (0.035)	-0.026 (0.035)	-0.020 (0.034)
Focus buyout	-0.371 (0.107)***	-0.365 (0.106)***	-0.367 (0.106)***	-0.371 (0.106)***	
Focus mezzanine	0.004 (0.136)	0.007 (0.135)	0.005 (0.135)	0.003 (0.135)	
Focus VC	-0.578 (0.109)***	-0.574 (0.109)***	-0.576 (0.109)***	-0.579 (0.109)***	
Years-since-last-fund dummies	Yes	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes	
Region dummies	Yes	Yes	Yes	Yes	
Year $\times$ region $\times$ focus dummies					Yes
Observations	31225	31225	31225	31225	30972
McFadden R-squared (adj.)	0.111	0.111	0.111	0.111	0.100
AIC	21636.0	21647.0	21639.6	21639.4	21828.8
Chi-sq. p-value	0.000	0.000	0.000	0.000	0.000
Log-Likelihood	-10757.0	-10762.5	-10758.8	-10758.7	-10349.4

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. Observations are at the firm-year level. The dependent variable in Panel A equals one if a vintage year is recorded in VentureXpert 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. Regions are U.S. census regions. Focus dummies in model 5 are obtained from the *focus* variables and equal to one if the firm has invested any amount in a given focus stage. Regression 5 has fewer observations because Stata drops some observations due to the large number of dummy variables. The intercept is included but not shown. Standard errors are clustered by VC firm and 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 commitments

	1	2	3	4	5
Follow-on ratio	-0.119 (0.036)***				-0.111 (0.037)***
Follow-on inv. (yes/no)		-0.008 (0.028)			
Log(follow-on investments+1)			-0.065 (0.024)***		
Follow-on inv. quantile				-0.128 (0.050)**	
Log(amount raised, cumulative)	-0.001 (0.009)	-0.002 (0.009)	-0.001 (0.009)	-0.002 (0.009)	-0.010 (0.009)
Log(firm age+1)	-0.044 (0.016)***	-0.048 (0.016)***	-0.045 (0.016)***	-0.045 (0.016)***	-0.059 (0.016)***
No investments	-0.052 (0.032)*	-0.029 (0.032)	0.016 (0.036)	-0.086 (0.038)**	-0.043 (0.032)
Log(investments+1)	0.205 (0.017)***	0.195 (0.017)***	0.257 (0.029)***	0.198 (0.016)***	0.217 (0.016)***
Log(exits+1)	0.087 (0.019)***	0.086 (0.019)***	0.088 (0.019)***	0.087 (0.019)***	0.089 (0.019)***
IRR of most recent fund(s)	0.347 (0.128)***	0.353 (0.130)***	0.351 (0.129)***	0.351 (0.129)***	0.350 (0.111)***
IRR not available	-0.078 (0.032)**	-0.074 (0.032)**	-0.078 (0.032)**	-0.076 (0.032)**	-0.065 (0.031)**
Focus buyout	-0.349 (0.102)***	-0.336 (0.102)***	-0.343 (0.101)***	-0.348 (0.101)***	
Focus mezzanine	-0.100 (0.134)	-0.087 (0.134)	-0.097 (0.134)	-0.099 (0.134)	
Focus VC	-0.599 (0.103)***	-0.603 (0.103)***	-0.598 (0.103)***	-0.603 (0.103)***	
Years-since-last-fund dummies	Yes	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes	
Region dummies	Yes	Yes	Yes	Yes	
Year × region × focus dummies					Yes
Observations	31225	31225	31225	31225	31066
McFadden R-squared (adj.)	0.125	0.125	0.125	0.125	0.113
AIC	26426.2	26438.4	26430.2	26431.2	26714.2
Chi-sq. p-value	0.000	0.000	0.000	0.000	0.000
Log-Likelihood	-13152.1	-13158.2	-13154.1	-13154.6	-12779.1

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

	1	2	3	4	5
Follow-on ratio	-0.222 (0.042)***				-0.197 (0.043)***
Follow-on inv. (yes/no)		-0.046 (0.032)			
Log(follow-on investments+1)			-0.141 (0.026)***		
Follow-on inv. quantile				-0.254 (0.058)***	
Log(amount raised, cumulative)	0.038 (0.011)***	0.036 (0.011)***	0.037 (0.011)***	0.037 (0.011)***	0.026 (0.011)**
Log(firm age+1)	-0.088 (0.019)***	-0.094 (0.019)***	-0.087 (0.019)***	-0.089 (0.019)***	-0.110 (0.019)***
No investments	0.034 (0.035)	0.071 (0.036)**	0.178 (0.041)***	-0.037 (0.042)	0.053 (0.036)
Log(investments+1)	0.263 (0.019)***	0.251 (0.020)***	0.379 (0.034)***	0.251 (0.019)***	0.277 (0.019)***
Log(exits+1)	0.096 (0.021)***	0.094 (0.021)***	0.099 (0.021)***	0.096 (0.021)***	0.093 (0.020)***
IRR of most recent fund(s)	0.574 (0.141)***	0.583 (0.144)***	0.582 (0.141)***	0.582 (0.142)***	0.579 (0.123)***
IRR not available	-0.034 (0.035)	-0.027 (0.035)	-0.034 (0.035)	-0.030 (0.035)	-0.026 (0.034)
Focus buyout	-0.389 (0.106)***	-0.366 (0.106)***	-0.381 (0.106)***	-0.388 (0.106)***	
Focus mezzanine	-0.018 (0.136)	0.003 (0.135)	-0.017 (0.136)	-0.018 (0.136)	
Focus VC	-0.565 (0.109)***	-0.570 (0.108)***	-0.563 (0.109)***	-0.573 (0.108)***	
Years-since-last-fund dummies	Yes	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes	
Region dummies	Yes	Yes	Yes	Yes	
Year $\times$ region $\times$ focus dummies					Yes
Observations	31225	31225	31225	31225	30972
McFadden R-squared (adj.)	0.112	0.111	0.112	0.112	0.101
AIC	21615.3	21647.9	21616.9	21626.2	21810.9
Chi-sq. p-value	0.000	0.000	0.000	0.000	0.000
Log-Likelihood	-10746.6	-10763.0	-10747.4	-10752.1	-10340.5

Table 5. Effect of non-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. Observations are at the firm-year level. The dependent variable in Panel A equals one if a vintage year is recorded in VentureXpert 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. Regions are U.S. census regions. Focus dummies in model 5 are obtained from the *focus* variables and equal to one if the firm has invested any amount in a given focus stage. Regression 5 has fewer observations because Stata drops some observations due to the large number of dummy variables. The intercept is included but not shown. Standard errors are clustered by VC firm and are shown in parentheses. Significance levels: *** p<0.01; ** p<0.05; * p<0.1.

Panel A: Effect of non-lead investments on the likelihood of new commitments

	1	2	3	4	5
Non-lead ratio	-0.073 (0.034)**				-0.070 (0.035)**
Non-lead investments (yes/no)		-0.064 (0.029)**			
Log(non-lead investments+1)			-0.043(0.022)*		
Non-lead investments quantile				-0.100 (0.038)***	
Log(amount raised, cumulative)	-0.003 (0.009)	-0.002 (0.009)	-0.003(0.009)	-0.003 (0.009)	-0.012 (0.009)
Log(firm age+1)	-0.049 (0.016)***	-0.049 (0.016)***	-0.049(0.016)***	-0.049 (0.016)***	-0.063 (0.016)***
No investments	0.023 (0.038)	-0.045 (0.032)	-0.006(0.033)	0.048 (0.042)	0.029 (0.038)
Log(investments+1)	0.194 (0.016)***	0.205 (0.017)***	0.228(0.024)***	0.200 (0.016)***	0.206 (0.016)***
Log(exits+1)	0.088 (0.019)***	0.086 (0.019)***	0.089(0.020)***	0.088 (0.019)***	0.090 (0.019)***
IRR of most recent fund(s)	0.349 (0.130)***	0.348 (0.130)***	0.350(0.129)***	0.347 (0.129)***	0.352 (0.111)***
IRR not available	-0.072 (0.032)**	-0.073 (0.032)**	-0.070(0.032)**	-0.072 (0.032)**	-0.060 (0.031)*
Focus buyout	-0.342 (0.101)***	-0.345 (0.102)***	-0.341(0.101)***	-0.344 (0.102)***	
Focus mezzanine	-0.085 (0.133)	-0.087 (0.133)	-0.087(0.133)	-0.084 (0.134)	
Focus VC	-0.595 (0.103)***	-0.597 (0.103)***	-0.596(0.103)***	-0.592 (0.103)***	
Years-since-last-fund dummies	Yes	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes	
Region dummies	Yes	Yes	Yes	Yes	
Year × region × focus dummies					Yes
Observations	31225	31225	31225	31225	31066
McFadden R-squared (adj.)	0.125	0.125	0.125	0.125	0.113
AIC	26433.7	26433.2	26434.2	26431.0	26720.1
Chi-sq. p-value	0.000	0.000	0.000	0.000	0.000
Log-Likelihood	-13155.8	-13155.6	-13156.1	-13154.5	-12782.0

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Table 5 (continued)**Panel B: Effect of non-lead investments on the likelihood of new funds**

	1	2	3	4	5
Non-lead ratio	-0.104 (0.038)***				-0.094 (0.039)**
Non-lead investments (yes/no)		-0.075 (0.032)**			
Log(non-lead investments+1)			-0.038(0.022)*		
Non-lead investments quantile				-0.113 (0.042)***	
Log(amount raised, cumulative)	0.035 (0.011)***	0.035 (0.011)***	0.035(0.011)***	0.035 (0.011)***	0.024 (0.011)**
Log(firm age+1)	-0.096 (0.019)***	-0.096 (0.019)***	-0.095(0.019)***	-0.096 (0.019)***	-0.117 (0.019)***
No investments	0.155 (0.045)***	0.062 (0.036)*	0.103(0.037)***	0.168 (0.048)***	0.162 (0.044)***
Log(investments+1)	0.242 (0.018)***	0.255 (0.019)***	0.272(0.027)***	0.248 (0.018)***	0.258 (0.018)***
Log(exits+1)	0.097 (0.021)***	0.094 (0.021)***	0.097(0.021)***	0.096 (0.021)***	0.093 (0.020)***
IRR of most recent fund(s)	0.580 (0.144)***	0.580 (0.144)***	0.583(0.143)***	0.579 (0.144)***	0.583 (0.125)***
IRR not available	-0.024 (0.035)	-0.025 (0.035)	-0.023(0.035)	-0.025 (0.035)	-0.017 (0.034)
Focus buyout	-0.371 (0.106)***	-0.374 (0.106)***	-0.367(0.106)***	-0.372 (0.106)***	
Focus mezzanine	0.009 (0.135)	0.007 (0.135)	0.006(0.135)	0.010 (0.135)	
Focus VC	-0.560 (0.108)***	-0.564 (0.108)***	-0.565(0.109)***	-0.559 (0.108)***	
Years-since-last-fund dummies	Yes	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes	
Region dummies	Yes	Yes	Yes	Yes	
Year × region × focus dummies					Yes
Observations	31225	31225	31225	31225	30972
McFadden R-squared (adj.)	0.111	0.111	0.111	0.111	0.100
AIC	21642.2	21644.4	21647.3	21642.3	21830.3
Chi-sq. p-value	0.000	0.000	0.000	0.000	0.000
Log-Likelihood	-10760.1	-10761.2	-10762.6	-10760.2	-10350.2

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 dummy variables. 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	-0.126 (0.04) ***	-0.241 (0.08) ***	-0.126 (0.04) ***	-0.432 (0.14) ***
Log(amount raised, cumulative)	-0.003 (0.01)	0.604 (0.02) ***	-0.003 (0.01)	0.602 (0.02) ***
Log(firm age+1)	-0.048 (0.01) ***	-0.198 (0.03) ***	-0.048 (0.01) ***	-0.272 (0.05) ***
No investments	-0.054 (0.03) *	0.014 (0.07)	-0.054 (0.03) *	-0.096 (0.10)
Log(investments+1)	0.194 (0.01) ***	0.140 (0.03) ***	0.194 (0.01) ***	0.422 (0.15) ***
Log(exits+1)	0.085 (0.02) ***	0.000 (0.03)	0.085 (0.02) ***	0.120 (0.08)
IRR of most recent fund(s)	0.359 (0.07) ***	0.716 (0.15) ***	0.359 (0.07) ***	1.098 (0.29) ***
IRR not available	-0.080 (0.03) ***	-0.056 (0.06)	-0.080 (0.03) ***	-0.173 (0.10) *
Focus buyout	-0.345 (0.10) ***	-0.037 (0.20)	-0.345 (0.10) ***	-0.551 (0.37)
Focus mezzanine	-0.101 (0.12)	-0.219 (0.24)	-0.101 (0.12)	-0.333 (0.31)
Focus VC	-0.608 (0.10) ***	-0.781 (0.21) ***	-0.608 (0.10) ***	-1.695 (0.55) ***
Standard deviation of errors		1.419 (0.01) ***		
Error correlation		0.046 (0.09)		
Inverse Mills ratio				2.022 (1.05) *
Years-since-last-fund dummies	Yes		Yes	
Year and region dummies	Yes		Yes	
Observations	31225		31225	
Of which observed	5881		5881	
Log-Likelihood	-23545.6			
R-squared (adj.)			0.487	

Panel B: Follow-on ratio

	Maximum-likelihood estimation		Two-step estimation	
	Selection eq.	Outcome eq.	Selection eq.	Outcome eq.
Follow-on ratio	-0.120 (0.03) ***	-0.493 (0.07) ***	-0.119 (0.03) ***	-0.644 (0.12) ***
Log(amount raised, cumulative)	-0.002 (0.01)	0.609 (0.02) ***	-0.001 (0.01)	0.609 (0.02) ***
Log(firm age+1)	-0.045 (0.01) ***	-0.176 (0.03) ***	-0.044 (0.01) ***	-0.240 (0.05) ***
No investments	-0.052 (0.03) *	-0.022 (0.07)	-0.052 (0.03) *	-0.117 (0.10)
Log(investments+1)	0.206 (0.01) ***	0.188 (0.03) ***	0.205 (0.01) ***	0.457 (0.16) ***
Log(exits+1)	0.086 (0.02) ***	0.003 (0.03)	0.087 (0.02) ***	0.112 (0.07)
IRR of most recent fund(s)	0.360 (0.07) ***	0.691 (0.15) ***	0.347 (0.07) ***	1.029 (0.28) ***
IRR not available	-0.084 (0.03) ***	-0.072 (0.06)	-0.078 (0.03) ***	-0.186 (0.10) *
Focus buyout	-0.350 (0.10) ***	-0.084 (0.20)	-0.349 (0.10) ***	-0.554 (0.36)
Focus mezzanine	-0.113 (0.12)	-0.279 (0.23)	-0.100 (0.12)	-0.392 (0.30)
Focus VC	-0.598 (0.10) ***	-0.761 (0.21) ***	-0.599 (0.10) ***	-1.575 (0.53) ***
Standard deviation of errors		1.414 (0.01) ***		
Error correlation		0.043 (0.09)		
Inverse Mills ratio				1.880 (1.03) *
Years-since-last-fund dummies	Yes		Yes	
Year and region dummies	Yes		Yes	
Observations	31225		31225	
Of which observed	5881		5881	
Log-Likelihood	-23528.0			
R-squared (adj.)			0.490	

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Table 6. Effect of style drift on amount committed (continued)**Panel C: Non-lead ratio**

	Maximum-likelihood estimation		Two-step estimation	
	Selection eq.	Outcome eq.	Selection eq.	Outcome eq.
Non-lead ratio	-0.072 (0.03) **	-0.210 (0.07) ***	-0.073 (0.03) **	-0.319 (0.11) ***
Log(amount raised, cumulative)	-0.003 (0.01)	0.605 (0.02) ***	-0.003 (0.01)	0.602 (0.02) ***
Log(firm age+1)	-0.049 (0.01) ***	-0.202 (0.03) ***	-0.049 (0.01) ***	-0.278 (0.06) ***
No investments	0.023 (0.04)	0.211 (0.08) **	-0.050 (0.03)	-0.102 (0.10)
Log(investments+1)	0.194 (0.01) ***	0.142 (0.03) ***	0.194 (0.01) ***	0.425 (0.16) ***
Log(exits+1)	0.087 (0.02) ***	0.005 (0.03)	0.088 (0.02) ***	0.127 (0.08)
IRR of most recent fund(s)	0.362 (0.07) ***	0.711 (0.15) ***	0.349 (0.07) ***	1.100 (0.29) ***
IRR not available	-0.078 (0.03) ***	-0.048 (0.06)	-0.072 (0.03) **	-0.163 (0.10) *
Focus buyout	-0.343 (0.10) ***	-0.038 (0.20)	-0.342 (0.10) ***	-0.549 (0.37)
Focus mezzanine	-0.097 (0.12)	-0.205 (0.24)	-0.085 (0.12)	-0.314 (0.31)
Focus VC	-0.594 (0.10) ***	-0.743 (0.21) ***	-0.595 (0.10) ***	-1.638 (0.54) ***
Standard deviation of errors		1.419 (0.01) ***		
Error correlation		0.046 (0.09)		
Inverse Mills ratio				2.079 (1.07) *
Years-since-last-fund dummies	Yes		Yes	
Year and region dummies	Yes		Yes	
Observations	31225		31225	
Of which observed	5881		5881	
Log-Likelihood	-23549.5			
R-squared (adj.)			0.487	

Table 7. Combinations of drift, follow-on and non-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 combine three measures of the VC firm's type by measuring the fractions of investments in each category. For example, "Drift & follow-on & non-lead inv." is the fraction of investment in the previous year that are drift, follow-on and non-lead investments. Standard errors are clustered by VC firm and are shown in parentheses. Significance levels: *** p<0.01; ** p<0.05; * p<0.1.

	1	2	3	4
Drift & follow-on & lead inv.	-0.224(0.082)***			
Drift & follow-on & non-lead inv.		-0.200(0.082)**		
Drift & no follow-on & lead inv.			-0.035(0.058)	
Drift & no follow-on & non-lead inv.				-0.052(0.078)
Log(amount raised, cumulative)	-0.002(0.009)	-0.002(0.009)	-0.002(0.009)	-0.003(0.009)
Log(firm age+1)	-0.047(0.016)***	-0.048(0.016)***	-0.049(0.016)***	-0.049(0.016)***
No investments	-0.033(0.031)	-0.034(0.031)	-0.031(0.032)	-0.030(0.032)
Log(investments+1)	0.197(0.016)***	0.195(0.016)***	0.192(0.016)***	0.192(0.016)***
Log(exits+1)	0.086(0.019)***	0.087(0.019)***	0.086(0.019)***	0.086(0.019)***
IRR of most recent fund(s)	0.348(0.130)***	0.348(0.129)***	0.353(0.130)***	0.353(0.130)***
IRR not available	-0.077(0.032)**	-0.074(0.032)**	-0.074(0.032)**	-0.074(0.032)**
Focus buyout	-0.347(0.102)***	-0.335(0.102)***	-0.335(0.101)***	-0.335(0.101)***
Focus mezzanine	-0.098(0.133)	-0.084(0.134)	-0.087(0.133)	-0.086(0.133)
Focus VC	-0.611(0.103)***	-0.597(0.103)***	-0.605(0.103)***	-0.603(0.103)***
Year, region, years-since-last-fund dum.	Yes	Yes	Yes	Yes
Observations	31225	31225	31225	31225
McFadden R-squared (adj.)	0.125	0.125	0.125	0.125
AIC	26429.5	26431.1	26438.1	26438.0
Chi-sq. p-value	0.000	0.000	0.000	0.000
Log-Likelihood	-13153.8	-13154.6	-13158.0	-13158.0
	5	6	7	8
No drift & follow-on & lead inv.	-0.001(0.044)			
No drift & follow-on & non-lead inv.		-0.069(0.054)		
No drift & no follow-on & lead inv.			0.133(0.035)***	
No drift & no follow-on & non-lead inv.				0.010(0.047)
Log(amount raised, cumulative)	-0.002(0.009)	-0.002(0.009)	-0.002(0.009)	-0.002(0.009)
Log(firm age+1)	-0.049(0.016)***	-0.048(0.016)***	-0.046(0.016)***	-0.049(0.016)***
No investments	-0.028(0.031)	-0.031(0.031)	0.034(0.035)	-0.026(0.032)
Log(investments+1)	0.193(0.016)***	0.195(0.016)***	0.201(0.016)***	0.193(0.016)***
Log(exits+1)	0.086(0.019)***	0.087(0.019)***	0.088(0.019)***	0.086(0.019)***
IRR of most recent fund(s)	0.353(0.130)***	0.353(0.130)***	0.343(0.128)***	0.353(0.130)***
IRR not available	-0.074(0.032)**	-0.073(0.032)**	-0.075(0.032)**	-0.074(0.032)**
Focus buyout	-0.335(0.101)***	-0.339(0.101)***	-0.357(0.101)***	-0.335(0.101)***
Focus mezzanine	-0.087(0.133)	-0.089(0.133)	-0.096(0.133)	-0.087(0.133)
Focus VC	-0.603(0.103)***	-0.601(0.103)***	-0.598(0.102)***	-0.604(0.103)***
Year, region, years-since-last-fund dum.	Yes	Yes	Yes	Yes
Observations	31225	31225	31225	31225
McFadden R-squared (adj.)	0.125	0.125	0.126	0.125
AIC	26438.4	26436.7	26423.0	26438.4
Chi-sq. p-value	0.000	0.000	0.000	0.000
Log-Likelihood	-13158.2	-13157.4	-13150.5	-13158.2

Table 8. Simultaneous tests for interactions and combinations of characteristics

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 in model 2 interact three investment characteristics at the VC firm level by measuring the fractions of investments in each category. The main variables of interest in model 3 combine the three characteristics at the investment level. For example, "Drift & follow-on & non-lead inv." is the fraction of investment in the previous year that are drift, follow-on and non-lead investments. The omitted category in model 3 is the fraction of no-drift, no-follow-on and lead investments, which is the category with the largest positive coefficient if included separately. Standard errors clustered by VC firm are shown in parentheses. Significance levels: *** p<0.01; ** p<0.05; * p<0.1.

	1	2	3
Drift ratio	-0.110 (0.037) ***	-0.114 (0.098)	
Follow-on ratio	-0.102 (0.037) ***	-0.133 (0.073) *	
Non-lead ratio	-0.054 (0.035)	-0.043 (0.054)	
Drift ratio × Follow-on ratio		0.038 (0.157)	
Drift ratio × Non-lead ratio		0.007 (0.122)	
Follow-on ratio × Non-lead ratio		-0.044 (0.093)	
Drift ratio × Follow-on ratio × Non-lead ratio		0.036 (0.216)	
Drift & follow-on & lead inv.			-0.280 (0.087) ***
Drift & follow-on & non-lead inv.			-0.249 (0.084) ***
Drift & no follow-on & lead inv.			-0.106 (0.061) *
Drift & no follow-on & non-lead inv.			-0.118 (0.079)
No drift & follow-on & lead inv.			-0.092 (0.050) *
No drift & follow-on & non-lead inv.			-0.155 (0.060) ***
No drift & no follow-on & non-lead inv.			-0.079 (0.052)
Log(amount raised, cumulative)	-0.002 (0.009)	-0.002 (0.009)	-0.002 (0.009)
Log(firm age+1)	-0.044 (0.016) ***	-0.044 (0.016) ***	-0.044 (0.016) ***
No investments	-0.035 (0.040)	-0.045 (0.050)	-0.091 (0.037) **
Log(investments+1)	0.205 (0.017) ***	0.205 (0.017) ***	0.206 (0.017) ***
Log(exits+1)	0.089 (0.019) ***	0.089 (0.020) ***	0.089 (0.020) ***
IRR of most recent fund(s)	0.339 (0.127) ***	0.339 (0.127) ***	0.338 (0.127) ***
IRR not available	-0.076 (0.032) **	-0.075 (0.032) **	-0.076 (0.032) **
Focus buyout	-0.359 (0.102) ***	-0.360 (0.102) ***	-0.363 (0.102) ***
Focus mezzanine	-0.098 (0.134)	-0.099 (0.134)	-0.102 (0.134)
Focus VC	-0.598 (0.103) ***	-0.598 (0.103) ***	-0.600 (0.103) ***
Years-since-last-fund dummies	Yes	Yes	Yes
Year and region dummies	Yes	Yes	Yes
Observations	31225	31225	31225
McFadden R-squared (adj.)	0.126	0.125	0.125
AIC	26418.0	26425.7	26424.5
Chi-sq. p-value	0.000	0.000	0.000
Log-Likelihood	-13146.0	-13145.9	-13145.3

Table 9. Stability of VC firm characteristics

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.

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

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 non-lead investments in the same way. Models 2, 4, and 6 use the decay parameter that maximizes the likelihood within this class of models. Benchmark models with $\gamma=1$ for follow-on and non-lead investments are omitted to conserve space and only benchmark models with $\gamma=0$ are shown. 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. Standard errors clustered by VC firm are shown in parentheses. Significance levels: *** $p<0.01$; ** $p<0.05$; * $p<0.1$.

	Drift			Follow-on		Non-lead	
	(1) $\gamma = 0$	(2) $\gamma = 0.399$	(3) $\gamma = 1$	(4) $\gamma = 0$	(5) $\gamma = 0.732$	(6) $\gamma = 0$	(7) $\gamma = 0.674$
Drift ratio cumulative	-0.223 (0.06)***	-0.307 (0.07)***	-0.107 (0.07)				
Follow-on ratio cumulative				-0.243 (0.06)***	-0.407 (0.07)***		
Non-lead ratio cumulative						-0.119 (0.06)**	-0.223 (0.06)***
Log(amount raised, cumulative)	-0.003 (0.01)	-0.004 (0.01)	-0.003 (0.01)	-0.001 (0.01)	0.002 (0.01)	-0.003 (0.01)	-0.003 (0.01)
Log(firm age+1)	-0.047 (0.02)***	-0.048 (0.02)***	-0.050 (0.02)***	-0.043 (0.02)***	-0.038 (0.02)**	-0.049 (0.02)***	-0.050 (0.02)***
No investments	-0.010 (0.03)	0.000 (0.03)	-0.020 (0.03)	0.009 (0.03)	0.028 (0.03)	-0.019 (0.03)	-0.013 (0.03)
Log(investments+1)	0.181 (0.02)***	0.181 (0.02)***	0.191 (0.02)***	0.208 (0.02)***	0.216 (0.02)***	0.192 (0.02)***	0.193 (0.02)***
Log(exits+1)	0.088 (0.02)***	0.086 (0.02)***	0.086 (0.02)***	0.088 (0.02)***	0.089 (0.02)***	0.089 (0.02)***	0.093 (0.02)***
IRR of most recent fund(s)	0.345 (0.13)***	0.342 (0.13)***	0.351 (0.13)***	0.345 (0.13)***	0.335 (0.12)***	0.349 (0.13)***	0.341 (0.13)***
IRR not available	-0.075 (0.03)**	-0.075 (0.03)**	-0.074 (0.03)**	-0.081 (0.03)**	-0.091 (0.03)***	-0.071 (0.03)**	-0.067 (0.03)**
Focus buyout	-0.343 (0.10)***	-0.354 (0.10)***	-0.346 (0.10)***	-0.349 (0.10)***	-0.373 (0.10)***	-0.341 (0.10)***	-0.357 (0.10)***
Focus mezzanine	-0.089 (0.13)	-0.094 (0.13)	-0.093 (0.13)	-0.102 (0.13)	-0.125 (0.14)	-0.086 (0.13)	-0.088 (0.13)
Focus VC	-0.608 (0.10)***	-0.621 (0.10)***	-0.615 (0.10)***	-0.596 (0.10)***	-0.590 (0.10)***	-0.596 (0.10)***	-0.589 (0.10)***
Years-since-last-fund dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year and region dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	31225	31225	31225	31225	31225	31225	31225
McFadden R-squared (adj.)	0.125	0.126	0.125	0.126	0.126	0.125	0.126
AIC	26425.0	26414.2	26435.3	26419.9	26395.4	26433.9	26422.3
Chi-sq. p-value	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Log-Likelihood	-13151.5	-13146.1	-13156.7	-13148.9	-13136.7	-13155.9	-13150.1

Table 10. Interaction of investment characteristics and macroeconomic environment

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 macroeconomic variables indicating the business climate (all lagged by one year). For each year, *Policy uncertainty* is the annual average of the US overall Economic Policy Uncertainty Index divided by 100 (Baker, Bloom, and Davis, 2016, obtained from www.policyuncertainty.com). *IPO volume* is the number of IPOs in the United States in the previous year in thousands (from Jay Ritter's website at <https://site.warrington.ufl.edu/ritter/files/2019/04/IPOs2018Statistics-1.pdf>, Table 8). *CFNAI* is the average of monthly CFNAI readings. *Sentiment* is the University of Michigan consumer sentiment index divided by 100. *Payroll growth* is the net monthly change in nonfarm payrolls reported by the Bureau of Labor Statistics (series CES0000000001, average over the past 12 months, in millions). The variable *macro variable × no investments* is the macroeconomic variable used in the model interacted with the dummy variable indicating that the VC firm made no investment in a year. Standard errors are clustered by VC firm and are shown in parentheses. Significance levels: *** p<0.01; ** p<0.05; * p<0.1.

Panel A: Drift ratio	1	2	3	4	5
Drift ratio × Policy uncertainty	-0.151 (0.11)				
Drift ratio × IPO volume		0.500 (0.20) **			
Drift ratio × CFNAI			0.085 (0.05) *		
Drift ratio × Sentiment				0.530 (0.27) *	
Drift ratio × Payroll growth					0.412 (0.19) **
Drift ratio	0.048 (0.12)	-0.230 (0.06) ***	-0.112 (0.04) ***	-0.577 (0.24) **	-0.167 (0.04) ***
Log(amount raised, cumul.)	0.000 (0.01)	-0.002 (0.01)	-0.002 (0.01)	-0.002 (0.01)	-0.002 (0.01)
Log(firm age+1)	-0.050 (0.02) ***	-0.048 (0.02) ***	-0.047 (0.02) ***	-0.048 (0.02) ***	-0.048 (0.02) ***
No investments	-0.060 (0.03) *	-0.052 (0.03)	-0.054 (0.03) *	-0.055 (0.03) *	-0.054 (0.03) *
Log(investments+1)	0.184 (0.02) ***	0.194 (0.02) ***	0.194 (0.02) ***	0.193 (0.02) ***	0.194 (0.02) ***
Log(exits+1)	0.083 (0.02) ***	0.085 (0.02) ***	0.086 (0.02) ***	0.086 (0.02) ***	0.086 (0.02) ***
IRR of most recent fund(s)	0.348 (0.13) ***	0.344 (0.13) ***	0.346 (0.13) ***	0.345 (0.13) ***	0.345 (0.13) ***
IRR not available	-0.077 (0.03) **	-0.075 (0.03) **	-0.074 (0.03) **	-0.075 (0.03) **	-0.075 (0.03) **
Focus buyout	-0.321 (0.11) ***	-0.344 (0.10) ***	-0.345 (0.10) ***	-0.347 (0.10) ***	-0.345 (0.10) ***
Focus mezzanine	-0.064 (0.14)	-0.089 (0.13)	-0.090 (0.13)	-0.090 (0.13)	-0.090 (0.13)
Focus VC	-0.579 (0.11) ***	-0.606 (0.10) ***	-0.609 (0.10) ***	-0.609 (0.10) ***	-0.609 (0.10) ***
Years-since-last-fund dummies	Yes	Yes	Yes	Yes	Yes
Year and region dummies	Yes	Yes	Yes	Yes	Yes
Observations	30208	31225	31225	31225	31225
McFadden R-squared (adj.)	0.127	0.126	0.125	0.125	0.126
AIC	25344.2	26422.4	26425.7	26424.8	26423.4
Chi-sq. p-value	0.000	0.000	0.000	0.000	0.000
Log-Likelihood	-12616.1	-13149.2	-13150.8	-13150.4	-13149.7

Continued on next page

Table 10 (continued) Interaction of investment characteristics and macroeconomic environment

Panel B: Follow-on ratio	1	2	3	4	5
Follow-on ratio × Policy uncertainty	-0.191 (0.08) **				
Follow-on ratio × IPO volume		0.665 (0.15) ***			
Follow-on ratio × CFNAI			0.079 (0.04) **		
Follow-on ratio × Sentiment				0.626 (0.22) ***	
Follow-on ratio × Payroll growth					0.341 (0.14) **
Follow-on ratio	0.092 (0.10)	-0.247 (0.05) ***	-0.103 (0.04) ***	-0.648 (0.19) ***	-0.149 (0.04) ***
Log(amount raised, cumul.)	0.003 (0.01)	0.002 (0.01)	0.000 (0.01)	0.001 (0.01)	0.000 (0.01)
Log(firm age+1)	-0.048 (0.02) ***	-0.047 (0.02) ***	-0.045 (0.02) ***	-0.047 (0.02) ***	-0.045 (0.02) ***
No investments	-0.063 (0.03) **	-0.053 (0.03) *	-0.052 (0.03) *	-0.058 (0.03) *	-0.053 (0.03) *
Log(investments+1)	0.194 (0.02) ***	0.201 (0.02) ***	0.204 (0.02) ***	0.201 (0.02) ***	0.204 (0.02) ***
Log(exits+1)	0.082 (0.02) ***	0.080 (0.02) ***	0.085 (0.02) ***	0.085 (0.02) ***	0.085 (0.02) ***
IRR of most recent fund(s)	0.345 (0.13) ***	0.338 (0.12) ***	0.347 (0.13) ***	0.337 (0.13) ***	0.345 (0.13) ***
IRR not available	-0.084 (0.03) ***	-0.084 (0.03) ***	-0.080 (0.03) **	-0.083 (0.03) ***	-0.081 (0.03) **
Focus buyout	-0.322 (0.11) ***	-0.340 (0.10) ***	-0.344 (0.10) ***	-0.344 (0.10) ***	-0.344 (0.10) ***
Focus mezzanine	-0.071 (0.14)	-0.090 (0.13)	-0.095 (0.13)	-0.094 (0.13)	-0.094 (0.13)
Focus VC	-0.565 (0.11) ***	-0.585 (0.10) ***	-0.594 (0.10) ***	-0.591 (0.10) ***	-0.593 (0.10) ***
Years-since-last-fund dummies	Yes	Yes	Yes	Yes	Yes
Year and region dummies	Yes	Yes	Yes	Yes	Yes
Observations	30208	31225	31225	31225	31225
McFadden R-squared (adj.)	0.128	0.126	0.126	0.126	0.126
AIC	25337.7	26409.6	26423.9	26419.5	26421.7
Chi-sq. p-value	0.000	0.000	0.000	0.000	0.000
Log-Likelihood	-12612.8	-13142.8	-13150.0	-13147.7	-13148.9

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Table 10 (continued) Interaction of investment characteristics and macroeconomic environment

Panel C: Non-lead ratio	1	2	3	4	5
Non-lead ratio × Policy uncertainty	-0.207 (0.10) **				
Non-lead ratio × IPO volume		0.517 (0.17) ***			
Non-lead ratio × CFNAI			0.060 (0.04)		
Non-lead ratio × Sentiment				0.512 (0.24) **	
Non-lead ratio × Payroll growth					0.281 (0.16) *
Non-lead ratio	0.148 (0.11)	-0.189 (0.05) ***	-0.066 (0.03) *	-0.520 (0.21) **	-0.103 (0.04) ***
Log(amount raised, cumul.)	0.001 (0.01)	-0.001 (0.01)	-0.002 (0.01)	-0.002 (0.01)	-0.002 (0.01)
Log(firm age+1)	-0.051 (0.02) ***	-0.049 (0.02) ***	-0.049 (0.02) ***	-0.049 (0.02) ***	-0.049 (0.02) ***
No investments	-0.055 (0.03) *	-0.046 (0.03)	-0.049 (0.03)	-0.050 (0.03)	-0.050 (0.03)
Log(investments+1)	0.185 (0.02) ***	0.194 (0.02) ***	0.194 (0.02) ***	0.193 (0.02) ***	0.194 (0.02) ***
Log(exits+1)	0.084 (0.02) ***	0.084 (0.02) ***	0.087 (0.02) ***	0.087 (0.02) ***	0.087 (0.02) ***
IRR of most recent fund(s)	0.349 (0.13) ***	0.346 (0.13) ***	0.350 (0.13) ***	0.346 (0.13) ***	0.349 (0.13) ***
IRR not available	-0.076 (0.03) **	-0.074 (0.03) **	-0.072 (0.03) **	-0.074 (0.03) **	-0.072 (0.03) **
Focus buyout	-0.317 (0.11) ***	-0.338 (0.10) ***	-0.340 (0.10) ***	-0.338 (0.10) ***	-0.340 (0.10) ***
Focus mezzanine	-0.057 (0.14)	-0.079 (0.13)	-0.082 (0.13)	-0.079 (0.13)	-0.081 (0.13)
Focus VC	-0.562 (0.11) ***	-0.586 (0.10) ***	-0.592 (0.10) ***	-0.587 (0.10) ***	-0.592 (0.10) ***
Years-since-last-fund dummies	Yes	Yes	Yes	Yes	Yes
Year and region dummies	Yes	Yes	Yes	Yes	Yes
Observations	30208	31225	31225	31225	31225
McFadden R-squared (adj.)	0.127	0.125	0.125	0.125	0.125
AIC	25347.0	26424.9	26433.6	26430.6	26432.3
Chi-sq. p-value	0.000	0.000	0.000	0.000	0.000
Log-Likelihood	-12617.5	-13150.4	-13154.8	-13153.3	-13154.2

Table 11. Exit type predicted by investment characteristics

This dependent variable in these models is the type of exit recorded in Thomson Reuters' database of VC-backed exits. The sample (N=79,193) consists of all investments in Thomson Reuters' Private Equity investments database for which an exit event can be identified. The unit of analysis is an individual investment by a VC firm in a portfolio company. Whenever an exit event for this combination of portfolio company and VC firm is recorded, all of the VC firm's investments in this portfolio firm are treated as having been exited. Columns (1) and (2) show results for probit models for the likelihood of observing a successful exit event (IPO, Reverse Takeover, Secondary Sale, Trade Sale). The baseline category in these models is Write-Off. Models (3) and (4) show results for multinomial logit models for all types of exits with Write-Off as the baseline category. The excluded baseline category for full interactions in models (2) and (4) is the effect for non-drift & non-follow-on & lead investments. Control variables are Log(company age+1), Log(firm age+1), Log(fund age+1), Log(amount raise, cumul.), Log(investments+1), Log(exits), syndication dummy, dummies for years since last fund, IRR of most recent fund(s), dummy variable equal to one if IRR is not available, focus buyout, focus mezzanine, focus VC, fund sequence, fund stage, company stage, and investment year dummy variables. Control variables at the VC firm level are lagged by one year in line with results presented in the previous tables. Standard errors shown in parentheses are clustered by VC firm. Significance levels: *** p<0.01; ** p<0.05; * p<0.1.

	1	2	3			
	Probit	Probit	Multinomial Logit			
	Successful Exit	Successful Exit	IPO	Reverse Takeover	Secondary Sale	Trade Sale
<i>Main effects only</i>						
Drift investment	-0.089 (0.03) **		-0.157 (0.08) **	-0.674 (0.24) ***	-0.006 (0.11)	-0.163 (0.07) ***
Follow-on investment	-0.065 (0.02) ***		-0.101 (0.04) **	-0.432 (0.11) ***	-0.201 (0.06) ***	-0.153 (0.04) ***
Non-lead investment	-0.000 (0.03)		-0.222 (0.05) ***	0.096 (0.19)	0.257 (0.09) ***	0.095 (0.05) ***
Control variables	Yes		Yes	Yes	Yes	Yes
Log-Likelihood	-17187		-69993			
Pseudo R-squared	0.053		0.141			
<i>Full set of interaction terms</i>						
			(4) Multinomial Logit			
Drift & Follow-on & Lead		-0.171 (0.06) ***	-0.322 (0.13) ***	-1.284 (0.39) ***	-0.364 (0.16) **	-0.354 (0.11) ***
Drift & Follow-on & No Lead		-0.166 (0.05) ***	-0.065 (0.11)	-1.070 (0.34) ***	-0.478 (0.18) ***	-0.419 (0.11) ***
Drift & No Follow-on & Lead		-0.068 (0.06)	-0.117 (0.12)	-0.852 (0.42) **	0.118 (0.16)	-0.144 (0.12)
Drift & No Follow-on & No Lead		-0.116 (0.05) **	0.098 (0.11)	-0.755 (0.39) *	-0.266 (0.16) *	-0.365 (0.11) ***
No Drift & Follow-on & Lead		-0.087 (0.03) ***	-0.121 (0.07) *	-0.412 (0.18) **	-0.223 (0.09) **	-0.205 (0.06) ***
No Drift & Follow-on & No Lead		-0.069 (0.03) **	0.120 (0.07)	-0.589 (0.22) ***	-0.445 (0.12) ***	-0.266 (0.07) ***
No Drift & No Follow-on & No Lead		-0.022 (0.03)	0.177 (0.06) ***	-0.116 (0.20)	-0.364 (0.10) ***	-0.138 (0.06) **
Control variables		Yes	Yes	Yes	Yes	Yes
Log-Likelihood		-17186	-69982			
McFadden R-squared (adj.)		0.053	0.141			

Table 12. Investment characteristics and performance

This tables shows results for the relationship between internal rate of return (IRR) and investment characteristics. The dependent variable is the firm's weighted net internal rate of return of their most recent fund(s). Drift ratio, follow-on ratio and non-lead ratio are the sum of the proportions of style drift, follow-on, and non-lead investments, respectively, in the previous two years. For drift ratio, this value is lagged by one period. All control variables are measured in the same firm year as the dependent variable. The sample consists of all firm-years in our main sample for which IRR is observed. The dynamic panel models are estimated using System GMM in models 1, 3, 4, and 5, and pooled-sample OLS in model 2. We use the standard GMM instruments for the difference equation (first difference of independent variables, lags of the dependent variable) and the levels equation (lagged difference of dependent variable). Robust standard errors are shown in parentheses. Significance levels: *** p<0.01; ** p<0.05; * p<0.1.

	GMM 1	OLS 2	GMM 3	GMM 4	GMM 5
Drift ratio	-0.028 (0.013) **	-0.013 (0.006) **	-0.031 (0.014) **		
Follow-on ratio	-0.024 (0.014) *	-0.012 (0.005) **		-0.026 (0.015) *	
Non-lead ratio	-0.011 (0.012)	-0.005 (0.006)			-0.016 (0.014)
IRR of most recent fund(s) – Lag	0.546 (0.028) ***	0.655 (0.105) ***	0.547 (0.028) ***	0.539 (0.029) ***	0.541 (0.029) ***
Log(amount raised, cumul.)	-0.026 (0.024)	-0.004 (0.003)	-0.027 (0.025)	-0.026 (0.024)	-0.027 (0.025)
Log(firm age+1)	0.024 (0.039)	0.015 (0.007)	0.015 (0.040)	0.021 (0.039)	0.012 (0.041)
No investments	0.003 (0.014)	0.000 (0.009)	-0.002 (0.014)	0.003 (0.015)	0.001 (0.014)
Log(investments+1)	-0.004 (0.014)	0.003 (0.005)	-0.003 (0.013)	-0.003 (0.014)	-0.002 (0.013)
Log(exits+1)	0.027 (0.007) ***	0.026 (0.007) ***	0.026 (0.007) ***	0.028 (0.007) ***	0.028 (0.007) ***
Focus buyout	0.370 (0.238)	-0.007 (0.022)	0.390 (0.243)	0.351 (0.235)	0.367 (0.242)
Focus mezzanine	0.476 (0.453)	-0.038 (0.035)	0.504 (0.465)	0.476 (0.458)	0.494 (0.469)
Focus VC	0.497 (0.322)	-0.018 (0.025)	0.496 (0.319)	0.468 (0.312)	0.477 (0.318)
Years-since-last-fund dummies	Yes	Yes	Yes	Yes	Yes
Year and region dummies	Yes	Yes	Yes	Yes	Yes
Observations	3360	3360	3360	3377	3377
Firms	485	485	485	488	488
Wald test statistic	3096.02		3010.52	2626.95	2690.74
F-test		36.43			
Wald/F-test p-value	0.000	0.000	0.000	0.000	0.000
R-squared		0.538			