The Fast and the Curious: VC Drift [1]

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Abstract

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Changes in investment allocations offer financial intermediaries an avenue to learn and gain from opportunism, but carry potential costs such as dilution of focus and experience. Given how skill-intensive a VC's nurture role is, these benefits and costs have ramifications not just for a specific investment but importantly for a VC firm's entire portfolio. To examine these portfolio-wide effects, we develop a measure of "drift" in investment style at the portfolio level. First, we find that drift is more likely among younger VCs and those facing pressure to invest their funds, but less likely among VCs who focus on early stage investments. Second, style drift is associated with poorer performance among seasoned VCs that are likely to have already developed specialized expertise through past investments, and among VCs that drift in a correlated fashion or "herd" with other VC firms. Third, in a VC's existing portfolio, the more recent investments (which need greater nurturing) are more adversely affected by drift than other investments in the VC's pre-drift portfolio. Taken together, our results indicate that style drift is detrimental, offering evidence for economies of style persistence.

JEL classification: G20, G24
Key words Venture capital, style persistence, style drift

1 Introduction

Venture capitalists (VCs) face the opportunities and risks of a fast-changing investment opportunity set. New ideas, new models, and often completely novel sectors emerge. Investing opportunistically in hitherto untested or unknown ideas offers considerable benefits and entails significant risks. For instance, early investors in novel internet-based search engine technology firms such as Lycos and Yahoo, were willing to change their investment allocations across sectors, i.e., "drift", to experiment and subsequently reap the rewards of venturing into unchartered territory.[1] In this paper, we develop a measure of investment style drift, and examine whether or not style drift is advantageous for VC firms.

We shed light on the dynamic portfolio implications of a VC's investment allocation decision. Drift in strategy, through investment in unexplored ideas or non-existing technologies, provides VCs the opportunity to acquire new knowledge and skills (Sørensen, 2008), which are used to actively nurture their portfolio companies in many ways, such as advising, mentoring, strategizing, and more.[2] Know-how may be transferable across investment types.[3] Innovative solutions often result from combining novel ideas with conventional knowledge (Uzzi et al., 2013). Thus, the benefits of such learning and experience flow to other firms in the VC's portfolio.

However, experimentation and opportunism, while beneficial, may be costly. A new investment requires effort and time, which come at the expense of existing investments in the VC's portfolio. Additionally, attention towards acquiring new skills in new sectors may dilute a VC's existing set of skills acquired over a long period, which may be valuable to other portfolio companies. Specialized skills are particularly useful given the resource-intensive nature of venture investing. So, a VC's decision to drift in its investment strategy imposes negative externalities on the remaining companies in the VC's portfolio. Whether drift benefits or hurts a VC's portfolio of investments, therefore, is an empirical question.

We start by identifying a set of investment "styles" that characterize the VC industry based on geography and industry sectors and map each VC investment to a given style.[4] We then create a measure of "style drift" as the distance between a VC firm's location in multidimensional style space in one year and its location the following year. Intuitively, style drift is a measure of the degree of change, through exploration or experimentation, taking place in the VC's *entire portfolio*. Importantly, we define the measure to make drift comparable across VC firms of different sizes.[5]

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[1]CMGI, an early investor in Lycos, started its operations in 1968 focusing on the sale of educational publishing products, then transformed itself into a database management business before investing in internet-based firms in the 1990s.

[2]See Lerner (1995) for VC directorships, Gorman and Sahlman (1989) for advising, Hellmann and Puri (2002) for professionalization, and Lindsey (2008) for strategic partnering roles of VC firms.

[3]This is similar to *economies-of-scope* in multi-product firms (Panzar and Willig, 1981).

[4]Given that we do not want too many styles, the industry categorization is fairly broad so as to allow for new sub-sectors within existing industry classification.

[5]Related to this, see Barrot (2014) for the relation between performance, funding, and future investments.

Our drift measure is different from the notion of *specialization* as in Gompers et al. (2009) and Fulghieri and Sevilir (2009). A VC firm that drifts from one small set of styles to another small set of styles remains specialized by virtue of investing in a few styles at a each point in time. However, the extent of style drift will depend on how different the new small set of styles is from the old small set of styles. Specialization is a static measure whereas drift is a dynamic construct. Because specialization and drift are distinct portfolio features, our empirical specifications control for the degree of specialization.

We document considerable style drift in the sample. Based on a panel of 250,293 VC fund-financing rounds, both domestic (U.S.-based) and international, over the period 1980–2010, we observe that the distribution of style drift in the cross-section of VCs is bimodal. That is, some VCs stay focused on a certain set of styles over time while others choose to drift across different styles. We find that a VC firm's life cycle, investment stage, and the pressure of investing funds are important drivers of its decision to drift. Drift is common among younger VC firms but is less attractive for VCs that specialize in early stage investments. Dry powder (uninvested funds) increases the VC's propensity to drift.

We construct a lagged measure of drift and examine its implication for subsequent portfolio performance. We consider two metrics of VC performance - likelihood of exit and time-to-exit, where exit occurs through an initial public offering (IPO), merger and acquisition (M&A), or secondary sale.[6] We find that VC firms that remained focused significantly outperform those that drift.

We examine why investments made by VCs with high drift are systematically less successful than those made by VCs with low drift. One hypothesis is that drift dilutes VC skills in a resource- and skill-intensive activity such as venture financing. To test this, we exploit the heterogeneity in the age composition of a VC's existing (pre-drift) portfolio. Recent (rather than older) existing investments need more of the attention and value-added services that VCs provide, and are more likely to bear the brunt of VC drift. Controlling for VC's overall recent performance, we find that greater VC drift reduces the speed of exit for recent investments rather than for older investments in the VC's portfolio.

We are careful to rule out alternate explanations based on omitted variables such as a common link to public markets in an investment year (Nanda and Rhodes-Kropf, 2013) by using year fixed effects. It is also possible that low VC ability is an unobserved variable driving drift and performance, and we control for this through variables for VC Age. We find that seasoned VCs who have already developed strong expertise (possibly through past drift and experimentation) and stand to lose more from drifting. Herding is another explanation– lacking appropriate skills, a VC may follow the herd and pay less attention to the investment quality. She may therefore make poorer investments as they change their portfolio (i.e., drift) in the process of herding. We find that herders do significantly worse by drifting than do

[6]Ideally, success would be measured as a percentage return. However it is difficult to obtain more detailed information on the financial performance of VC investments, and therefore exit and time-to-exit are standard measures in the literature. As Sørensen (2008) points out, this definition of performance is consistent with evidence that VCs generate most of their returns from a few successful investments. Moreover, Gompers and Lerner (2000) compare different measures of performance and find that using exits as a measure of success produces qualitatively similar results as the others.

contrarians.[7]

We document the *predictive power* of drift in terms of future performance in the Granger-causality sense.[8] This suggests that knowledge of a VC's previous drift can potentially be used by limited partners in their investment decisions and by entrepreneurs in identifying appropriate VCs for funding.

To further mitigate concerns about unobserved heterogeneity between high and low drift VCs driving our results, we use a coarsened exact matching (CEM) approach (see Iacus et al. (2012)) to match high drift (the treatment group) and low drift (the control or comparison group) firms on a number of factors.[9] We assess the effect of a particular "treatment" (i.e., high drift) on the speed of exit relative to the control. The results are consistent with our prior analyses.

Besides concerns about reverse causality and omitted variables, another explanation for our findings could be that they capture a mechanical relation between drift and performance. In the VC industry, successful investments attract multiple financing rounds from the same VC who would thereby automatically exhibit lower drift. By contrast, poorer performance frees up capital to drift into newer investments. We address this concern by restricting our performance specifications to include only the first round of a VC's investment in any portfolio company. Our results continue to hold. Overall, given these alternative methods, there is robust evidence that VCs who drift make poorer investment choices, resulting in poorer subsequent performance.

Our paper is related to a growing literature on the role of financial intermediaries in general, and managerial skills in venture financing in particular. Kaplan and Schoar (2005) find significant persistence in VC returns and offer heterogeneity in investors' skills as the most likely explanation. Gompers et al. (2009) find that a VC firm's success is positively related to the degree of its individual VC fund manager's specialization.[10] Hochberg et al. (2007) consider the implication of individual VC influence (centrality) as another source of skill differentiation among VCs based on their network. Our paper offers another dimension of managerial skills, based on style drift, as a natural and complementary extension to the literature on venture investment performance. Using a broad characterization of venture investment types based primarily on industry and geography combinations, we complement the work of Gompers et al. (2009) and Cumming et al. (2009) who focus on specific dimensions of venture investments, industry and stage (early versus late), respectively. Hochberg and Westerfield (2010) consider industry-geography groups (as we do) but focus on the relation between the VC's portfolio size and specialization. Our results suggest that VC firms

[7] See Scharfstein and Stein (1990) and Gompers et al. (2008).

[8] Granger causality is commonly analyzed in the macro econometrics literature. See Stock and Watson (1999); Lettau and Ludvigson (2001)

[9] Matching is an effective tool for assessing the effect of a particular "treatment" and is now frequently used in the corporate finance literature. See Saunders and Steffen (2011), Campello et al. (2010), among others.

[10] Correspondingly, there is evidence of specialization being better in mutual funds, see Kacperczyk et al. (2005).

are unable to profitably time their entry into or exit from venture investing styles, consistent with the findings in Ball et al. (2011) and with what is popularly recognized among practitioners in the industry—Coller Capital in their "2008 Global Private Equity Barometer" report that 84% of fund limited partners perceive style drift negatively.

The paper proceeds as follows. Section 2 describes our metric for normalized style drift. Examples are provided in the Appendix to explain how style drift is determined and to highlight the attractive properties of our new measure of style drift. The section also presents a description of the data and describes the sample selection process, financing rounds, and the data needed to determine exits. Section 3 characterizes the various styles and looks at the variation in drift, both cross-sectionally and over time. Section 4 presents empirical findings about the determinants of drift. Section 5 shows that style drift explains weaker performance after controls, i.e., style persistence pays. Section 6 concludes.

2 Definitions and Data

2.1 Defining style drift

Unlike mutual funds where a fund may exhibit passive drift as the value of the fund's portfolio changes with market conditions, VC firms demonstrate *active* drift when they change investment strategy from fund to fund or reallocate across styles. Moreover, investment decisions of a VC fund typically involve people from across the VC firm, making active investing a firm-level exercise.[11] Therefore, it is natural to explore styles at the VC firm level rather than the fund level. Our methodology for calculating drift captures the effect of changes in investment at the VC firm's *portfolio* level. VC fund investment rounds are each allocated into one of K style categories. These data on round-level investments by VC funds are then aggregated by VC firm to determine their investment styles.

A VC's style at the end of any year is denoted by a vector whose dimension is the number of styles ($k = 1...K$). A style proportion vector is denoted $P_{jt} = [P_{j1t}, P_{j2t}, \ldots, P_{j,K,t}]'$, where variables P_{jkt} that are the proportion of funds invested by VC j in style k in year or subperiod t. For each VC *firm*, we construct style-proportion vectors year-by-year, as follows.

1. For each VC *fund*, we cumulate invested amounts year by year into each style, starting from the first year of the fund. The main point of cumulating investments by style is that we want to identify deviations from past investment proportions.

2. If a VC fund is fully invested after a few years, we continue to populate its cumulative investment style vector until ten years from inception, after which the fund is assumed to have been realized. This means that the same cumulative investment carries down

[11] At the time of raising a new fund, the limited partnership agreement may identify the fund's focus. However, it could be along a variety of possible dimensions, such as preferred investment stage, industry, or geography, which itself is a choice VCs make. For instance, Sequoia Capital XI fund invested in both shoe stores and network security firms (Hochberg and Westerfield (2010)). Moreover, even within the confines of the limited partnership agreement VCs have flexibility in their investment choices.

year after year, even after full investment. If the vector does not change, our metric for drift (see below) returns a zero value, as it should.

3. Hence, each VC fund has cumulated data for a maximum of 10 years (unless it came into existence less than 10 years preceding the initial date of the database, 1980). A VC firm may have several funds, and after each fund's style vectors have been created for each year, we construct the firm's style vector by aggregating all its investments in various funds within styles year by year. We do not subtract exits during this 10 year period as these are not reflections of active style changes, even though the portfolio of investments by a fund has been altered through an exit.[12]

4. Next, for each year, the invested style amounts for each VC firm are converted into proportions adding up to one. At the end of this procedure, for each VC firm-year, we have a *style proportion vector*.

5. We define the style drift score for VC j from one year to the next as one minus the cosine similarity between consecutive years' style vectors:

$$d_{jt} = 1 - \frac{P_{jt} \cdot P_{j,t-1}}{||P_{jt}|| \times ||P_{j,t-1}||} = 1 - \cos(\theta) \in [0, 1], \tag{1}$$

where θ is the angle between P_{jt} and $P_{j,t-1}$, the numerator is a dot product, and the denominator is the product of two style vector norms. The overall drift score for VC firm j is the mean of period-by-period style drifts, i.e.,

$$\text{Overall drift score} = D_j = \frac{1}{T-1} \cdot \sum_{t=2}^{T} d_{jt} \in [0, 1], \tag{2}$$

where T is the number of years in the life of a VC firm, and our count begins from $t = 2$, i.e., using first the drift between years 1 and 2 of the VC firm. By construction, the drift score is normalized such that the values lie between 0 and 1. We also compute average drift scores for subperiods in rolling period analysis.

The style drift measure has three properties.

1. *Size invariance*: Given that proportions are used, it is invariant to the size of the investments undertaken by a particular VC.

2. *Sequence invariance*: The measure of drift returns an average drift over time for a VC that is the same irrespective of the sequence in which investments are made. That is, for example, if a VC's investments in years t and $t + h$ are interchanged, ceteris paribus, the average drift of the VC remains unchanged.

3. *Time consistency*: Comparing two VCs that make identical investments in styles, the VC that makes the investments at a slower pace will show lower style drift.

In Appendix A we present some examples to support the methodology, illustrate the three properties above, and clarify exception handling.

[12]In our empirical analysis, we control for a VC's exit experience.

2.2 Sample

The data are from VentureXpert, a commonly used data source for VC research offered by Thomson Reuters (e.g., Hochberg and Westerfield (2010)). The initial sample includes information on investments made by private equity firms including venture capital firms, buyout firms, angel investor networks, and other similar entities whose primary activity is private equity investment.[13] We purge from the sample private equity × financing round pairs that involve non-VCs such as individuals, angel investors, and management, and remove observations for which information on company location is not available. Thus, we obtain a final sample of 250,293 VC fund × financing rounds as observations (121,419 unique financing rounds), both in the United States and internationally, conducted exclusively by VCs. Most papers using this dataset exclude non-U.S. investments. However, since our paper is about VC investment strategy, it is important to consider a VC's non-U.S. portfolio.[14]

Our sample period for investments is 1980–2010. We use 1980 as the starting point as it coincides with the growth in venture capital following the 1979 Employee Retirement Income Security Act's (ERISA) "prudent man" rule that allowed pension fund managers to invest up to 10% of their capital in venture funds as an asset class (Gompers, 1994). Prior to 1980 venture capital investments were relatively small.

In order to focus our attention on venture financing and not buyout financing, we decided to restrict the sample to VCs in non-buyout activity. Most VCs are involved in transactions across the venture lifecycle, including buyout transactions. In fact, even if a VC's focus is venture financing, a buyout transaction may be an outcome of the natural progression of an investment made when the venture was in early stages. So, eliminating all VC firms who have been involved in even a single buyout transaction seems inappropriate. Therefore, to circumvent the financing lifecycle issue, we consider a venture's stage of financing when a VC invests in it for the first time. This is based on the plausible assumption that first-time investment in a venture is a truer reflection of a VC's stage preferences. We consider all those VCs who invest at least 75% of their first-time deals in non-buyout rounds. As an additional constraint, we require these VCs to have at least one financing round where their stated stage preference is for non-buyout financing (VentureXpert variable name is "firm_stage_pref"). Finally, we also include in our sample those VCs for whom every investment round shows a non-buyout stated stage preference. This criterion continues to satisfy the 75% non-buyout financing in the first-time investment in a portfolio company.

It is worth pointing out that this sampling method will continue to include VCs who may

[13] Venture capital is often understood as a subset of private equity, though some practitioners only think of private equity as encompassing leveraged buyouts (LBOs) and other buyout-related activity. For our purposes, we use private equity in the broader sense of all investments in non-public firms. However, for robustness, we run all our multivariate specifications excluding funds with an investment preference for buyouts. The results remain qualitatively unchanged.

[14] Our sample is roughly evenly split between U.S. and non-U.S. portfolio companies, at 48% and 52%, respectively. We do not restrict our sample to only U.S.-based firms. We classify any VC firm with at least one fund in the United States as a U.S. VC. Where there are VC firms with missing information on their location, we treat it as non-U.S., the assumption being that such information is more likely to be missing for non-U.S. than U.S. firms. As a result, about 68% of the VCs in our sample are U.S. firms.

have a few rounds of buyout financing rounds. What is certain is that our revised sample of VCs will only include those VCs who are primarily in the venture financing business. We feel comfortable that for a paper that is exploring "drift" in investment styles, allowing for different forms of financing (which could include some buyout rounds) is desirable.

The resulting sample data are structured at three levels. At the coarsest level, the data contain 51,155 unique venture-backed companies for which we collect geographic and industry classification variables. Next, for each company we include financing round levels, which augments the data to 121,419 company-round observations. At the round level, we include the financing date, the company stage in the given round, and the round number. The third and finest level of data accounts for the fact that multiple VC firms and VC funds can participate in a financing round. This augments the data to 250,293 observations.[15] For each company-round-firm/fund financing, we include variables on individual VC firms such as company-round financing amounts, VC firm location, fund investment preferences, fund size, and founding years of the VC firm and VC fund. The final dataset includes 6,904 unique VC firms.

2.3 Identifying venture capital exits

While it is possible for VCs to sell their investments privately (Ibrahim, 2012), in practice they usually realize a return on their investment by (a) taking the company public through an IPO, (b) finding a suitor in the M&A market, or (c) selling to a buyout fund.[16] At that point, the VC is said to have "exited" the company. Since we do not have any information on private sales of VC stakes or fund returns,[17] we follow the literature (e.g., Cochrane (2005), Das et al. (2003)) by restricting our exit definition to IPOs, M&A activity, and buyouts.

While Maats et al. (2008) find the IPO data in VentureXpert to be fairly accurate, the M&A data may be complemented from other sources. Instead of relying entirely on exit data from VentureXpert, we track each VC-backed company in the IPO and mergers and acquisitions databases in SDC Platinum with the help of the "company situation" and "company situation date" variables in VentureXpert which refer to the most recent situation for a given company. We also use the IPO flag and IPO date available in the database. Finding matches is an onerous process complicated by the fact that VentureXpert uses the most recent company name to identify a company while SDC uses the historical name. Nonetheless, we are able to match 2,886 companies that went public and 6,925 companies that were involved in an M&A transaction.

To identify secondary sales (or buyout) exits, we use the VentureXpert company stage variable. Specifically, if a financing round on a given company is marked as a buyout, the round date is used as the exit date for all the previous rounds of financing. We make the

[15]In some rounds, there are multiple observations for the same fund. Consequently, the dataset has 250,324 observations in total.

[16]Also called secondary sales, buyout refers to the sale of a VC's portfolio investment to another fund.

[17]Phalippou and Gottschalg (2009), for instance, point to various biases in funds' self-reporting of the net asset value (NAV), particularly of on-going funds.

simplifying assumption that at that date all VCs that have entered the company's equity structure in previous rounds have exited and been replaced by a new VC that specializes in buyouts. This new buyout VC can exit through an IPO, an M&A, or in some cases through another buyout. This process results in 2,524 buyout exits.[18]

3 Styles and Drift

3.1 Investment styles

Our approach to identifying VC investment styles is analogous to that of the mutual fund literature, based on asset class characteristics. Chan et al. (2002) divide mutual fund investments into as few as four styles, based on market capitalization (large versus small) and the book-to-market ratio (growth versus value). Hedge funds are also found to undertake style-based investments, though the number of styles encompasses a much wider classification—see Dor et al. (2003). Likewise, VC investing styles are more varied. Over our entire sample period, we assign all investment rounds to 20 different styles, arising primarily from combinations of industry and locale of financing (see Table 1).

Our broad initial binary classification of investment styles falls into buyout and non-buyout financing rounds. Within the *buyout* group, the broad categories are U.S. and non-U.S. portfolio firms. Within the *non-buyout* group, the first level of separation is industry with six categories: Biotech, Communications/Media, Computers, Medical, Non-high-tech, and Semiconductors. Within each industry, firms are classified into non-U.S. firms, U.S. firms excluding California and Massachusetts (non-CA/MA), and firms in California and Massachusetts (CA/MA). Besides complementing the "California effect" uncovered in Bengtsson and Ravid (2011), such a broad geographical classification is also necessary to keep the number of styles within reasonable limits. Based on this classification, we create 20 distinct styles.[19] Hochberg and Westerfield (2010) also use geography-industry combination as a measure of specialization in their analysis of ventures. Hochberg et al. (2011) use factor analysis to uncover primary VC characteristics and determine loadings on stage, geography, and industry.

One might argue that it is rare for a VC firm located in the United States and that specializes in the biotech industry to invest in both the European market and the computer industry. In other words, industry and location choice are not decision variables. However, such a conjecture would be misplaced. Sørensen (2008) finds that it is common for funds to make investment decisions across many industries. Our data show that VCs often invest in different regions and industries. For example, Delphi Ventures, founded in 1988, focuses on

[18] It is possible for a portfolio company to go through multiple exits. For example, initial investors in America Online (AOL) exited through a buyout in mid-1985. Subsequently AOL had an IPO in early 1992 allowing its investors from the buyout round to exit. However, an investor from a given financing round can only experience one exit type.

[19] We also conduct a cluster analysis of investment rounds and obtain a similar classification of investment types primarily by industry and geography.

healthcare and has only one office located in Menlo Park, California. However, its investment portfolio has changed from one year to the next both in terms of VentureXpert industry classification and location across U.S. states.[20,21]

3.2 Empirical features of styles

In Table 1, we present descriptive statistics for our 20 styles at the investment round level. We assign a unique style to each of the 121,419 financing rounds, but the same company could appear in multiple styles if it experiences a buyout, which is a distinct style. As a consequence the total number of portfolio companies in Table 1 is 52,894, while the number of unique companies in our sample is 51,155. A VC firm could be invested in multiple styles based on the companies it invests in. As a result, there are 6.904 unique VCs and the total VC firms $\times$ styles is 28,627. Finally, since styles and therefore exits are at the round level, the count of exits exceeds the number of exits at the company level. The largest style is Computer US CA/MA, comprising 17,952 financing rounds, which reflects a Silicon Valley orientation.[22] The least frequent style is Biotech.

Table 1 also reports a VC's age at the time of the round of financing. Age is measured by the VC firm's founding year.[23] VCs investing in the Biotech, Medical, and Semiconductors industries in the United States tend to be older, and those in the Computer industry are

[20] To illustrate the rapid, year to year, changes in location and industry for Delphi Ventures consider the following. In 1994, Delphi Ventures had 4 investments in California, 1 in Pennsylvania, and 1 in Massachusetts. 5 of these investments were in the Medical/Health/Life Science industry, and 1 was in Biotechnology. In 1995, it had 1 investment in California, 1 in Massachusetts, and 1 in North Carolina. 2 investments were in Medical/Health/Life Science and 1 in Computer Related. In 1996, 2 investments were in California, 1 in Massachusetts, 1 in Tennessee, 1 in Ohio, and 1 in Florida. 4 investments were in Medical/Health/Life Science, 1 in Computer Related, and 1 in Non-High-Technology.

[21] We find similar evidence of drift in large and well-known VC firms. For example, Oak Investment Partners was founded in 1978 in Connecticut but now has additional offices in Minneapolis and Palo Alto. Oak Investment Partners made the following investments in 2007: 4 in California, 1 Massachusetts, 2 in Colorado, 1 in Ohio, 2 in New York, and 2 located outside the U.S. 3 investments were in Computer Related, 1 in Communications and Media, 7 in Non-High-Technology, and 1 in Medical/Health/LifeScience. In 2008, 4 investments were in California, 1 in Georgia, 1 in New Mexico, and 2 were located outside the U.S. 2 were in Computer Related, 2 in Communications and Media, 4 in Non-High-Technology. The category, Non-High-Technology, contains a broad variety of investments, including clean energy and payment services. Most of these investments were made out of the Oak Investment Partners XII fund, a $2.5 billion fund raised in 2006.

[22] Both California (CA) and Massachusetts (MA) are large clusters and we find many players have business in both these clusters. So treating them as two different clusters could potentially exaggerate the extent of drift. In addition, it would also greatly increase the number of styles. The challenge is to keep the number of styles within limit and still say something meaningful about drift. Finally, it is common in the literature to combine CA and MA.

[23] Founding year data are rather noisy. In those cases where the same VC firm has multiple dates as its founding year, we use the year of the VC's earliest fund in the sample as the VC firm's founding year. Finally, we recognize some obvious errors in the founding years, where some founding years are as far back as 1803 in the dataset. In fact, about 1% of the firms in our dataset have founding years before 1961. So, to minimize the bias, we truncate all pre-1961 founding years to 1961. Alternatively, we could measure age as of the first investment. Our results are qualitatively similar. The correlation between these alternative age measures is 76%.

younger. Median investment is larger in later stages (such as buyouts) and smaller in non-U.S. transactions. The concentration index, HHI (Herfindahl-Hirschman Index), for stage (or industry) is the sum of the squared share of each stage (or industry) in total number of investments. By definition, stage HHI is at its maximum for styles 1 and 2 which are based on the buyout stage. Among all the 20 styles, there is more dispersed spending by financing stage in the biotech industry in the United States, and hence a lower stage HHI. Industry HHI, based on the invested amount, would be at its maximum for each of the industry specific styles. To make it more interesting, we use a finer partition of 10 industry classes available in VentureXpert to calculate industry HHI. Industry HHI is lower in the non-High-Technology sector, given its catch-all nature.[24]

Over the 1980–2010 sample period, 35,997 (30%) rounds exited out of a total of 121,419 rounds, 8,308 (7%) through IPOs and 21,301 (18%) through M&A transactions. In general, exits are lower for non-U.S. styles, and higher for the CA/MA styles, confirming evidence of the benefits from geographical agglomeration. Using days to exit as a measure of success, we find initial evidence that non-U.S. rounds generally exit sooner, as do buyout rounds since they naturally take place at a later stage in a company's lifecycle. Overall, there is significant variation across styles.

3.3 Drift characteristics

Based on annual style drift averaged across VCs, we show in Figure 1 that there is a substantial variation in style drifts from year to year. In high drift years, the average drift is as much as 10 times that in low drift years. It is possible that drift is a function of new money coming in to a VC fund, so that the initial years drift is higher and declines subsequently, leading to the pattern we see in the first ten years of Figure 1. However, new funds were being set up every year, Hence, the drift down to zero during the first ten years cannot be explained by funds reaching the end of their life. Therefore, we check if this is the case in Table 2, which shows the number of new funds in our data and amounts invested. We examined the pairwise correlation between average annual drift (across VCs) each year and total new funds ($ billion) raised each year. This correlation is -0.002 (not significant even at the 10% level). Also, the correlation between average drift and number of new funds is 0.182 (again, not significant at 10%). If the relationships were mechanical based on the definition of drift, we would expect these correlations to be highly positive and significant, which is not the case. This suggests that the demographic longitudinal shifts in drift over time are not caused by mechanical effects, but instead are the result of economic variation in decisions made by VCs.

Another reason why this concern is ameliorated is that most VC firms raise multiple funds. We undertake drift analysis at the VC firm level which in fact injects smoothing in investments. In any case we have controls in our ensuing multivariate regressions for "New Fund Yr". Hence, were this to be the cause of drift, the drift variable itself would be

[24]For our empirical analysis, we use transformed versions of variables of interest calculated at an annual level.

subjugated by New Fund Yr if they were highly correlated, which we know is not likely to be the case from the results indicated in Table 2.

The distribution of average annual style drift of each VC firm is shown in Figure 2. A number of VC firms, about 607, have no drift as seen in the histogram. These zero-drift VC firms have an average of 2 years of investment data, compared with 6 years for firms with non-zero drift, are half as old (4 years), with only 3 rounds of investment (vs. 16 rounds). There are two mechanical reasons for VC firms having zero-drift. One is that they do not survive long enough to make new investments, and the other is that they are newly created and thus too new to exhibit drift.

In subsequent analyses, we treat zero-drift VC firms differently to ensure that they do not distort the results. In our panel regressions, we consider 5-year rolling windows to moderate the effect of mistiming in reporting data over some years as being the source of zero drift.

4 Determinants of Drift

4.1 VC characteristics

Table 3 shows the descriptive statistics of VCs in our final sample, where we segregate the sample into VC firms with just one fund (either because they are new players or because they failed and did not raise another fund), versus VC firms with more than one fund. A VC invests in 4 styles on average, and this naturally leads to a high concentration among the 20 styles for each VC. The single-fund VCs tend to invest in fewer styles (2.48 on average), whereas the VCs with more funds invest in more styles (7.33 on average).

The average age of VCs in our sample is 9 years, though those with multiple funds tend to be older. On average, 58% of the VCs are independent and 19% are located in the CA/MA geographical cluster. These numbers are lower for single-fund VCs. Given the nature of venture financing, there is not much variation between VCs with single or multiple funds in the proportion of early-stage financing (about 42%). Syndication is a common feature in the VC industry — about two-thirds of the financing is syndicated, and this is similar across the various subsamples, and we control for syndication in all our performance regressions. The mean HHI for style is about 0.57, which denotes a fairly high level of style concentration. Geographical concentration in investments is also high, with an HHI of 0.79.

4.2 Univariate analysis

We next focus on understanding the characteristics of VCs based on their propensity to drift. We perform our analysis at the VC firm-year level. We discard all VC firms that have only one year of investments, since no drift can be computed for such firms. For the remaining firms, we calculate the VC's annual style drift between years $t-1$ and t. We notice from Figure 1 that the average drift level across all firms varies from year to year quite substantially. Hence, to normalize the year-by-year variation in overall drift, we allocate VC firms' drifts into quartiles each year. Keeping those with zero drift in a separate category (called "zero" quartile $Q0$), the remaining VC firm-year observations are distributed into four quartiles. Table 4 shows various VC characteristics within drift quartiles. Note that $Q4$ is the one with highest drift, and $Q1$ has the lowest drift (except zero), the difference being highly significant.

Comparing nonzero drift quartiles, the number of styles the highest drift VCs invest in is weakly statistically different than that of VCs in the bottom quartile (though VCs in the intermediate quartiles did invest in significantly more styles). This suggests that changes in allocation between a given set of styles, and not just changes in the number of styles, drive drift. Thinking about specialization or diversification in terms of number of styles a VC invests in, we see that VCs may drift even without being more diversified, and vice versa, clarifying the distinction between the dynamic concept of drift/persistence and the static construct of diversified/specialized portfolios.

VCs that are less active in terms of number of funds raised, number of companies and rounds invested in, and more active in terms of number of different industries and geographies of portfolio companies tend to drift more. Indeed, one might have expected more rounds to lead to more drift, but this is not the case. Likewise, one may have surmised that VCs with more funds would also drift more, which again, turns out not to be the case.

Table 4 considers dummies for each *time-invariant* VC characteristic, namely the organization form (Independent VC or Financial Institution VC) and location of VC firms (CA/MA or not, U.S./non-U.S.). Evidence points to the role of different ownership forms of VC firms. For instance, Hellmann et al. (2008) show that VC arms of financial institutions (FI VCs) may have systematically different success rates. The proportion of independent VCs in the top drift quartile is lower (61%) than that in the bottom quartile (64%). It is qualitatively no different for FI VCs.

There is also a difference in the proportion of VCs in the top and bottom quartiles based on VC location. The proportion of VCs based in the California and Massachusetts regions (CA/MA) as well as VCs located in the U.S. is lower in the top drift quartiles than in the lower quartiles.

Among *time-varying* VC characteristics, we consider a number of variables. There are many dimensions of VC experience and skill identified in the VC literature as being important (Kaplan and Schoar, 2005; Sørensen, 2007). One proxy for experience is the VC's age at the time of financing, measured as the time between the year of financing and the firm's founding. Age is particularly useful for thinking about a VC firm's lifecycle, and is another reason for looking at the year of founding rather than the VC's entry into VentureXpert. We proxy for VC skill by using the rate at which it is able to take its portfolio companies public (*IPO Rate*).[25] Early stage companies entail unique challenges and investors with prior experience financing those companies are likely to be different in terms of skills. We define *Early Stage Focus* as the proportion of cumulative number of companies that the VC invested in at an early stage prior to the financing round. Syndication is another important feature

[25]For a recent review, see Krishnan and Masulis (2012). We follow their paper in calculating the IPO rate since they find that the number of IPOs in a VC's portfolio over the prior three calendar years relative to the number of companies it actively invested in is a good predictor of portfolio company performance.

of VC activity. It may allow a VC to spread its resources across many companies, thereby facilitating greater drift. We define *Syndication Experience* as the cumulative proportion of syndicated rounds prior to the financing round.

Style HHI is a concentration measure based on the cumulative count of a VC's portfolio companies in different styles prior to the year of financing. This allows us to think about drift separately from how specialized or diversified a VC is in terms of styles. To gauge the pressure of funds as a driver of drift, we calculate *% Funds Invested*, which is the proportion of a VC's active funds invested prior to the financing year. All time-variant variables are calculated as the logarithm of one plus the one-year lagged value of the variables. The final variable, *New Fund Yr*, is a dummy variable that takes the value 1 if the VC raised a new fund in the previous year. This captures differences in VCs' investing decisions when a new fund is raised.

The univariate information in Table 4 shows that higher drift firms are younger, have significantly lower IPO success in the recent past, and have fewer early stage investments. It is possible that younger firms are still in the process of discovering their comparative advantage via a process of drifting, and that the older, more experienced firms have many projects and cannot afford to drift as much given how thinly spread they already are. We also see that high drift firms are more likely to have raised a new fund in the past year and have more uninvested funds, suggesting that the pressure of investing committed funds is an important determinant of VC drift.

VCs with zero-drift tend to be even less active, though more experienced, than VCs in the top quartile. They are also less likely to have a new fund. Despite having more uninvested funds, these VCs are not spurred into drifting. However, zero-drift does not necessarily mean better performance as they exhibit lower IPO success when compared with the highest drifters. This univariate result could be due to the fact that zero-drift firms are not as heavily invested in CA/MA or are more likely to be owned by a financial institution.[26] The tests of difference in means in Table 4 show that zero-drift VCs are significantly different from others.

Overall, those that drift more tend to be younger, more concentrated, have less experience in terms of investments, and have larger amounts of uninvested funds. While these differences between quartiles are statistically significant on a univariate basis, it remains to be seen how well these variables explain drift on a multivariate basis.

4.3 Multivariate analysis

To better understand the drivers of drift, we move to a multivariate setting using panel regressions. The unit of observation is VC firm×year. We regress VC firm drift quartiles based on annual drift (keeping zero-drift observations as a separate category) on a number of VC firm characteristics. Results are shown in Table 5.

The first regression is a pooled OLS specification with VC age and time-invariant firm

[26] We also compared characteristics of single-fund VCs with those having multiple funds. The aforementioned drift quartile properties do not seem to differ across the two categories.

characteristics, namely VC ownership and VC location. We find some evidence that particular types of VCs, based on ownership, drift more – coefficients on independent VCs and U.S. VCs are positive and highly significant. Whether the VC is in CA/MA or a FI VC does not seem to influence drift.

While specification (1) controls for some key observable characteristics, there may be omitted unobservable factors that would bias our results. It is possible that the VC firm's high levels of intrinsic skill affects both its IPO success and its decision to drift. Alternatively, market conditions in a given year could lead to more or less drift. To address these concerns of omitted variable bias, all the remaining specifications in Table 5 include firm fixed effects. Therefore, we no longer include time-invariant firm characteristics (i.e., firm location and ownership variables). Our identification relies on within-firm variation in VC characteristics. In specifications (3) - (7), we also include year fixed effects. Additionally, we use one-year lagged values of variables to ameliorate concerns about reverse causality. Column (7) shows the full specification.

Across all specifications in Table 5, we find that seasoned VC firms drift less. It suggests interesting life cycle dynamics at play. With little or no style-specific expertise initially, VC firms drift in their early years. But as they mature over time and acquire skills specific to their set of styles, they have less incentive to drift. Seasoned VCs are unable to exploit these benefits if they drift into other styles. They are therefore more careful since they have more to lose at the margin. Our result is consistent with the economies of persistence hypothesis rather than the economies of styles hypothesis. As in Sørensen (2008), VC firms learn by investing, and complementary to the analysis in that paper where VC firms learn about their portfolio companies, our results suggest that VCs also learn about their own skills and preferences.

Firms with more experience in early stage investment (*Early Stage Focus*) drift less. Early stage investing is risky, and requires more attention and a unique skill set. This leads VCs to have greater style persistence and drift less. However, the extent of a VC's syndication does not appear to influence drift. Finally, one might assume that well-diversified firms with investments in many styles might experience less drift because they would tend to stay with a diversified pool of investments. We do not find evidence to support this. In fact, in the full specification (7), *Style HHI* has a negative coefficient and is significant at the 10% level, i.e., firms that are less diversified drift less or alternatively, firms that are well diversified drift more, though these are consistent with the univariate results.

In specifications (4) and (5), we separately include proxies for the VC's pressure to invest if it has uninvested funds and for the nascency of the VC fund. We find that a recently raised fund or a greater proportion of uninvested funds spurs VC firms to drift more.[27] The result is consistent with the pressure of investing, given the unique structure of VC funds with a typical fixed fund life of 10 years and the long duration to exit from these investments.[28]

[27]We also note that since VC firms have overlapping funds there may be many such events where invested funds increase with the creation of a new fund within any 10-year window.

[28]It is possible that the 10-year fund life rule is not as binding as it sounds. Fund life can be extended by mutual limited partner-general partner agreement. However, reputation concerns would still weigh in on

These results continue to hold in the full specification. The other control variables continue to have the same sign and statistical significance even after controlling for new funds and size of uninvested funds.

4.3.1 Herding

In specification (6) of Table 5, we introduce another variable, *Herding*, which measures the lagged correlation between a VC's style and the average style proportions across all VC firms over the previous five years. To construct this metric, we first compute the average (value-weighted) style proportion vector (denoted $P_{0,t}$) for each year taken across the entire sample. (Note that we use the subscript $j = 0$ for the average value across the sample.) This is a vector of dimension 20, which is the number of styles in this paper. We then stack these vectors for five consecutive years to obtain a style vector of 100 values, denoted $P_{0,t,t+4}$. We do the same for each VC firm over a five-year period, resulting in a 100-component vector analogous to that of the average VC style vector, i.e., $P_{j,t...t+4}$. Then, for each VC firm j we regress the individual five-year style vector on the average style vector:

$$P_{j,t,t+4} = a + b \cdot P_{0,t,t+4} + \epsilon_{j,t,t+4}$$

The coefficient b is our measure of *Herding*, which is the extent of correlation between a VC's portfolio and that of the average VC firm. For subsequent tests on VC performance, we bifurcate VCs into two types based on b. If $b > 0$ in year t, then we label firm j as a *herder*, and a *contrarian* otherwise.

While VCs that herd or follow the broad trends of investment would seem more likely to drift, specification (6) shows that herding does not seem to influence drift. Finally, specification (7) shows the full model including the herding variable. All results still hold. In particular, we continue to find that older VCs drift less.

Table 6 drills down further into the propensity of VCs to drift based on their years since founding (*VC Age*). Regressing drift on subsets of the sample by age shows that VCs who focus on early stage investments and have less invested funds will drift more. This confirms the results from Table 5 within age strata. We define variable *Seasoned (Young)* VCs as those with at least (less than) 11 years of experience.[29] We find that among the *Young VCs*, more experienced VCs drift less, and this effect is driven by VCs who have more than 7 years experience. Also within each strata, *New Fund Yr* is not significant, suggesting that the creation of a new fund is not a reason for VC firms to drift more, once experience is controlled for.

Overall, we find evidence that a firm's life cycle and the pressure to invest funds, even after controlling for a new fund raised in the previous year, are important drivers of VC drift in investment decisions. The pressures of early stage investments are a deterrent to drifting. These results hold even after we control for year and time-invariant firm-specific factors in all our specifications.

general partners who have uninvested funds.

[29] 11 years is the age of a median firm in our regression sample.

5 Consequences of Drift

We examine the implications of VC drift for investment performance. We follow the literature and define success as exit via an IPO, merger, or buyout. We consider two alternative measures of success - the speed of exit and the likelihood of exit. We provide descriptive statistics on exits in Section 5.1. In Section 5.2, we show results of multivariate analyses and a number of robustness checks. Section 5.3 explores VC heterogeneity to assess underlying bases for the relation between drift and performance. In Section 5.4, we consider and address alternative explanations for our results.

5.1 Univariate analysis

Table 7 reports information on the number of days between the investment round and exit date by drift quartile. The analysis is at the VC firm×round level, which is our unit for performance analysis. Considering all exit types (IPO, M&A, and buyouts) together, VCs in higher drift quartiles take longer to exit on average (though the *median* days for the top and bottom quartiles are the reverse). Those in the bottom quartile (Quartile 1, with the lowest drift, leaving the zero-drift category aside) exit in 1268 days compared with 1353 days for those in the highest quartile, a difference of about three months and statistically significant at the 1% level. In Table 8 we find similar trends among different subsets of VCs, namely seasoned and young VCs, and herder and contrarian VCs. However, the difference in exit days between the top and bottom drift quartiles is statistically significant only for seasoned VCs and herder VCs. Thus, drift adversely affects seasoned VCs more than young VCs and herders more than contrarians.

5.2 Multivariate analysis

We examine the relation between drift and investment performance in a multivariate setting to control for other characteristics and factors that may affect exit performance. We consider two alternative models for performance: a Cox proportional hazards model for time to exit and probit for likelihood of exit. The estimations take the following form:

$$Y_{ij} = \alpha_1 \; Lagged\ Drift\ Qtle_i + \alpha_2 X_i + \alpha_3 X_j + \phi_t + \theta_s + \epsilon_{ij} \tag{3}$$

The unit of observation is VC firm×round level. So we analyze the performance implications of all investment rounds in each VC's portfolio. The dependent variable, Y_{ij}, is the outcome of investment j in VC_i's portfolio. All our specifications have year fixed effects, ϕ_t, to control for differences in macroeconomic conditions across periods. It is possible that some styles may affect both drift and performance. For instance, certain styles are more amenable to early-stage investment (e.g., style # 10, Computer U.S. CA/MA), which affects the propensity to drift as well as performance. To address this omitted variable bias, we also include fixed effects, θ_s for each style, s, and in these specifications, we do not include separate controls for the portfolio company's geography and industry.

The main variable of interest is the annual variable *Lagged Drift Qtle*, which is VC_i's quartile based on five-year rolling average annual style drifts, lagged by one year. As before, there is a separate category for VCs with zero drift. We rely on the literature to motivate the controls for VC- and round-level characteristics, X_i and X_j. We include a dummy for whether the round is an early-stage round; given their inherent risky nature, we expect worse performance for early-stage financing rounds. The literature has shown a positive effect of syndication on performance, so we include a dummy for whether a round is syndicated or not. As before, we include controls for time-invariant VC characteristics, namely ownership structure and geographical location. Finally, to focus on style drift as a source of skill and driver of performance, we control for alternative sources of reputation and ability identified in the literature, namely *VC Age*, *IPO Rate*, and *Early Stage Focus*. VC networks that arise through syndication links affect VC performance (Hochberg et al. (2007)). We therefore include *Synd Experience* to capture the potential benefits from a VC's past syndication experience. We also control for *Style HHI* which is used to measure the concentration of a VC in a few sectors and is a measure of specialization that has been shown to explain returns (Gompers et al., 2009). All time-varying variables are lagged by one year. The standard errors are clustered at the portfolio company level to account for the same portfolio company receiving multiple financing rounds.

5.2.1 Speed of exit

The first three specifications in Table 9 present the results of a Cox proportional hazards model to assess how drift affects a VC's performance, measured by the speed of exit. A key advantage of the Cox model is that it addresses censoring issues. VC investments may take between three and five years to mature and exit. Because some investments may not have had sufficient time to mature, using the Cox model allows us to include all investment data. We report the results in the form of the exponential hazards ratio. Coefficient values greater than one indicate an acceleration of exit, and less than one indicate a deceleration.

Across all three specifications, the hazard ratio for drift is less than one and statistically significant at the 1% level. Thus, greater drift is associated with slower exit. Among the controls in specifications (2) and (3), round-level variables are statistically significant. Syndicated rounds exit appreciably sooner, and early stage deals take longer to exit. Independent VCs exit their portfolio companies faster, as do financial institution VCs. VCs with an early stage focus exit slower. VCs benefit from syndication experience as well as their location in the CA/MA clusters and exit faster from their portfolio companies. Neither *Style HHI* nor *IPO Rate* is statistically significant in the final specification (3). Hence, after controlling for known performance drivers and other covariates, including year and style fixed effects, higher style drift continues to be associated with poorer exit speed of a VC firm's portfolio companies. In the full specification (3), an increase in VC's drift by one quartile decreases the hazard of exit by about 2 percent.

5.2.2 Likelihood of exit

To provide further evidence on how drift affects performance, specifications (4) - (6) in Table 9 provide probit estimates that model the probability of successful exit within 10 years of the investment round. Coefficients in the probit are reported as signed values, i.e., positive values imply that the variable increases the likelihood of successful exit whereas negative values signify declines in the probability of exit. All the results of our full sample probit are similar to the Cox results in terms of sign and significance. In addition, greater reputation and skill with taking firms public (*IPO Rate*) enhances performance through a greater likelihood of exit. After all controls, style drift reduces the success probability for a VC's portfolio companies.

5.3 VC heterogeneity and performance

We next examine possible channels through which drift influences investment performance. While drift is associated with poorer performance, we also ask whether drift has differential performance effects by VC type. We consider the implications of age of each investment in the VC's portfolio prior to drift ("recent" or "older" investment), VC firm life cycle (young VC or seasoned VC), and extent of correlated investments among VCs (herder or contrarian VC).

5.3.1 Drift impacts recent investments more

Not all investments are identical, therefore the implications of drift may vary across the portfolio. Recent investments in the pre-drift portfolio would likely benefit more from a VC's attention, skills, and expertise compared with investments that have been in the portfolio for a longer period of time. Therefore, under the economies of persistence hypothesis, one would expect more recent investments to exhibit poorer performance when a VC drifts.

In Table 10 we present Cox specifications (1) and (2) for the speed of exit for an existing investment in period $t-1$. The specifications, in terms of the control variables, are similar to those used in Table 9, but instead of using the average drift over five years, we use one- and three-year drift to ensure that some investments are recent. Besides the VC's drift quartile, we include the investment's age in the portfolio as of period $t-1$ from the VC's year of first investment in the portfolio company. Specification (1) uses VC's drift quartile in period t while specification (2) considers the VC's drift quartile based on the average drift over period t to $t+2$. The key variable of interest is the interaction term between drift and portfolio company's age, which is positive and statistically significant. We get analogous but weaker results in the probit specifications (3) and (4) for the likelihood of exit. Drift adversely affects more recent investments in the VC's portfolio, which is in line with the economies of persistence (or equivalently, diseconomies from lack of persistence) hypothesis.

5.3.2 Young versus seasoned VCs, and a rational response to aging

Table 5 presented evidence that seasoned firms are less likely to drift than younger VC firms. This is a rational response by VCs as they age—the economies-of-persistence hypothesis suggests that older VCs may exhibit worse performance if drift steers them away from style-specific skills acquired through the initial years of experimentation. However, younger VCs with fewer style-specific skills drift more and have less to lose, with minimal impact on their performance from drift.

Table 11 reports results for Cox and probit specifications based on analogous specifications ((3) and (6), respectively) in Table 9. Each specification is estimated separately for young and seasoned VCs. We see that drift is a significantly adverse characteristic for seasoned VCs, whereas it is not so for younger VCs.[30] Conditional on surviving the initial life cycle years of drifting, and therefore acquiring specific skills, drifting becomes detrimental.

5.3.3 Herders versus contrarians, it is better to drift different

Investors drift toward popular investment styles in herds. Herder VCs, by definition, underweight their own information and overweight that of others; they will drift in a different way than will contrarian VCs. We examine which type of "drifter" underperforms. We split the sample into contrarians (specifications (3) and (7) in Table 11) and herders (specifications (4) and (8)).[31] For contrarians, drift is associated with significantly faster exit (weakly so for the likelihood of exit). In contrast, the effect of drift on performance is negative and significant for herders, i.e., the more they drift, the more adverse is the speed of exit and the less likely their exit as well.

5.4 Robustness testing

5.4.1 Past performance, reverse causality

VCs experiencing poor investment performance may choose drift as an antidote. Despite including lagged drift in all our specifications, to rule out reverse causality, we perform a Granger causality test. We run two regressions, one each for VC performance and drift at time t, on lagged values of VC performance and drift. Given that we are considering lagged performance values, we can no longer use the outcome of a specific financing round as the performance measure; instead, we do this analysis at the firm-year level. We measure a VC firm's performance at time t as the ratio of the cumulative number of IPOs to the number of cumulative investments as of time t. Drift is measured in quartiles with a separate bucket for zero drift as before.

[30]That drift adversely affects seasoned VCs is evidence that small and marginal VCs are not driving our results. We separately run all our specifications based only on VCs with investment in at least five unique companies. All our results hold.

[31]As explained before, we define herders (contrarians) as those whose portfolio style composition has a positive (nonpositive) correlation with that of the average VC firm. We winsorize the variable at the 1% level, but our results hold even without this modification.

Table 12, specifications (1) and (2) show the results from the performance and drift regressions, respectively. We include all covariates seen in the full specification (3) in Table 9 except for time-invariant VC characteristics since we include VC fixed effects in our specifications here. We find that while the coefficient on lagged drift in the performance regression (1) is negative and statistically significant at the 5% level, the coefficient on lagged performance in the drift regression (2) is not statistically significant. Therefore, performance is Granger caused by lagged drift, but drift is not caused by past performance. This result ameliorates concerns about reverse causality in our performance regressions.

5.4.2 Unobservable and time-invariant firm-specific factors

One concern with our performance analysis is that it may not capture many firm-specific factors, such as VC ability, that could affect firm performance. Low ability VCs may inherently lack focus and drift from one set of styles to another after experiencing poor performance, and also, by virtue of low ability, will have worse performance. We have considered a number of proxies for firm-specific ability or skill or reputation, through variables such as VC age and IPO rate. Nevertheless, to the extent that there are time-invariant unobservable VC characteristics, we use a first difference approach to address this concern. Based on the firm-year measure of performance, our test (unreported here) shows that changes in drift have a significant impact on firm performance. Low drift firms that increase drift are associated with lower performance. While first difference analysis has its limitations, it serves as another check on the validity of our results.

5.4.3 Matched sample tests

For robustness, we compare the performance of high drift firms (the treatment group) with that of a matched sample of low drift firms (the control group). High (low) drift VCs are those whose lagged five-year drift is above (below) the median for the year. We use the coarsened exact matching (CEM) method to construct the matched control and treatment groups.[32] The advantage of this matching method is that it allows users to choose the balance between treated and control groups based on covariates before the treatment rather than after the fact through the usual process of checking and rechecking and repeatedly re-estimating under alternative matching methods such as propensity score.[33] We match high drift VCs (treatment group) and low drift VCs (control group) each year, ignoring zero drift VC firms, along the following pre-treatment covariates: age at time $t-1$, VC's geographic location

[32]Recent examples of papers that use this methodology include Azoulay et al. (2010) and Aggarwal and Hsu (2013).

[33]See King et al. (2011) for a discussion on CEM and a comparative analysis of alternative matching procedures, including the commonly used propensity score matching. Unlike propensity score estimation, we do not match precisely on covariates. Instead, CEM is a nonparametric procedure that coarsens the joint distribution of the covariates into a finite number of strata. We choose a match for the treated observation if the control observation lies in this strata. Then the "exact matching" algorithm is applied to the coarsened data to determine the matches. Finally, the coarsened data are discarded while the original (uncoarsened) values of the matched data are used.

(U.S. or non-U.S., CA/MA cluster or not), ownership form (FI, independent, or others), early stage focus, syndication experience, past performance in the form of IPO exits, and Style HHI. While we match the VCs exactly on their geographic location, we coarsen the distribution of age and the remaining continuous variables into quartiles.

Table 12 presents the results of the Cox proportional hazards model in specification (3). Adding the variables despite the matching procedure allows us to control for any remaining imbalance. The specification compares average differences across firms that are quite similar except for the drift dimension.The key variable of interest is *Treated*, which takes the value of 1(0) for the treatment (control) group. The coefficient is less than one and is statistically significant. So, our main result continues to hold: higher drift is associated with slower exit.

5.4.4 Multiple financing rounds

Our analysis uses all financing rounds of a portfolio company. One concern with such an analysis may be that VCs that invest in early stages of a portfolio firm's life cycle may have less discretion in the decision to invest in subsequent rounds and stages of financing of the portfolio firm, and it is possible that these less-discretionary investments are driving drift in our data. New investments are the key markers of a conscious drift decision while follow-on investments may be less discretionary. Alternatively, multiple rounds of financing of the same company is a likely sign of good performance and would also imply low drift. So the negative relation between drift and performance may be purely mechanical. Along the same lines, similar-styled follow-on investments are also more likely when the firm is successful, leading to a possible positive correlation between performance and lower drift, though Bergemann et al. (2009) show that more rounds tend to occur when the investments are more risky and have lower probability of exit. To ameliorate these concerns, we restrict the sample to each VC fund's first investment in a portfolio company. Results are shown in specification (4) of Table 12. As before, we see that the speed of exit declines significantly as drift increases, controlling for other variables.

6 Discussion and Conclusions

As financial intermediaries, VCs offer a unique channeling of investable funds into diverse investments, and their asset allocation strategies are of growing interest. This paper examines the dynamics of VC portfolios, by studying investment style drift, an area that has been extensively analyzed for financial intermediaries such as mutual funds and hedge funds, but has not received much attention in the VC literature.

We defined a drift metric that is easy to compute and has three useful properties: size invariance, sequence invariance, and time consistency. A VC firm that drifts trades off the benefits of persistence from staying with the same set of investment styles for possible gains from opportunistically moving to new investment styles. In other words, we assess whether VC firms are able to time the private equity market. Our results suggest no such ability, thereby advocating style-persistence.

Performance implications of style drift vary by VC type. VCs drift more early in their life cycles. However, seasoned VCs rather than young VCs tend to suffer greater declines in performance when they drift more. Interestingly, style drift is negatively related to performance for VCs who herd (i.e., whose style proportions are positively correlated with the average VC firm), but not for VCs who are contrarians. From a portfolio composition viewpoint, more recent investments suffer more than older ones when VCs drift. Our results are consistent after the application of several robustness tests.

Our results both complement and contrast the literature on the drivers of VC performance. Prior literature has identified skill (Kaplan and Schoar, 2005), the degree of investment specialization (Gompers et al., 2009), contract type (Caselli et al., 2013), and syndication and VC networks (Hochberg et al., 2007; Das et al., 2011) as important determinants of VC performance. We control for these variables, and find that style drift has significant effects on performance. Further, we make a sharp distinction between specialization and style persistence and find that persistence pays off more than opportunism. Specifically, we find that specialized firms tend to drift less (i.e., have greater style persistence) and this pays off for younger VCs but not for seasoned ones, a nuance on the specialization result in the extant literature (Gompers et al., 2009; Cressy et al., 2007).

Our research opens up the possibility for many extensions. Whereas we find that style drift has deleterious results on performance on average, it may well be that specific forms of drift may be advantageous. For instance, a firm that is a first mover into a style may reap gains from early entry. Do such style leaders who drift early perform better, and do the followers perform relatively worse? What types of VCs tend to be leaders? Is there persistence of returns in a style? When does a style become "hot" and what is the lifecycle of such styles? Can we develop style-based benchmarks to evaluate the performance of VC funds and firms, as is done for hedge funds (see Jagannathan et al., 2010)? We leave these questions for future research.

Appendix

A Style Drift Examples

We present some examples that illustrate and provide intuition for the various approaches that might be taken in determining style drift, and thereby explain why the approach selected in the paper is preferred.

We begin by examining why cumulative investments are better than simply accounting for the actual investment in each year. This is best understood by assuming a simple setting with just two hypothetical VC styles, and a total investment of 100 across two years. There are three options that might be pursued. One, style vectors comprise the actual investment made each year. Two, style vectors comprise the proportions invested in each style each year. Three, our chosen one, implements style vectors as the proportions of cumulative investments made by a fund in each year. In order to set ideas, assume that two VC funds make the following investments (a total amount of 50 across years) in each of two years:

	VC Fund 1	
	Style 1	Style 2
Year 1	48	1
Year 2	0	1

	VC Fund 2	
	Style 1	Style 2
Year 1	29	1
Year 2	1	19

If we treat these templates as the style vectors in each year and compute style drifts $d_{jt} \in (0, 1)$ using equation (1) in Section 2.1, we get the style drift of VC Fund 1 as $d_{12} = 0.9792$, and that of Fund 2 as $d_{22} = 0.9131$. Common sense dictates that Fund 2 changes its policy more than Fund 1, yet the drift measure is higher for Fund 1. Moreover, the measure is impacted by the size and not the proportion of investments.

What if the metric for drift is modified to be computed from the style proportions rather than the absolute investment amounts? The new tables appear as follows:

	VC Fund 1	
	Style 1	Style 2
Year 1	48/49	1/49
Year 2	0	1

	VC Fund 2	
	Style 1	Style 2
Year 1	29/30	1/30
Year 2	1/20	19/20

We get the style drift of VC Fund 1 as $d_{12} = 0.9792$, and that of Fund 2 as $d_{22} = 0.9131$. Therefore, we see that using absolute dollar amounts or proportions does not change the results, Fund 2 has a lower style drift, even though it experiences a bigger reallocation of its portfolio weights across the two styles.

A final approach is to use cumulative proportions instead. We adopt this approach for this paper. The table is as follows:

	VC Fund 1	
	Style 1	Style 2
Year 1	48/49	1/49
Year 2	48/50	2/50

	VC Fund 2	
	Style 1	Style 2
Year 1	29/30	1/30
Year 2	30/50	20/50

We get the style drift of VC Fund 1 as $d_{12} = 0.0002$, and that of Fund 2 as $d_{22} = 0.1493$. Here we see that Fund 2 now has a greater style drift than Fund 1, as intuitively desired. The drift of the portfolio is minimal as expected in the case of Fund 1 and it is reasonable as in the case of Fund 2.

We now examine a few more tableaus to gain an understanding of more complicated cases. Consider the following two VC funds with five years of absolute value investments.

	VC Fund 1	
	Style 1	Style 2
Year 1	98	0
Year 2	0	1
Year 3	0	0
Year 4	0	0
Year 5	0	1

	VC Fund 2	
	Style 1	Style 2
Year 1	98	0
Year 2	0	0
Year 3	0	1
Year 4	0	0
Year 5	0	1

We see here that the sequence of financing differs. Converting these investments into cumulative proportions and computing their drifts results in the following tables:

	VC Fund 1		
	Style 1	Style 2	Drift
Year 1	1	0	–
Year 2	98/99	1/99	5.206×10^{-5}
Year 3	98/99	1/99	0
Year 4	98/99	1/99	0
Year 5	0.98	0.02	5.204×10^{-5}

	VC Fund 2		
	Style 1	Style 2	Drift
Year 1	1	0	–
Year 2	1	0	0
Year 3	98/99	1/99	5.206×10^{-5}
Year 4	98/99	1/99	0
Year 5	0.98	0.02	5.204×10^{-5}

Hence, the average drift for both funds across these years is the same, as it should be. What if the rate at which investments are made differs? Take as an example investments in the following two funds:

	VC Fund 1	
	Style 1	Style 2
Year 1	90	1
Year 2	0	2
Year 3	0	2
Year 4	5	0

	VC Fund 2	
	Style 1	Style 2
Year 1	90	1
Year 2	0	0
Year 3	0	0
Year 4	0	2
Year 5	0	0
Year 6	0	0
Year 7	0	2
Year 8	5	0

Without detailed calculations, we can see that the average drift of Fund 2 will be smaller than that of Fund 1 because it has years of zero drift that are more numerous than in the case of Fund 1. Clearly the speed at which investments are made will be related to the drift, again, as is intuitively desired.

In our model implementation we assume that funds live for 10 years on average, and the example above will result in an aggregate cumulative funding at the VC firm level across both Fund 1 and Fund 2 as follows:

	VC Firm	
	Style 1	Style 2
Year 1	180	2
Year 2	180	3
Year 3	180	5
Year 4	185	8
Year 5	185	8
Year 6	185	8
Year 7	185	10
Year 8	190	10
Year 9	190	10
Year 10	190	10

The style drift is then computed for all 10 years off the aggregate proportion values. In the case when the two funds begin in different years, then the aggregate cumulative proportions will extend up to 10 years from the inception of the last fund to start.

B Variable Definitions

Variable	Description
Time-varying VC characteristics	
Drift	VC's annual drift
5-year Drift Qtle	VC's drift quartile, using annual drift averaged over five-year window, with zero-drift VCs in a separate category.
3-year Drift Qtle	VC's drift quartile, using annual drift averaged over three-year window, with zero-drift VCs in a separate category.
VC Age	Natural log of one plus the VC's one-year lagged age, in years, where age is from its founding until the year of the financing round.
Synd Experience	Natural log of one plus proportion of cumulative rounds that the VC has syndicated as of the year prior to the financing round.
Early Stage Focus	Natural log of one plus the proportion of the VC's cumulative companies that received early stage financing, as of the year prior to the financing round.
IPO Rate	Natural log of one plus the VC's ratio of IPOs to number of portfolio companies in the last three years, as of the year prior to the financing round.
Style HHI	Natural log of one plus the VC's style HHI, based on the number of investments in different styles as of the year prior to the financing round.
New Fund Yr	Equals 1.0 if VC raised a new fund in the prior year.
% Funds Invested	Natural log of one plus the proportion of VC's all active funds invested cumulatively as of the year prior to the financing round.
Seasoned (Young) VC	Equals 1.0 if VC's age is at least (less than) 11 years (0 otherwise).
Herder (Contrarian)	Equals 1.0 VC firm whose style drift vector is positively (negatively) correlated with the average style drift vector across VCs (0 otherwise).
VC AUM	Natural log of one plus the sum of the VC's all active funds under management in the prior year.
Early Stage (Dummy)	Equals 1.0 if the round is an early or seed stage financing and zero otherwise.
Syndication (Dummy)	Equals 1.0 if the round is syndicated, zero otherwise.
Portfolio Age	number of years the company has been in the VC's portfolio.
Time-invariant VC characteristics	
Independent VC	Equals 1.0 is the VC is an independent VC.
Fin Inst VC	Equals 1.0 is the VC is a financial institution VC.
VC Firm U.S./non-U.S.	Equals 1.0 if the VC is in the USA.
VC Firm CA/MA	Equals 1.0 if the VC is in the state of CA or MA.

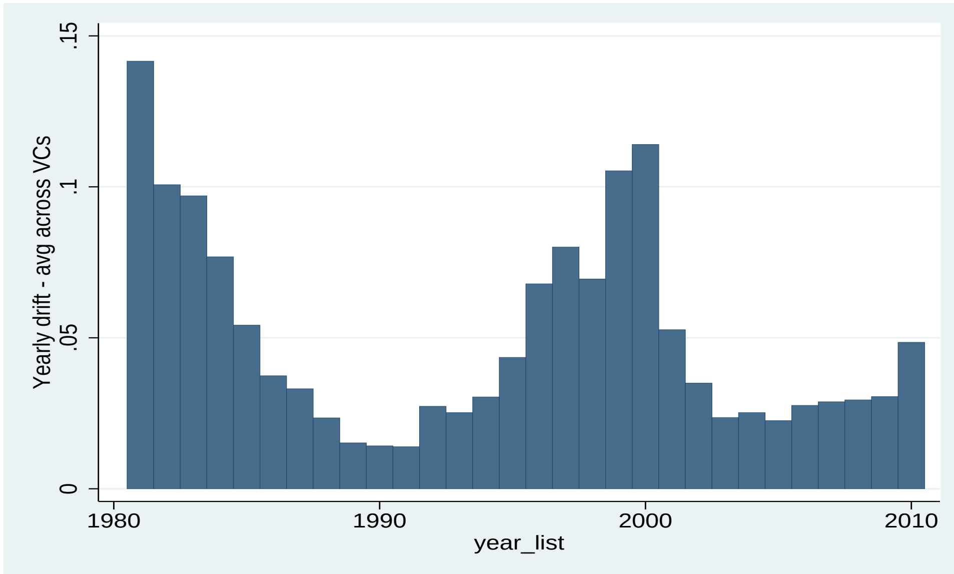

Figure 1: Style drift for each year. The year's style drift is equal to the equally-weighted average of style drifts of each VC for the year.

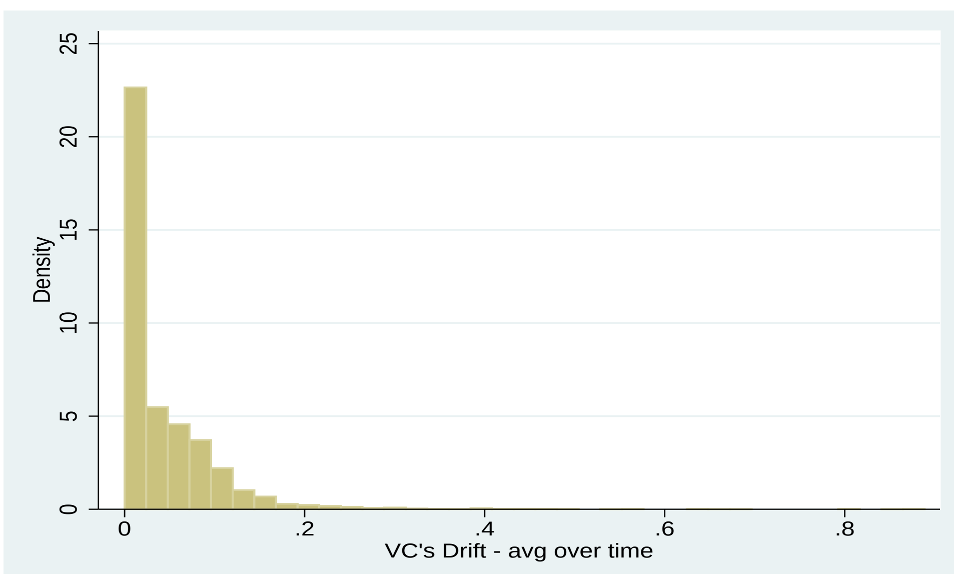

Figure 2: Distribution of style drifts across VCs. The VC's style drift is equal to the equally-weighted average of style drifts of each VC across all years.

Table 1: Descriptive statistics for venture styles. Where not stated in the column heading, the number represents a mean value. The data sample period is 1980–2010. *Rounds with Exits* include exits through IPO, M&A, or Buyouts. HHI is the Herfindahl-Hirschman Index of the sum of squared investment shares.

		#VC	VC	Unique	#Port	Inv $mm		Indus	Stage	Rounds	IPO	M&A	Days to Exit	
Style	Description	Firms	Age	Rounds	Cos	Mean	Mdn	HHI	HHI	w/Exits	Exits	Exits	Mean	Mdn
1	Buyout-nonU.S.	978	13.02	2500	2228	48.92	5.56	0.19	1.00	795	53	320	552	234
2	Buyout-U.S.	1223	15.94	3505	2722	50.81	10.82	0.14	1.00	1833	188	614	938	444
3	Biotech - nonU.S.	956	12.45	3157	1401	10.32	3.39	1.00	0.27	550	211	247	1389	1180
4	Biotech - U.S. CA/MA	941	15.58	3326	815	23.07	12.37	1.00	0.21	1303	611	595	1390	1120
5	Biotech - U.S. non CA/MA	936	15.62	2971	903	13.88	5.93	1.00	0.21	913	382	477	1419	1112
6	Comm/media - nonU.S.	1453	11.13	4594	2565	11.09	3.23	0.60	0.32	713	193	346	1212	1006
7	Comm/Media - U.S. CA/MA	1647	13.59	6374	1825	20.47	11.00	0.59	0.24	2743	619	1900	1377	1034
8	Comm/Media - U.S. non CA/MA	1659	13.38	5420	1920	27.37	8.00	0.55	0.26	2049	461	1219	1347	1050
9	Computer - nonU.S.	2170	10.47	11283	6565	6.61	2.50	0.39	0.33	1653	361	895	1291	1068
10	Computer - U.S. CA/MA	2621	12.27	17952	5669	14.24	8.12	0.41	0.25	7056	1331	4984	1414	1067
11	Computer - U.S. non CA/MA	2579	12.17	15345	5540	11.15	5.67	0.41	0.25	5290	766	3690	1455	1120
12	Medical - nonU.S.	983	12.75	3155	1614	8.73	2.81	1.00	0.27	546	201	225	1323	1110
13	Medical - U.S. CA/MA	1100	15.54	4867	1279	17.55	9.30	1.00	0.21	1829	577	1109	1579	1271
14	Medical - U.S. non CA/MA	1265	14.99	5454	1738	13.35	5.37	1.00	0.22	1880	552	1039	1598	1270
15	non High Tech - nonU.S.	1844	10.69	9944	7207	11.21	1.55	0.39	0.33	863	310	230	1238	924
16	non High Tech - U.S. CA/MA	1294	14.57	4362	1660	15.05	4.84	0.35	0.24	1035	265	569	1757	1257
17	non High Tech - U.S. non CA/MA	1645	13.75	7553	3638	11.54	3.00	0.36	0.24	1938	417	1055	1802	1285
18	Semiconductors - nonU.S.	1044	12.33	3210	1746	9.01	2.43	1.00	0.31	493	154	221	1444	1187
19	Semiconductors - U.S. CA/MA	1284	14.93	4040	1108	18.26	9.82	1.00	0.24	1666	455	1037	1628	1314
20	Semiconductors - U.S. non CA/MA	1005	15.83	2407	751	14.73	6.27	1.00	0.23	849	201	529	1607	1281
	TOTAL	28627	13.21	121419	52894	15.29	5.50	0.60	0.28	35997	8308	21301	1417	1071

Table 2: Annual Drift and New Funds. This table shows the average annual drift across VCs from year $t-1$ to t (column 1), the number of new funds closed (column 2) and amount of new funds raised, in \$ billion (column 3), in year $t-1$.

Year	Avg Drift (1)	# New Funds (2)	$ New Funds (Billion) (3)
1981	0.142	88	0.90
1982	0.101	157	1.60
1983	0.097	195	2.57
1984	0.077	277	3.22
1985	0.054	264	4.01
1986	0.037	196	3.10
1987	0.033	155	2.82
1988	0.023	111	2.92
1989	0.015	95	5.20
1990	0.014	106	3.94
1991	0.014	56	2.17
1992	0.027	47	2.10
1993	0.025	81	5.60
1994	0.030	103	4.05
1995	0.044	130	6.58
1996	0.068	252	9.23
1997	0.080	263	12.71
1998	0.069	402	20.31
1999	0.105	446	28.64
2000	0.114	929	64.00
2001	0.053	1479	112.04
2002	0.035	663	65.30
2003	0.024	411	18.14
2004	0.025	255	15.14
2005	0.023	335	30.11
2006	0.028	351	38.38
2007	0.029	391	52.58
2008	0.029	443	52.38
2009	0.031	337	43.72
2010	0.049	235	17.26
Correlation with Avg Drift		0.182	−0.002

Table 3: Sample statistics - VC firm and VC fund. This table provides mean (median) and standard deviation of characteristics of VC firms (separately for single fund and multiple fund VCs) and VC funds. VC Age is the difference between its founding year and year of last investment. Indept VC (VC Firm CA/MA) is a dummy which takes value 1 if the VC is independent (VC firm is located in CA/MA). Early Stage Cos is the proportion of VC portfolio companies that received investment in the early stage. Synd Rds is the proportion of rounds that were syndicated. Style HHI, invt amt (# cos) is the concentration of amount invested (number of portfolio companies) by style. Indus (Geog) HHI is the concentration of number of portfolio companies by industry (geography).

	All VCs (N=6904)		VCs with fund=1 (N=4535)		VCs with fund>1 (N=2369)		VC funds (N=13653)	
	Mean (Median)	Std. Dev	Mean (Median)	Std. Dev	Mean (Median)	Std. Dev	Mean (Median)	Std. Dev
# Styles	4.15 (3.00)	3.69	2.48 (2.00)	2.09	7.33 (7.00)	3.98	3.90 (3.00)	3.12
Styles/yr	1.87 (1.40)	1.30	1.37 (1.00)	0.65	2.82 (2.43)	1.64	1.84 (1.50)	1.11
# Industries	2.72 (2.00)	1.69	1.98 (2.00)	1.26	4.12 (4.00)	1.50	2.69 (2.00)	1.58
# Portfolio Geog	1.67 (1.00)	0.77	1.38 (1.00)	0.61	2.21 (2.00)	0.75	1.65 (1.00)	0.73
# Funds	1.98 (1.00)	2.30	1.00 (1.00)	0.00	3.85 (3.00)	3.17	4.64 (3.00)	5.41
# Porfolio Cos	17.09 (4.00)	45.06	4.87 (2.00)	9.46	40.45 (20.00)	70.09	10.69 (5.00)	19.91
# Rounds	36.26 (6.00)	125.45	6.76 (3.00)	14.97	92.73 (34.00)	201.47	18.33 (6.00)	38.08
VC Age	9.04 (7.00)	8.73	6.59 (4.00)	7.71	13.74 (12.00)	8.67	6.55 (5.00)	6.64
Indept VC	0.58 (1.00)	0.49	0.55 (1.00)	0.50	0.64 (1.00)	0.48	0.64 (1.00)	0.48
VC Firm CA/MA	0.19 (0.00)	0.39	0.15 (0.00)	0.36	0.26 (0.00)	0.44	0.25 (0.00)	0.43
Early Stage Cos	0.42 (0.40)	0.35	0.42 (0.35)	0.39	0.43 (0.43)	0.23	0.39 (0.33)	0.33
Synd Rds	0.73 (0.88)	0.34	0.72 (1.00)	0.38	0.75 (0.83)	0.24	0.75 (0.90)	0.32
Style HHI (invt amt)	0.57 (0.52)	0.34	0.68 (0.75)	0.35	0.38 (0.32)	0.21	0.57 (0.51)	0.32
Style HHI (# cos)	0.54 (0.44)	0.33	0.67 (0.56)	0.32	0.30 (0.25)	0.17	0.39 (0.25)	0.36
Indus HHI (# cos)	0.61 (0.51)	0.30	0.72 (0.78)	0.30	0.41 (0.37)	0.18	0.59 (0.50)	0.30
Geog HHI (# cos)	0.79 (1.00)	0.26	0.86 (1.00)	0.23	0.66 (0.63)	0.24	0.77 (1.00)	0.26

Table 4: VC characteristics in style drift quartiles. This table provides mean, median, and standard deviation of key VC characteristics. The unit of observation is VC firm - year. Based on one-year style drift *Drift*, VCs are allocated to quartiles each year, with a separate category for VCs with zero drift. # Styles, # Funds, # Portfolio Cos, # Rounds, # Industries are annual figures for each VC. # Portfolio Geog is the unique number of locations of a VC's portfolio of companies, categorised as non-U.S., CA/MA, and non-CA/MA. The time-invariant variables about the VC firm's ownership and location are based on dummies. The remaining time-variant variables are the logarithm of one plus lagged values. These are defined in Appendix B. The last panel tests for the equality of characteristic means of VCs in Q4 and Q1, and Q4 and zero drift VCs (Q0), respectively. ***, **, and * denote significance at the 1%, 5% and 10% levels, respectively.

# Unique VCs	Q0 1605			Q1 2074			Q2 2423			Q3 2752			Q4 3190			Test of Mean Equality	
	Mean	Median	SD	Mean	Median	SD	Mean	Median	SD	Mean	Median	SD	Mean	Median	SD	Q4-Q1	Q4-Q0
Drift	0.000	0.000	0.000	0.001	0.001	0.002	0.008	0.004	0.010	0.033	0.020	0.036	0.291	0.191	0.267	***	***
# Styles	1.153	1.000	0.494	2.849	2.000	2.483	4.066	3.000	3.038	3.621	3.000	2.594	2.769	2.000	1.982	**	***
# Funds	1.052	1.000	0.268	1.809	1.000	1.440	2.201	2.000	1.637	1.871	1.000	1.322	1.466	1.000	0.953	***	***
# Portfolio Cos	1.537	1.000	1.433	6.639	3.000	11.387	9.952	5.000	13.471	7.371	4.000	9.454	4.663	3.000	5.717	***	***
# Rounds	1.596	1.000	1.573	7.957	3.000	15.683	12.379	6.000	18.125	9.035	5.000	13.152	5.422	3.000	7.525	***	***
# Industries	1.126	1.000	0.424	2.143	2.000	1.370	2.813	3.000	1.576	2.628	2.000	1.451	2.210	2.000	1.282	***	***
# Portfolio Geog	1.025	1.000	0.162	1.488	1.000	0.651	1.730	2.000	0.709	1.681	2.000	0.694	1.493	1.000	0.629		***
Indept VC	0.556	1.000	0.497	0.643	1.000	0.479	0.687	1.000	0.464	0.650	1.000	0.477	0.612	1.000	0.487	***	***
FI VC	0.133	0.000	0.340	0.112	0.000	0.316	0.104	0.000	0.306	0.117	0.000	0.321	0.126	0.000	0.332	**	
CA/MA VC	0.163	0.000	0.370	0.321	0.000	0.467	0.343	0.000	0.475	0.286	0.000	0.452	0.238	0.000	0.426	***	***
US/non-US VC	0.727	1.000	0.446	0.935	1.000	0.246	0.956	1.000	0.206	0.923	1.000	0.267	0.853	1.000	0.354	***	***
VC Age	1.556	1.609	0.996	2.183	2.197	0.764	2.160	2.197	0.786	1.939	1.946	0.836	1.639	1.609	0.953	***	***
IPO Rate	0.043	0.000	0.117	0.065	0.037	0.098	0.059	0.036	0.082	0.055	0.028	0.087	0.048	0.012	0.095	***	**
Early Stage Focus	0.294	0.288	0.246	0.337	0.353	0.153	0.334	0.348	0.145	0.300	0.305	0.157	0.235	0.229	0.169	***	***
Synd Experience	0.488	0.668	0.264	0.567	0.623	0.157	0.575	0.622	0.140	0.570	0.622	0.155	0.551	0.647	0.204	***	***
Style HHI	0.535	0.693	0.195	0.279	0.248	0.133	0.250	0.215	0.128	0.270	0.233	0.140	0.372	0.318	0.194	***	***
% Funds Invested	0.358	0.307	0.274	0.607	0.693	0.168	0.583	0.693	0.181	0.516	0.645	0.215	0.374	0.348	0.253	***	**
New Fund Yr	0.060	0.000	0.237	0.132	0.000	0.338	0.188	0.000	0.391	0.181	0.000	0.385	0.164	0.000	0.370	***	***

Table 5: Who Drifts? This table reports OLS estimates where the observations are at the VC - year level. The dependent variable is a VC's Drift Quartile which is based on lagged one-year drift. See Appendix B for a description of all independent variables. Time-varying independent variables are lagged by one year. Specification (2) has VC firm fixed effects, while specifications (3) to (7) have both year and VC firm fixed effects. Robust standard errors, clustered at the VC firm level, are in parentheses. ***, **, and * denote significance at the 1%, 5% and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
VC Age	-0.261***	-0.347***	-0.280***	-0.248***	-0.273***	-0.489***	-0.391***
	(0.01)	(0.02)	(0.03)	(0.04)	(0.03)	(0.10)	(0.10)
Independent VC	0.059**						
	(0.03)						
Fin Inst VC	0.049						
	(0.04)						
US/non-US VC	0.171***						
	(0.05)						
CA/MA VC	0.026						
	(0.03)						
Early Stage Focus			-2.685***	-2.549***	-2.666***	-3.013***	-2.831***
			(0.11)	(0.13)	(0.11)	(0.23)	(0.25)
IPO Rate			-0.295***	-0.242**	-0.285***	-0.117	-0.100
			(0.10)	(0.11)	(0.10)	(0.11)	(0.12)
Synd Experience			0.171	0.125	0.174	0.258	0.564*
			(0.12)	(0.13)	(0.12)	(0.28)	(0.31)
Style HHI			-0.118	-0.779***	-0.102	0.212	-0.502*
			(0.10)	(0.11)	(0.10)	(0.27)	(0.30)
% Funds Invested				-1.140***			-1.267***
				(0.08)			(0.13)
New Fund Yr					0.106***		0.051**
					(0.02)		(0.02)
Herding						0.032	0.047
						(0.03)	(0.03)
Constant	2.557***	3.012***	3.165***	3.653***	3.123***	3.612***	4.178***
	(0.05)	(0.03)	(0.12)	(0.14)	(0.12)	(0.25)	(0.27)
Observations	28,565	28,565	28,556	22,647	28,546	16,321	13,948
Number of firm_id	4,824	4,824	4,820	3,249	4,819	3,031	2,319
Year FE	NO	NO	YES	YES	YES	YES	YES
Firm FE	NO	YES	YES	YES	YES	YES	YES
Adj R^2	0.040	0.040	0.087	0.115	0.088	0.049	0.067

Table 6: Who Drifts - By VC Age Category? This table reports OLS estimates where the observations are at the VC - year level, using subsamples based on the VC's age (in years since founding) at the time of investment. Specification (6) ((7)) is based on observations when a VC's age is less than (at least) 11 years, which is the median age in the sample. The dependent variable is a VC's Drift Quartile which is based on lagged one-year drift. See Appendix B for a description of all independent variables. Time-varying independent variables are lagged by one year. All specifications have both year and VC firm fixed effects. Robust standard errors, clustered at the VC firm level, are in parentheses. ***, **, and * denote significance at the 1%, 5% and 10% levels, respectively.

Age Category:	0-6 (1)	7-10 (2)	11-15 (3)	16-20 (4)	Over 20 (5)	Young VC (6)	Seasoned VC (7)
VC Age	-0.404	-8.039***	-3.257	4.042	-0.091	-2.606***	0.164
	(0.39)	(1.88)	(3.53)	(8.24)	(1.28)	(0.51)	(0.27)
Early Stage Focus	-3.034***	-3.353***	-4.681***	-2.278***	-3.459***	-3.269***	-2.908***
	(0.78)	(0.51)	(0.63)	(0.88)	(0.79)	(0.38)	(0.40)
IPO Rate	0.154	0.311	-0.191	0.007	-0.616**	0.045	-0.307**
	(0.68)	(0.29)	(0.24)	(0.28)	(0.27)	(0.23)	(0.14)
Synd Experience	2.397	-1.090	1.200	-0.889	1.558**	0.233	0.439
	(1.46)	(0.88)	(0.81)	(1.55)	(0.77)	(0.51)	(0.46)
Style HHI	1.522	0.141	0.835	0.646	-0.119	-0.307	-0.230
	(0.95)	(0.66)	(0.81)	(0.89)	(1.13)	(0.45)	(0.50)
% Funds Invested	-0.417	-1.263***	-0.838**	-1.077**	-1.016***	-0.894***	-0.996***
	(0.57)	(0.31)	(0.38)	(0.54)	(0.34)	(0.22)	(0.19)
New Fund Yr	0.109	0.052	0.011	0.085	0.029	0.046	0.046
	(0.08)	(0.04)	(0.05)	(0.06)	(0.05)	(0.03)	(0.03)
Herding measure	0.020	0.070	0.176	-0.085	0.023	0.022	0.033
	(0.18)	(0.09)	(0.11)	(0.14)	(0.09)	(0.06)	(0.05)
Constant	2.041	5.669***	7.015	-9.716	3.528	3.813***	3.191***
	(1.37)	(0.74)	(4.43)	(27.94)	(3.55)	(0.47)	(0.65)
Observations	1,926	4,312	3,241	1,988	2,481	6,238	7,710
Number of firm_id	1,281	1,590	1,122	658	462	1,835	1,411
Year FE	YES	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES	YES
Adj R^2	0.115	0.055	0.050	0.045	0.042	0.075	0.046

Table 7: Days to exit by style drift quartiles. The table provides exit experience at the VC firm - round level, by lagged drift quartile, which is based on annual drift averaged over the last five-year window with a separate category of zero drift. It shows the mean (median) number of days from the investment date to the exit date, for all forms of exit (*All Exits*), i.e., either an IPO, an M&A, or Buyout, as well as each of these separately. Significance of the difference in the mean values in Q1 and Q4 is shown below the panel. ***, **, and * denote significance at the 1%, 5% and 10% levels, respectively.

Drift Quartiles	All Exits	IPOs	M&As	Buyouts
0	1453 (1062)	1086 (906)	1686 (1341)	1359 (664)
1	1268 (1024)	1131 (978)	1330 (1067)	1233 (927)
2	1253 (965)	1045 (841)	1354 (1057)	1184 (767)
3	1287 (975)	1094 (888)	1389 (1054)	1223 (816)
4	1353 (1049)	1112 (869)	1437 (1130)	1447 (968)
Total	1280 (993)	1087 (890)	1370 (1070)	1243 (831)
Q1 - Q4	***	–	***	***

Table 8: Days to exit by style drift quartiles - by VC type. The table provides exit experience at the VC firm - round level, by lagged drift quartile, which is based on annual drift averaged over the last five-year window with a separate category of zero drift. It shows aggregate of all forms of exit (*All Exits*), i.e., either an IPO, an M&A, or Buyout, as well as each of these separately. Exit experience is in the terms of the mean (median) number of days from the investment date to the exit date. Panel A (Panel B) provides exit data for seasoned and young VCs (herders and contrarians) on the left and right parts, respectively. Significance of the difference in the mean values in Q1 and Q4 are shown below each panel. ***, **, and * denote significance at the 1%, 5% and 10% levels, respectively.

Drift Quartiles	All Exits	IPOs	M&As	Buyouts	All Exits	IPOs	M&As	Buyouts
Panel A:	Seasoned VCs				Young VCs			
0	1474 (1148)	943 (757)	1742 (1398)	1553 (932)	1399 (996)	1400 (1015)	1535 (1148)	630 (601)
1	1254 (1007)	1100 (941)	1319 (1054)	1239 (913)	1352 (1129)	1338 (1213)	1396 (1122)	1202 (1050)
2	1218 (932)	996 (783)	1320 (1035)	1178 (757)	1379 (1090)	1233 (1062)	1472 (1142)	1210 (807)
3	1221 (918)	1025 (806)	1300 (994)	1238 (840)	1384 (1062)	1190 (990)	1521 (1164)	1197 (777)
4	1307 (978)	1048 (763)	1401 (1095)	1410 (963)	1388 (1092)	1164 (995)	1463 (1154)	1478 (974)
Total	1238 (959)	1035 (828)	1325 (1037)	1231 (821)	1380 (1087)	1210 (1043)	1476 (1148)	1276 (855)
Q1 - Q4	***	*	***	***	–	***	*	***
Panel B:	Herders				Contrarians			
0	1459 (1044)	1130 (951)	1672 (1202)	1293 (655)	1452 (1411)	956 (533)	1729 (1677)	2176 (1379)
1	1278 (1036)	1135 (987)	1342 (1075)	1242 (941)	1091 (824)	1076 (850)	1108 (859)	1060 (621)
2	1278 (981)	1068 (868)	1381 (1076)	1195 (776)	952 (758)	824 (659)	1005 (818)	1012 (677)
3	1317 (994)	1113 (907)	1415 (1076)	1281 (849)	1067 (811)	965 (739)	1189 (954)	829 (513)
4	1386 (1076)	1130 (897)	1472 (1157)	1505 (999)	1128 (892)	989 (663)	1208 (1009)	1055 (685)
Total	1303 (1007)	1104 (906)	1393 (1088)	1269 (849)	1051 (806)	937 (724)	1128 (917)	965 (622)
Q1 - Q4	***	–	***	***	–	–	*	–

Table 9: VC Firm and Drift. This table reports estimates of a Cox proportional hazards model (specifications (1) - (3)) and a probit model (specifications (4) - (6)). The dependent variable is the Cox model is the number of days from financing to the earlier of exit or March 16, 2011. In the probit model, the dependent variable is 1.0 if there is a successful exit, and 0 otherwise. Exits include IPO, M&A, or buyouts. Observations are at the VC firm - investment round level. The key variable of interest is lagged drift quartile, which is based on annual drift averaged over the last five-year window.See Appendix B for a description of all independent variables. Time-varying independent variables are lagged by one year. All specifications have year and style fixed effects. Robust standard errors, clustered at the portfolio company level, are in parentheses. ***, **, and * denote significance at the 1%, 5% and 10% levels, respectively.

		Cox			Probit	
	(1)	(2)	(3)	(4)	(5)	(6)
Lagged 5-year Drift Qrtl	0.972***	0.974***	0.982**	-0.022***	-0.021***	-0.017**
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
VC Age			1.043**			0.022
			(0.02)			(0.02)
Early Stage (Dummy)		0.738***	0.738***		-0.214***	-0.214***
		(0.02)	(0.02)		(0.02)	(0.02)
Syndication (Dummy)		1.553***	1.553***		0.329***	0.329***
		(0.04)	(0.04)		(0.02)	(0.02)
Independent VC		1.158***	1.162***		0.117***	0.119***
		(0.03)	(0.03)		(0.02)	(0.02)
Fin Inst VC		1.159***	1.153***		0.110***	0.107***
		(0.04)	(0.04)		(0.03)	(0.03)
US/non-US VC		1.113	1.116		0.029	0.031
		(0.08)	(0.08)		(0.05)	(0.05)
CA/MA VC		1.073***	1.071***		0.056***	0.055***
		(0.02)	(0.02)		(0.02)	(0.02)
Style HHI		0.783**	0.867		-0.216**	-0.161*
		(0.09)	(0.11)		(0.09)	(0.10)
Synd Experience		2.109***	2.115***		0.527***	0.531***
		(0.23)	(0.24)		(0.08)	(0.08)
Early Stage Focus		0.724***	0.713***		-0.269***	-0.277***
		(0.06)	(0.06)		(0.06)	(0.06)
IPO Rate		1.106	1.098		0.129**	0.126**
		(0.08)	(0.08)		(0.06)	(0.06)
Constant				-1.465***	-1.941***	-2.026***
				(0.06)	(0.09)	(0.11)
Observations	146,518	146,517	146,517	146,835	146,834	146,834
Year FE	YES	YES	YES	YES	YES	YES
Style FE	YES	YES	YES	YES	YES	YES
Pseudo R^2	0.007	0.009	0.009	0.116	0.129	0.129

Table 10: Performance of pre-drift portfolio. Specifications (1) and (2) report the estimates of a Cox proportional hazards model, where the dependent variable is the number of days from financing to the earliest of exit (IPO, M&A, or buyout) or March 16, 2011. Specifications (3) and (4) report the estimates of a probit model in which the dependent variable is 1.0 if there is a successful exit within 10 years of the investment round, and 0 otherwise. Observations are at the VC firm - investment round level. VC's drift quartile (Drift Qtl) is based on two alternative time frames - VC's annual drift in the first year ahead and annual drift averaged over the first three years ahead. Portfolio age of the investment is the number of years the company has been in the VC's portfolio. The key variable of interest is the interaction term, drift x portfolio age. See Appendix B for a description of all independent variables. Time-varying control variables are lagged by one year. All specifications have year and style fixed effects. Robust standard errors, clustered at the portfolio company level, are in parentheses. ***, **, and * denote significance at the 1%, 5% and 10% levels, respectively.

	Cox		Probit	
	1 year (1)	3 year (2)	1 year (3)	3 year (4)
Drift Qtl	0.993	1.005	-0.006	0.007
	(0.01)	(0.00)	(0.01)	(0.00)
Portfolio Age	1.004	1.014*	0.003	0.011*
	(0.01)	(0.01)	(0.01)	(0.01)
Drift Qtl x Portfolio Age	1.009***	1.006**	0.007**	0.004*
	(0.00)	(0.00)	(0.00)	(0.00)
VC Age	1.027***	1.026***	0.017**	0.016**
	(0.01)	(0.01)	(0.01)	(0.01)
Early Stage (Dummy)	0.739***	0.741***	-0.208***	-0.206***
	(0.01)	(0.01)	(0.01)	(0.02)
Syndication (Dummy)	1.637***	1.661***	0.360***	0.382***
	(0.03)	(0.03)	(0.01)	(0.01)
Independent VC	1.102***	1.101***	0.087***	0.087***
	(0.02)	(0.02)	(0.01)	(0.01)
Fin Inst VC	1.140***	1.142***	0.107***	0.110***
	(0.03)	(0.03)	(0.02)	(0.02)
US/non-US VC	1.148***	1.173***	0.064**	0.101***
	(0.05)	(0.05)	(0.03)	(0.03)
CA/MA VC	1.079***	1.078***	0.060***	0.062***
	(0.02)	(0.02)	(0.01)	(0.01)
Style HHI	0.870***	0.865***	-0.112***	-0.112***
	(0.05)	(0.05)	(0.04)	(0.04)
Synd Experience	1.858***	1.882***	0.434***	0.449***
	(0.11)	(0.11)	(0.04)	(0.04)
Early Stage Focus	0.716***	0.735***	-0.250***	-0.223***
	(0.04)	(0.04)	(0.04)	(0.04)
IPO Rate	1.169***	1.160**	0.174***	0.156***
	(0.07)	(0.07)	(0.05)	(0.05)
Constant			-1.655***	-1.367***
			(0.06)	(0.06)
Observations	177,432	157,629	177,782	157,897
Year FE	YES	YES	YES	YES
Style FE	YES	YES	YES	YES
Pseudo R^2	0.011	0.011	0.106	0.088

Table 11: VC Firm Heterogeneity. Specifications (1) to (4) report estimates of a Cox proportional hazards model, where the dependent variable is the number of days from financing to the earlier of exit or March 16, 2011. Specifications (5) to (8) report estimates of a probit model in which the dependent variable is 1.0 if there is a successful exit within 10 years of the investment round, and 0 otherwise. Observations are at the VC firm - investment round level. The key variable of interest is lagged drift quartile, which is based on annual drift averaged over the last five-year window. Specifications (1) and (5) ((2) and (6)) are based on observations when a VC's age is less than (at least) 11 years. Specifications (3) and (7) ((4) and (8)) are based on observations when a VC is a contrarian (herder). See Appendix B for a description of all independent variables. Time-varying independent variables are lagged by one year. All specifications have year and style fixed effects. Robust standard errors, clustered at the portfolio company level, are in parentheses. ***, **, and * denote significance at the 1%, 5% and 10% levels, respectively.

	Cox				Probit			
	Young VC (1)	Seasoned VC (2)	Contrarian (3)	Herder (4)	Young VC (5)	Seasoned VC (6)	Contrarian (7)	Herder (8)
Lagged Drift Quartile	0.999	0.970***	1.053**	0.975***	-0.004	-0.027***	0.031*	-0.023***
	(0.01)	(0.01)	(0.03)	(0.01)	(0.01)	(0.01)	(0.02)	(0.01)
VC Age	0.918	1.097***	1.133**	1.024	-0.078	0.066***	0.062	0.006
	(0.07)	(0.03)	(0.06)	(0.02)	(0.06)	(0.02)	(0.04)	(0.02)
Early Stage (Dummy)	0.770***	0.724***	0.711***	0.740***	-0.190***	-0.225***	-0.234***	-0.211***
	(0.03)	(0.02)	(0.05)	(0.02)	(0.03)	(0.02)	(0.05)	(0.02)
Syndication (Dummy)	1.489***	1.575***	1.560***	1.551***	0.302***	0.339***	0.299***	0.332***
	(0.06)	(0.04)	(0.10)	(0.04)	(0.03)	(0.02)	(0.04)	(0.02)
Independent VC	1.096**	1.187***	1.111*	1.168***	0.080***	0.132***	0.090**	0.121***
	(0.04)	(0.03)	(0.07)	(0.03)	(0.03)	(0.02)	(0.04)	(0.02)
Fin Inst VC	1.103*	1.163***	1.027	1.169***	0.064	0.116***	0.056	0.116***
	(0.06)	(0.04)	(0.10)	(0.04)	(0.04)	(0.03)	(0.06)	(0.03)
US/non-US VC	0.897	1.336***	1.252	1.060	-0.094	0.133**	0.148	-0.015
	(0.09)	(0.13)	(0.21)	(0.08)	(0.07)	(0.06)	(0.11)	(0.05)
CA/MA VC	1.065**	1.068***	0.962	1.081***	0.044*	0.055***	-0.038	0.065***
	(0.03)	(0.03)	(0.06)	(0.02)	(0.03)	(0.02)	(0.05)	(0.02)
Style HHI	1.067	0.752*	0.672	0.895	-0.018	-0.256**	-0.350	-0.124
	(0.19)	(0.12)	(0.22)	(0.12)	(0.14)	(0.13)	(0.22)	(0.11)
Synd Experience	2.340***	1.960***	2.020***	2.244***	0.560***	0.503***	0.547***	0.555***
	(0.38)	(0.27)	(0.46)	(0.29)	(0.12)	(0.10)	(0.15)	(0.09)
Early Stage Focus	0.682***	0.702***	0.757	0.719***	-0.332***	-0.279***	-0.177	-0.277***
	(0.08)	(0.07)	(0.16)	(0.06)	(0.09)	(0.08)	(0.15)	(0.07)
IPO Rate	1.225	1.027	1.022	1.142*	0.209**	0.068	0.064	0.167**
	(0.16)	(0.09)	(0.20)	(0.09)	(0.10)	(0.07)	(0.15)	(0.07)
Constant					-1.714***	-2.208***	-2.394***	-1.943***
					(0.21)	(0.14)	(0.25)	(0.12)
Observations	43,376	103,141	21,188	125,262	43,468	103,366	21,233	125,534
Year FE	YES	YES	YES	YES	YES	YES	YES	YES
Style FE	YES	YES	YES	YES	YES	YES	YES	YES
Pseudo R^2	0.009	0.010	0.016	0.008	0.120	0.134	0.144	0.119

Table 12: VC Firm Performance -Alternative Explanations. This table presents results for three alternative tests - Granger causality (columns 1 and 2), Matching model (column 3) and First time investments only (column 4). Column (1)((2)) shows OLS regression results of performance (style drift). VC's Performance at time t is the ratio of cumulative number of IPOs at time t to the cumulative number of investments at time t. Drift Quartile at time t is based on the VC's annual drift at time t. The observations are at the firm-year level. The key variables of interest in columns (1) and (2) are *Lagged Performance* and *Lagged Drift Qtl*. The specifications include year and VC firm fixed effects. Columns (3) and (4) show hazard rates from a Cox proportional hazards model and the dependent variable is the number of days from financing to the earlier of exit (i.e., IPO, M&A, or buyout) or March 16, 2011. In the matching model, observations are at the VC firm - investment round level. The key variable of interest is *Treated* which takes the value of 1(0) for the treatment(control) group. The treatment group comprises VCs with above median lagged five-year drift (excluding zero drift), while the control group has below median drift. Each of these is a matched sample of high drift and low drift VC firms. The matching is done using coarsened exact matching (CEM) method, and is based on age, VC's geographic location, ownership type, early stage focus, syndication experience, past IPO exit performance, Style HHI, and the investment year. Treated captures the difference in speed of exit between high and low drift VCs. We include year and style fixed effects. In the last model (column 4), observations are at the VC fund - investment round level and only includes each VC fund's first investment in a portfolio company. The key variable of interest is *Lagged Drift Qtl* based on annual drift averaged over the last five-year window. We include year and style fixed effects. Each of the three models includes controls used in Table 9 and are defined in Appendix B. ***, **, and * denote significance at the 1%, 5% and 10% levels, respectively.

	Granger Test: OLS		Matching Model: Cox	First Invt Only: Cox
	Performance	Drift Quartile	Above/Below Median	
	(1)	(2)	(3)	(4)
Lagged Performance	0.401***	-0.164		
	(0.02)	(0.23)		
Lagged Drift Qtl	-0.001***	0.070***		0.978***
	(0.00)	(0.01)		(0.01)
Treated			0.858***	
			(0.02)	
VC Age	0.007***	-0.421***	1.188***	1.022
	(0.00)	(0.05)	(0.04)	(0.02)
Early Stage (Dummy)			0.650***	0.739***
			(0.02)	(0.02)
Syndication (Dummy)			1.382***	1.588***
			(0.05)	(0.04)
Independent VC			1.184***	1.129***
			(0.05)	(0.03)
Fin Inst VC			1.116	1.132***
			(0.08)	(0.03)
U.S./non-U.S. VC			1.036	1.134*
			(0.51)	(0.09)
CA/MA VC			1.013	1.086***
			(0.03)	(0.02)
Style HHI	-0.030***	0.340**	1.621***	0.767**
	(0.01)	(0.15)	(0.30)	(0.09)
Synd Experience	0.021***	0.210	3.112***	2.105***
	(0.01)	(0.17)	(0.47)	(0.21)
Early Stage Focus	0.010	-2.640***	0.513***	0.596***
	(0.01)	(0.14)	(0.06)	(0.05)
IPO Rate			0.580***	1.133*
			(0.10)	(0.08)
Constant	0.005	3.832***		
	(0.01)	(0.19)		
Observations	24,893	24,888	29,732	72,804
Year FE	YES	YES	YES	YES
Firm FE	YES	YES	NO	NO
Style FE	NO	NO	YES	YES
Adj R^2 / Pseudo R^2	0.845	0.318	0.015	0.011

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