The Fast and The Curious: VC Drift[1]

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Abstract

Fast and Curious: VC Drift

Rapid changes in investment behavior offers a VC an opportunity to learn but carries potential costs such as dilution of skills. These benefits and costs may have ramifications not just for a specific investment but importantly for a VC's entire portfolio. To capture these ideas, we first locate each VC financing round in one of twenty styles, and develop a measure of change in a VC's investment styles ("style drift") at the level of her portfolio. We find that drift is more likely among younger VCs, those without a focus on early stage investments and those who experience the pressure to invest their funds. Style drift is associated with poorer performance among seasoned VCs who are likely to have already developed expertise through past investments, and for VCs who drift in a correlated fashion (herd) with other VC firms. Finally, the more recent investments in the VC's portfolio are more adversely affected when the VC drifts than other investments in the VC's pre-drift portfolio. Our results offer evidence for economies of style persistence.

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

1 Introduction

From innovative to traditional industries, venture capitalists (VCs) invest in and nurture a wide range of new firms. Changes in investment style (or "drift") occur because VCs are either experimenting or being opportunistic, or both. These decisions are influenced by the learning potential from new investments (Sørensen (2008)). Nanda and Rhodes-Kropf (2013) find that VCs learn and experiment during peaks of the investment cycle as more innovative firms are financed in those periods.

The benefits from style drift accrue across a VC's portfolio. Know-how may be transferable across investment types, making experimentation more attractive.[1] Introduction to new business models and new technologies whose impact span industries is particularly attractive to VCs. Innovative solutions often result from combining novel ideas with conventional knowledge (Uzzi et al. (2013)).

However, experimentation and opportunism, while beneficial, may be costly. First, learning takes effort and time which comes at the expense of existing investments in the VC's portfolio. Second, specialized skills are particularly useful given the resource-intensive nature of venture investing.[2] However, drifting prevents honing specialized skills turning the VC into a "jack of all trades and master of none." Third, investing in innovative firms is competitive and while VCs over time might develop the necessary capacity to take their novel investments to fruition, they may still lag behind the VCs they encroach upon.

We examine how drift affects outcomes not just for the investment in question but for the entire VC investment portfolio. To implement this, we start by defining a set of investment "styles" that characterize the VC industry based on geography and industry sectors and maps each VC investment to a given style. We then create a measure of "style drift" as the distance between a VC's location in the multi-dimensional 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 portfolio. We document considerable style drift in the sample and observe that the distribution of style drift in the cross-section of VCs is bi-modal. That is, some VCs stay focused on a certain set of styles over time while others choose to drift across different styles. Two questions we consider in this paper are: (a) Which VCs tend to drift more in style and why? (b) How does style drift affect the performance of a VC's investment portfolio?

Based on a panel of 344,491 VC firm-financing rounds, both domestic and international, over the period 1980–2010, our empirical evidence suggests that a VC firm's lifecycle, investment stage, and the pressure of investing funds are important drivers of its decision to drift. Drift is common amongst younger VC firms but is less attractive for VCs who specialize in early stage investments. We also show that dry powder increases the VC's propensity to drift.

We then examine the relation between style drift and VC firm performance. We consider

[1] This is similar to *economies-of-scope* in multi-product firms (Panzar and Willig, 1981). The scope benefits in the form of falling average costs suggests that firms should be on the look out for new activities or products which would enable them to exploit the source of these economies of scope.

[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.

two metrics of VC success - likelihood of exit and time-to-exit, where exit occurs through an IPO, M&A, or secondary sale.[3] We find that on average, VC firms that focus on a set of styles significantly outperform those that drift across sets of styles from one year to the next. This empirical result is largely driven by seasoned VCs who have already developed a strong expertise (possibly through past drift and experimentation) and therefore stand to lose more from drifting. We also investigate the performance implications of drift for VCs who are herders (follow the crowd) or contrarians (those that go against the crowd). We find that herders do significantly worse by drifting than do contrarians.[4]

Finally, drift directly examines portfolio effects. When a VC drifts, she invests in a set of styles that is different from her current portfolio. We exploit the heterogeneity in the age composition of a VC's portfolio and consider the performance of investments in *existing* styles if a VC subsequently drifts into another set of styles. Recent (rather than older) existing investments need the attention and value-added services that VCs provide, and are more likely to bear the brunt of VC drift. We find that greater VC drift reduces the speed of exit for recent investments rather than for older investments in the VC's portfolio. Overall, drift has ramifications across a VC's investment portfolio.

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 given 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. All our empirical specifications that examine the role of persistence control for the degree of specialization.

We conduct a variety of robustness tests. First, the relationship between drift and performance may be mechanical, i.e., poorer performance frees up capital to drift into newer investments, while successful investments involve multiple financing rounds in the same company with lower drift. 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 remain unchanged. Second, a concern may be that a VC decides to drift precisely when her investment strategy is ineffective and her performance poor. Using a Granger-causality test, we find that while past drift affects VC performance, past VC performance does not affect a VC's current decision to drift. Another concern is that our analyses cannot capture many of the firm-specific determinants of performance, such as VC ability which may be driving both their decision to drift and the performance outcome. We examine the changes in firm performance between years based on first-difference analysis and continue to find evidence that drift adversely affects investment performance.

Fourth, our analysis compares "average" high and low drift firms and their performance. However, comparing such averages may confound other factors leading to a potential bias in

[3] 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 sucess produces qualitatively similar results as the others.

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

our estimation of the causal effect of drift on performance. To ameliorate this concern, we use a novel Coarsened Exact Matching (CEM) approach (see Iacus et al., 2008) to match high drift (the treatment group) and low drift (the control or comparison group) firms on a number of factors.[5] We assess the effect of a particular "treatment" (i.e., high drift) on the speed of exit relative to the control. Our results are consistent with our prior analysis.

We conclude that VC firms 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.

In addition to answering the two primary questions of this paper, this study makes methodological contributions to the VC literature and broadly to the literature on the theory of the firm. First, 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. Another paper, by Hochberg and Westerfield (2010), considers industry-geography groups (as we do) but focus on the relation between VC's portfolio size and specialization.

Second, while papers such as Wermers (2010) and Brown and Harlow (2002) have studied style drift in the context of mutual funds, we examine the notion of drift in the context of venture investing. Indeed, the VC setting is a suitable one in which to examine style persistence versus drift. Given the riskiness of VC investing and the importance of VCs' value-added role in their portfolio companies, the benefits of persistence are intuitive and transparent. Moreover, the payoffs from opportunistic investing in varying styles take a lot longer to accrue in the case of new ventures than in the case of various stock investing styles in mutual funds, making the underlying decision to persist or drift across styles more deliberate in the VC context.

Third, there is a growing literature examining managerial skills and their implications for VC performance. 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.[6] 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, a natural and complementary extension to the literature on venture investment performance.

The paper proceeds as follows. Section 2 presents a description of the data and describes the sample selection process, financing rounds, and the data needed to determine exits. Section 3 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. We also characterize the various styles and look at the variation in

[5]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.

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

drift, both cross-sectionally and over time. Section 4 presents empirical findings about the determinants of drift. Section 5 shows that style drift is detrimental to performance, i.e., style persistence pays. Section 6 concludes.

2 Data

2.1 Sample selection

The data is 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.[7] 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 344,491 observations that includes financing rounds, both in the U.S. 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.[8]

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 pension fund managers were allowed to invest upto 10% of their capital in venture funds as an asset class (Gompers, 1994). Prior to 1980 venture capital investments were relatively small.

The sample data is structured at three levels. At the coarsest level, the data contain 83,273 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 178,036 company-round observations. At the round level, we include the financing date, the company stage at 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 344,491 observations.[9] 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, founding

[7]Venture capital is often understood as a subset of private equity, though some practitioners only think of private equity as encompassing 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.

[8]Our sample is roughly evenly split between U.S. and non-U.S. portfolio companies, at 48% and 52%, respectively. For the same reason, we do not restrict our sample to only U.S.-based firms. We classify any VC firm with at least 1 fund in the U.S. 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.

[9]In some rounds, there are multiple observations for the same fund. Consequently, the dataset has 443,948 observations in total.

years of the VC firm and VC fund. The final dataset includes 9,895 unique VC firms.

The VentureXpert data is not without shortcomings. According to Kaplan et al. (2002), the VentureXpert database oversamples larger financing rounds and California companies. However, they conclude that the database provides unbiased, albeit noisy, measures of financing amounts and valuations. In our empirical analysis, we adopt a variety of controls (e.g., for the CA/MA style) and conduct a variety of robustness tests to address concerns about data quality.

2.2 Identifying venture-capital exits

While it is possible for VCs to sell their investments privately (Ibrahim, 2012), in practice VCs usually realize a return on their investment by (a) taking the company public through an IPO, (b) by finding a suitor in the M&A market, or (c) being bought out by a buyout fund.[10] 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,[11] we follow the literature [e.g., Cochrane (2005), Das et al. (2003) and others] 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 SDC IPO and SDC Merger and Acquisition databases with the help of the "company situation" and "company situation date" variables in VentureXpert which refer to the latest known 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 3,965 companies which went public and 11,825 companies which were involved in an M&A transaction.

In order 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 and we make the simplifying assumption that at that date all VCs which 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 6,872 buyout exits.[12]

Like other papers in the field, we take a pragmatic approach, and offer a number of alternative measures of investment performance. Maats et al. (2008) suggest that the VentureXpert database often treats staged funding as new rounds. This may be problematic

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

[11] 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.

[12] It is possible for a portfolio company to go through multiple exits. For example, America Online (AOL)'s initial investors exited through a buyout in mid-1985, and 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 1 exit type.

since our performance analysis is at the VC firm$\times$round level. So, as one of our robustness checks, we consider only the performance of first round investments that VCs make in a portfolio company. Given concerns about data on types of exit, we also use a follow on round of funding as a measure of success for the previous round. This lowers the reliance on the other exit types. To identify sequential rounds, we take a conservative approach, and only consider those cases where the given round numbers are consecutive and the dates are appropriately sequential.

3 Styles and Drift

3.1 Investment styles

The approach taken in the paper to 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 four styles (or nine, depending on how many categories are chosen), based on stock size (large versus small) and stock type (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.

Our broad initial binary classification of investment styles falls into buyout and non-buyout financing rounds. Within the *buyout* group, the broad categories are US and non-US portfolio firms. However, within the *non-buyout* group, the next level of separation is industry, and there are six industries: Biotech, Communications/Media, Computers, Medical, Non high-tech, Semiconductors. Within each industry, firms are classified into non-US firms, US (non CA/MA) firms, and firms in 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 arrived at 20 distinct styles.[13] 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 very rare for a VC firm located in the US and specializing in the biotech industry to move into the European market and the computer industry, i.e., industry and location choice is not a decision variable. However, such a conjecture is misplaced. Sørensen (2008) finds that each fund makes many investment decisions across many industries. Our data show that VCs often will invest in different regions and industries. For example, Delphi Ventures, founded in 1988, focuses on healthcare and only has an office in Menlo Park, California. However, its investment portfolio has changed from one year to the next both in terms of VentureXpert industry classification as well as location across states

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

in the U.S.[14] [15]

3.2 Empirical features of styles

In Table 1, we present descriptive statistics for the twenty styles at the investment round level. We assign a unique style to each of the 178,036 financing rounds, and the same company would 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 88,200, while the number of unique companies in our sample is 83,273. By the same logic, a VC firm would be in different styles, based on the styles of its financing rounds. The total of VC firms $\times$ styles is 39,067 as against the sample size of 9,895 unique VCs, because VCs invest in multiple styles. 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 a catch-all category of "non High-Tech, non-US", comprising 22,901 financing rounds. The next highest frequency of style allocation occurs in "Computer - US CA/MA" coming from a Silicon Valley orientation. There are an almost equal number of buyout style rounds by geography, with 15,475 in the US, and 15,173 non-US. 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 from the VC firm's founding year.[16] VCs investing in the Biotech, Medical and Semiconductors industries in the U.S. tend to be older, and those in the Computer industry are younger. Median investment is larger in later stages (such as buyouts) and smaller in non-US transactions. The concentration index, HHI (Herfindahl-Hirschman Index), for stage (or industry) is the sum of 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. Amongst all the 20 styles, there is more dispersed spending by financing stage in the biotech industry in the US, and hence a lower Stage HHI. Industry HHI, based on invested

[14] In our sample, for Delphi, in 1994 these states (and the number of investments) were CA(4), PA(1), MA(1), and industry were Medical/Health/Life Science(5), Biotechnology(1). For 1995: CA(1), MA(1), NC(1); Medical/Health/Life Science(2); Computer Related(1). For 1996: CA(2), MA(1), TN(1), OH(1), FL(1); Medical/Health/Life Science(4); Computer Related(1); Non-High-Technology(1). Hence, even year to year, rapid changes in location and industry (i.e., style) are clearly in evidence.

[15] We find similar evidence of drift in large and well-known VC firms, e.g., Oak Investment Partners. It was founded in 1978 in Connecticut, but now also has offices in Minneapolis and Palo Alto. Oak Investment Partners made the following investments in 2007: CA(4), MA(1), CO(2), OH(1), NY(2), non-US(2); Computer Related(3), Communications and Media(1), Non-High-Tech(7), Medical/Health/LifeScience(1); in 2008: CA(4), GA(1), NM(1), non-US(2); Computer Related(2), Communications and Media(2), Non-High-Tech(4). The category, Non-High-Tech, contains a broad variety of investments, including Clean Energy, Payment Services, etc. Most of these investments were made out of the Oak Investment Partners XII fund, a $2.5 billion fund raised in 2006.

[16] 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 pre-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 though we cannot use our drift measure based on longer horizons in some specifications. The correlation between these alternative age measures is 76%.

amount, would be at its maximum for each of the styles from 3-20 since each of these is industry-specific. 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 Tech sector, given its catch-all nature.[17]

Over the 1980–2010 sample period, 54,797 (30%) rounds exited out of a total of 178,036 rounds, 6% through IPOs and 16% 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 Determining VC style drift

We develop a methodology for calculating drift with the intent of capturing the effect of changes in investment at the VC's portfolio level. VC firms' investment rounds are each allocated into a style category (of which there are 20). These data on round level investments by VC funds are then aggregated by VC firm to get styles of VC firm investing. It is natural to explore styles at the VC firm level rather than the fund level. 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* style shift if and when they change investment style strategy from fund to fund or when they 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.[18]

A VC's style at the end of any year is denoted by a vector whose dimension is the number of styles ($K = 20$). Style proportion vectors may be computed separately for each year or specified sub-period, i.e., variables P_{jkt} that are the proportion of funds invested by VC j in style k in year or sub-period t. Hence a style proportion vector is denoted $P_{jt} = [P_{j1t}, P_{j2t}, \ldots, P_{j,20,t}]'$. 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

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

[18]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 guidelines that are agreed upon, 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 ten years (unless it came into existence less than 10 years preceding the date of the database). 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 ten-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.[19]

4. Then, 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*. Differences in style-proportion vectors for consecutive years are then used to determine style drift.

5. *Style Drift*: We define the style drift score for VC j from one period to the next as one minus the cosine distance 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. Since the value lies between zero and one, the drift score is normalized. 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. We may also compute average drift scores for sub-periods in rolling period analysis. In our empirical analysis, we consider the relation of alternative measures of the drift score to VC performance.

The style drift measure we use has three important 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, to take an 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 evidence lower style drift.

In Appendix A we present some examples to exposit and explain the approach in this procedure, illustrate the three properties above, as well as clarify exception handling.

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

3.4 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.

The distribution of average annual style drift of each VC firm is shown in Figure 2. A large number of VC firms, about 1000, have no drift as seen in the histogram. These zero-drift VC firms have an average of 2 years of investment data, compared with 4 years for firms with non-zero drift, are half as old (5 years), with only 4 rounds of investment (vs. 21 rounds). Zero-drift VC firms did not survive for too long and hence did not experience any drift at all, or were VCs who have recently set up shop (almost 25% of the zero-drift VCs came into existence after 2005). The presence of this category of VCs could potentially distort our analysis. Note that either explanation for zero drift, i.e., failure of VC firms or inadequate time to invest and exit, stacks the odds against finding a beneficial effect from being style persistent. Yet, we find that opportunism is detrimental for performance. Additionally, in our robustness tests, we explicitly exclude investments made after 2005 to allow sufficient time for investments to exit, and find qualitatively similar results.

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

4 Determinants of Drift

4.1 VC characteristics

Table 2 shows the descriptive statistics of VCs in our final sample, where we segregate the sample into VC firms with just one fund (which may be 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 amongst the 20 styles for each VC. The single fund VCs tend to invest in fewer styles (2.36 on average), whereas the VCs with more funds invest in more styles (6.67 on average). Investing in multiple styles does not necessarily suggest that VCs drift from one year to the next. However, that VCs invest in fewer styles per year than the total number of styles provides initial evidence that VCs drift across styles over time. Even with very broad classifications for industry and geography, we find evidence of VCs investing in more than one industry and geography.[20] This also suggests that focusing on just industry or geography separately as the basis for VC investment style would misrepresent their true style.

The average age of VCs in our sample is ten years, though those with multiple funds tend to be older. On average, 60% of the VCs are independent and 16% are located in the CA/MA geographical cluster. These numbers are lower for one-time VCs. Given the nature

[20]Part of the reason for fewer geographical investments is our decision to allow only 3 broad geographies, namely non-U.S., CA/MA and U.S. non-CA/MA, so that we may keep the number of styles within reasonable limit.

of venture financing, there is not much variation among VCs with single or multiple funds in the proportion of early stage financing (about 32%). 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. The mean Herfindahl-Hirschman Index (HHI) for style is about 0.57, which denotes a fairly high level of style concentration. Geographical concentration in investments is also high, with the HHI at 0.80.

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, in order 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 $Q0$), for reasons discussed previously, the remaining VC firm - year observations are distributed into four quartiles. Table 3 shows various VC characteristics within drift quartiles. (Note that $Q4$ is the one with highest drift, and $Q1$ with the lowest drift (except zero)).

Comparing non-zero drift quartiles, the number of styles the highest drift VCs invest in is statistically no different than that of VCs in the bottom quartile (though VCs in the intermediate quartiles did invest in more styles). This suggests that changes in allocation within styles, and not just changes in 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 who 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.

Table 3 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.). Existing 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 (62%) than those in the bottom quartile (64%). It is no different for FI VCs.

Prior literature has also identified the effects of geographical clustering among VCs, particularly in the California and Massachusetts regions (CA/MA) where, among other things, flow of information through local social networks may be more likely. We may also expect different drift responses from VCs based on whether they are in the U.S. or not. The proportions of CA/MA- and U.S.-based VCs are lower in the top drift quartile than in the bottom drift quartile.

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 (see 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 year of financing and founding of the VC firm. 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 using *IPO Rate*, or the rate at which it is able to take its portfolio companies public.[21] Early stage financing entails unique challenges and may be considered to be different in terms of value and skills than an investor without such experience. 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 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 VC's active funds invested prior to the financing year. All time-variant variables are calculated as the logarithm of one plus the 1-year lagged value of the variables. The final variable, *New Fund Yr*, is a dummy variable which takes value 1.0 if the VC raised a new fund in the previous year. This allows for VC's investing decisions to be different in light of having raised a new fund recently.

The univariate information in Table 3 shows that higher drift firms are younger, have significantly lower IPO success in the recent past and fewer early stage investments. It is possible that younger firms are still in the process of discovering their relative advantage via a process of drifting, and that the older 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.

Zero drift VCs 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. Zero drift VCs have lower IPO success than the highest drifters. This may have something to do with their lower likelihood of reaping the agglomeration benefits of CA/MA and their greater likelihood of financial institution ownership structure.[22] The tests of difference in means in Table 3 show that zero drift VCs are quite different from the others across characteristic variables.

Overall, those who drift more tend to be younger, more concentrated, have lesser experience in terms of investments and have larger uninvested funds. While these differences

[21] For a recent review, see Krishnan and Masulis (2011). 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 3 calendar years relative to the number of companies it actively invested in is a predictor of portfolio company performance.

[22] We also compared characteristics of VCs with only one fund and those with multiple funds. The aforementioned drift quartile properties do not seem to differ across these two categories of VC firms.

between quartiles are statistically significant on a univariate basis, it remains to be seen how well these variables explain drift on a multivariate basis. This will be assessed next.

4.3 Multivariate analysis

To better understand the drivers of drift, we move to a multivariate setting using panel OLS regression. 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 discussed above. The results are shown in Table 4.

The first regression is a pooled OLS specification with VC age and time-invariant firm characteristics, namely VC ownership and VC location. We find that younger VC firms drift more. We find no evidence that particular types of VCs, based on ownership, drift more or less - coefficients on independent VCs and financial institution VCs are both statistically insignificant. However, US VCs and CA/MA VCs seem to drift more, and the coefficients on these variables are positive and highly significant.

There are a number of observable and unobservable factors that may affect 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 as well as 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 4 include time and firm fixed effects. So, we rely on within-firm changes in VC characteristics. We therefore no longer include time-invariant firm characteristics (i.e., firm location and ownership variables). Additionally, we use one-year lagged values of variables to ameliorate concerns about reverse causality.

Table 4 reports our results. First, across all specifications, we find that seasoned VC firms drift less. It suggests interesting lifecycle 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 lower 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 rather than the economies of styles hypothesis. As in Sørensen (2008) VC firms learn by investing, and complimentary 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.[23]

Second, firms with more experience in early stage investment (*Early Stage Focus*) drift less. Early stage investing is much more risky, requires more attention and unique skills which are valuable. This leads VCs to have greater style persistence and drift less. Third, firms that syndicate more tend to drift more. Syndication offers opportunity to access deals in new industries and geographies. It also allows a VC to access other skills and more monitoring, lessening the need for style persistence. Finally, one might assume that well-diversified firms with investments in many styles might experience less drift as they would

[23]In another context, Seru et al. (2010) find that retail investors' performance improves as they become more experienced.

tend to stay with a diversified pool of investments. Surprisingly, Style HHI has a negative and significant coefficient, 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.

Next, in specifications (4) - (5), we separately include proxies for the VC's pressure to invest if it has uninvested funds as well as 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. The result is consistent with the pressure of investing, given the unique structure of VC funds with fixed fund life of typically 10 years and the long duration for exit from these investments.[24] The other control variables continue to have the same sign and statistical significance.

4.3.1 Herding

In specification (6), we introduce another variable, *Herding*, which measures the lagged correlation between VC's style and the average style proportions across all VC firms over the previous 5 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 twenty, which is the number of styles in this paper. We then stack up these vectors for five consecutive years to obtain a style vector of hundred values, denoted $P_{0,t,t+4}$. We do the same for each VC firm over a five year period as well, resulting in a hundred-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.

It is possible that VCs who herd, i.e., follow the broad trends of investment, may be more likely to drift. However, specification (6) shows that whether a VC is a herder or not does not seem to influence drift. Finally, specification (7) shows the full model including the herding variable. All results still hold. 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. These and other results appear in the following section.

Overall, we find evidence that a firm's lifecycle stage and the pressure of investing 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. Offsetting this, a higher propensity to syndicate deals provides greater freedom to drift. These results hold even after we control for Style HHI, year as well as time-invariant firm-specific factors (observable and unobservable) in all our specifications.

[24]It is possible that the 10-year fund life rule is not as binding as it sounds. Fund life can be extended by mutual LP-GP agreement. However, reputational concerns would still weigh in on GPs who have uninvested funds.

5 Consequences of Drift

We examine the implication of VC drift for investment performance. We follow the literature and define success as exit via an IPO, merger, or buyout. As a robustness test, we also consider next round financing as an alternative measure of success. 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 5 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. Those in the bottom quartile (Quartile 1, with the lowest drift, leaving the zero drift category aside) exit in 1156 days as against 1251 days by those in the higher quartile, a difference of over 3 months, statistically significant at the 1% level. This is true for M&A and buyout exits separately as well while the difference is not statistically significant for IPOs alone.

In Table 6, Panel A, we report exit information for seasoned and young VCs separately. We define seasoned (young) VCs as those with at least (less than) 11 years of experience.[25] For both categories separately, our results are similar. VCs in the lower drift quartiles exhibit significantly quicker exit than those in the higher drift quartiles (opposite when IPOs are considered separately). In Table 6, Panel B, we separate herders from contrarians. Interestingly, while herders in the lower drift quartiles tend to exit sooner (except for IPOs), the results are statistically insignificant or significant only at the 10% level for the contrarians. Thus drift matters much more for herders.

Since these univariate statistics do not control for other characteristics and factors that may affect exit performance, we examine performance in a multivariate setting in the following section.

5.2 Multivariate analysis

We consider two alternative models for performance - a Cox proportional hazards model for time to exit and probit for likelihood of exit. The main variable of interest is the annual variable *Lagged Drift Qtle* which is the quartile of each VC 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 the round level characteristics, and for VC time-invariant and time-variant factors. The literature has shown a positive effect of syndication on performance. So we include a dummy for whether a round is syndicated or not. Similarly, we include a dummy for whether the round is an early stage round -

[25]We use 11 years because after lagging by one year the bifurcation point is 10 years.

given the inherent risky nature of early stage rounds, we expect worse performance for such financing rounds. As before, we include controls for time-invariant VC characteristics, namely ownership structure and geographical location. Finally, in order to focus on style drift as a source of skill and driver of performance, we control for alternative sources of reputation, skill, and expertise 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).

The unit of observation is VC firm×round level. So we analyze the performance implications of all investment rounds in each VC's portfolio. All our specifications have year fixed effects to control for differences in macroeconomic conditions across periods. Finally, 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 US CA/MA) which affects the propensity to drift as well as performance. To address this omitted variable bias, we also include style fixed effects. As a result, we do not include separate controls for portfolio company's geography and industry. All time-varying variables are lagged by one year. The standard errors are clustered at the portfolio company level.

5.2.1 Speed of exit - main specification

Table 7 presents the results of a Cox proportional hazards model to assess how drift affects VCs' performance, measured by the speed of exits. A key advantage of the Cox model is that it addresses censoring issues. VC investments may take several (between 3-5) 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 exponentiated hazards ratio. Coefficient values greater than one indicate an acceleration of exit, and less than one indicate a deceleration.

The first set of three specifications comprises regressions (1)–(3) and covers the entire sample. 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, 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.

Style concentration diminishes exit speeds, i.e., diversified VCs do better. VCs benefit from syndication experience and exit faster from their portfolio companies. Greater reputation and skill with taking firms public (*IPO Rate*), enhances performance through faster exit. Hence, after controling for known performance drivers, higher style drift reduces the successful exit speed of a VC firm's portfolio companies.

5.2.2 Robustness checks

These results in Table 7 continue to be robust when we make a number of changes. Our main specifications use five-year lagged drift quartile and assesses the implications for performance.

To test the robustness of drift, we use the three-year lagged drift quartile instead of the five-year variable in specification (4). The results remain unchanged in that increasing drift reduces exit speed.

Next, we restrict the sample to include investment data only until year 2005. This addresses a few important data issues. One is a possible concern about data quality since 2005, where full reporting of the ten-year fund cycle may not be assumed to have occurred towards the end of the sample. Two, we wish to consider only those cases where the investments would have sufficient time to exit, about 5 years since investment (because investments may take 3 to 5 years on average to exit). Three, as we mentioned previously, almost 25% of the zero-drift VCs came into existence post-2005. Looking only at pre-2005 data reduces the likelihood of zero-drift VCs distorting our results. The results are shown in specification (5) in Table 7. We again find that the probability of exit declines significantly with increasing drift. The coefficient of the drift quartile variable for speed of exit is no longer statistically significant, though it has the right sign.

Our analysis uses all financing rounds of a portfolio company. One concern with such an analysis may be that VCs who invest in early stages of a portfolio firm's lifecycle may have less discretion in the decision to invest in subsequent round 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's first investment in a portfolio company. Results are shown in specification (6) of Table 7. We see that the speed of exit declines significantly as drift increases, controlling for other variables as before.

It is possible that the drift measure is capturing changes in proportions within the same styles and that changes in the style set are few and far between. Drift is more interesting when driven by large discrete changes which occur when a VC moves in or out of styles. Therefore, as an additional robustness test, we define drift only in terms of changes in style components and re-do all our performance specifications. The results remain qualitatively the same (details not reported here). Therefore, our results are not driven exclusively by changes in style proportions.

The literature has sometimes treated venture capital funds as distinct from buyout funds. We estimate our basic specifications (i.e., the tables on who drifts and why, and the performance regressions) after excluding funds with an investment preference for buyouts. The results (not reported for parsimony) remain qualitatively unchanged.

5.2.3 Performance - likelihood of exit

To provide further evidence for the implication of drift for performance, Table 8 reports 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. After all controls, style drift reduces the success probability of a VC's portfolio companies. Our results hold even under the corresponding robustness tests.

5.2.4 Success to include follow-on financing

Following Hochberg et al. (2007), we measure a company's performance in terms of proceeding to the next round of financing or exiting via an IPO or M&A transaction within ten years rather than winding down. We investigate the first three rounds of financing separately and show the results in Table 9. While the Cox specifications (1)–(3) find that drift is significant (and denotes negative performance) only in round 1, the probit regressions in specifications (4)–(6) find that drift is negative and significant in each of the first three rounds. Therefore, drift also impacts the likelihood of swiftly moving on to exit or the next round of financing.

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 types. We consider the implications of VC firm lifecycle (young VC or seasoned VC), extent of correlated investments among VCs (herder or contrarian VC) and age of investment in the VC's portfolio prior to drift ("recent" investment or not).

5.3.1 Young VCs versus seasoned VCs

Table 4 presented evidence that seasoned firms are less likely to drift than younger VC firms. 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 10 reports results for Cox and probit specifications based on the the baseline specification (3) in Tables 7 and 8. We first break out the sample into younger VCs and seasoned VCs, i.e., VCs with less than and more than 11 years of experience, respectively.[26]

Specifications (1) and (5) are restricted to investments made by young VCs, while specifications (2) and (6) are restricted to seasoned VCs, i.e., VCs with at least 11 years of experience. Drift is a significantly adverse characteristic for seasoned VCs, whereas it is not so for younger VCs.[27] Conditional on surviving the initial lifecycle years of drifting, and

[26]Using subsamples allows for each subsample to reflect an independent structure. Besides, interpreting interaction effects is particularly difficult to do in non-linear settings, such as Cox and probit.

[27]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 5 unique companies. All our results hold.

therefore acquiring specific skills, drifting becomes detrimental.

5.3.2 Herders versus contrarians

We next examine whether the type of "drifter" matters, i.e., do Contrarian drifters underperform or do the Herders? We split the sample into Contrarians (specifications (3) and (7) in Table 10) and Herders (specifications (4) and (8)).[28] For Contrarians, the effect of drift is not significant. The effect of drift on performance is significant for Herders, i.e., the more they drift, the more adverse is the speed of exit. Hence, following the crowd leads to underperformance. We get the same qualitative results in the probit specifications as we did with the Cox regressions.

5.3.3 Performance - pre-drift portfolio

Previous subsections considered the implication of drift for *all* investments in the VC's portfolio. Not all investments are identical, and therefore the implications of drift may vary across the pre-drift portfolio. More recent investments would likely benefit more from a VC's attention, skills, and expertise compared to investments that have been in the portfolio for a longer period of time. One would expect more recent investments to exhibit poorer performance when a VC drifts.

We consider only drift that results from changes in component styles and not from changes in proportions across styles between two periods. We consider two alternative drift measures - one based on drift in one period t, and the other based on the average drift over 3 years. Unlike specifications in Tables 7 and 8, taking the average drift over a longer time horizon, such as 5 years, is less appropriate since investments considered relatively "recent" in period $t-1$ may no longer fit that bill 5 years hence.

Table 11 shows the results of this analysis. We run 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 7. 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. We find that the coefficient on the interaction term is statistically insignificant in specification (1) but is positive and statistically significant in specification (2). We get analogous results in the probit specifications (3)-(4) for the likelihood of exit. Drift adversely affects more recent investments in the VC's portfolio.

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

5.4 Alternative explanations

5.4.1 Reverse causality

The above analyses have implicitly treated VC drift as exogenous and used it as an independent variable. This assumption may be questioned. A VC may choose to invest in a new style in anticipation of superior investment performance. Though our current specifications already include style fixed effects, i.e., any style-specific performance expectation is already controlled for, the expectation of an investment's performance may lead the VC to drift in order to acquire a different set of expertise. To test this, 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.

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 7 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. This result ameliorates concerns about reverse causality in our performance regressions.

5.4.2 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. A low ability VC may drift from one set of styles to another after experiencing poor performance. At the same time, by virtue of low ability, the VC will have worse performance. 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.

Another related concern may arise from the fact that VCs with different drift levels are intrinsically different. Comparing "average" high and low drift firms may confound other factors. In order to compare a high drift VC firm with a counterfactual VC firm with low drift, we adopt an alternative approach of comparing the performance of high drift firms (the treatment group) with that of a matched sample of low drift firms (the control group).

We use the Coarsened Exact Matching (CEM) method.[29] The advantage of this matching method is that it allows users to choose the balance between treated and control groups ex-ante rather than after the fact through the usual process of checking and rechecking and

[29]While the matching methodology falls short of a controlled experiment to entirely address the endogeneity issue, we believe it takes us a step closer to a setting in which one compares the impact of high drift on VC firm performance with that of "counterfactual" firms that have low drift.

repeatedly re-estimating under alternative matching methods such as propensity score.[30] For our analysis, we match high drift VCs (treatment group) and low drift VCs (control group) each year, ignoring zero drift VC firms, along the following covariates: age at time $t-1$, VC's geographic location (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. We use the resulting weights on the matched VC firms in the Cox proportional hazards model. The result no longer compares the average difference between VC firms with high and low drift, but instead compares average difference across firms that are quite similar except for the drift dimension.

Table 12 presents the results of the Cox proportional hazards model in specifications (3) and (4). Adding the variables despite the matching procedure allows us to control for any remaining imbalance. The key variable of interest is *Treated*, which takes the value of 1(0) for the treatment (control) group. We consider two different specifications. In specification (3), the treatment (control) group consists of VCs whose lagged 5-year drift is above (below) the median for the year. In specification (4), the treatment (control) group comprises of VCs in the top (bottom) quartile of the lagged 5-year drift distribution for the year. In both these specifications, our main result continues to hold: higher drift is associated with slower exit.

6 Discussion and Conclusions

In this paper, we examine style drift in the VC industry, and its implication for VC performance. To start with, we allocated all VC firm investment rounds to twenty VC investment types or styles, based primarily on industry and geography of the investment. Styles as defined in the mutual funds and hedge funds industry are inappropriate for the VC industry. Our style classification in this paper builds upon and offers a suitable complementary analysis to earlier work. Understanding styles and implications of style drift is valuable for participants such as private investors in VC funds (Limited Partners - LPs).[31]

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 a lot trades off the benefits of persistence, i.e., staying with the same set of investment styles, for the gains from opportunistically moving to new investment style areas. In other words, we assess, in one sense, whether VC firms are able to time the market for private equity investing. Our results suggest no such ability, when measured in terms of the time to exit or the probability

[30] 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 non-parametric 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 (see Azoulay et al., 2010). 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.

[31] An alternative may be to consider style classifications for exits based on acquirer motives, see Achleitner et al. (2012).

of exit.

We document that the performance implication of style drift varies by VC types. VCs drift more early on in their lifecycle. However, seasoned VCs rather than young VCs tend to suffer greater declines in performance when they drift more. Similarly, 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. 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. Kaplan and Schoar (2005) point to heterogeneity in VC skills as a likely explanation for persistence in VC returns. Degree of investment specialization (Gompers et al. (2009)) and syndication and VC networks (Hochberg et al. (2007)), among others, are important sources of heterogeneity among VCs and contribute to performance differentials. In this paper, we control for these variables, and identify style drift as an additional significant feature of VC that explains performance in this industry. Further, we make a sharp distinction between specialization and style persistence. Whereas we find that persistence pays off more than opportunism, Gompers et al. (2009), and Cressy et al. (2007) find that being specialized pays more than being diversified. We find that specialized firms tend to drift less (i.e., 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.

There are many extensions we intend to take up in subsequent research. 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 life-cycle 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))? These and other questions that surround the rubric of VC timing ability are to be pursued in further research.

Appendix

A Style Drift Examples

We present some examples that illustrate and provide intuition for the various approaches that might be taken to 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 two VC funds, that 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), 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, and is the one we adopt 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 not evidenced 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 ten 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 ten 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 ten 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 5-year window, with zero-drift VCs in a separate category.
3-year Drift Qtle	VC's drift quartile, using annual drift averaged over 3-year window, with zero-drift VCs in a separate category.
VC Age	Natural log of one plus the VC's 1-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.
Time-invariant VC characteristics	
Independent VC	Equals 1.0 if there is the VC is an independent VC.
Fin Inst VC	Equals 1.0 if there is the VC is a financial institution VC.
VC Firm US/non-US	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.

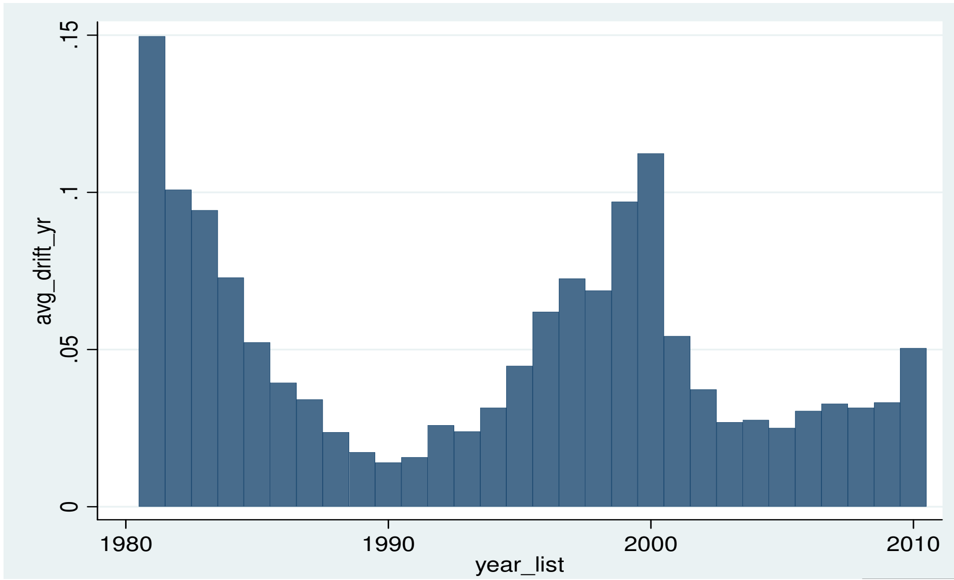

Figure 1: Style drift for each year. The year's style drift is equal to the equally-weighted average of style drifts of each VC for the year.

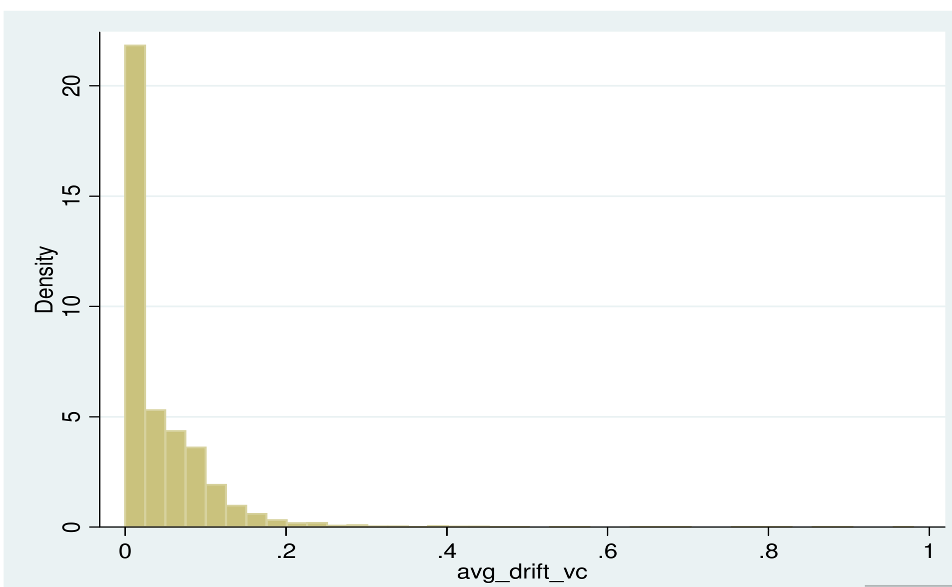

Figure 2: Distribution of style drifts across VCs. The VC's style drift is equal to the equally-weighted average of style drifts of each VC across all years.

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 squred investment shares.

Style	Description	#VC Firms	VC Age	Unique Rounds	#Port Cos	Inv $mm Mean	Inv $mm Mdn	Indus HHI	Stage HHI	Rounds w/Exits	IPO Exits	M&A Exits	Days to Exit Mean	Days to Exit Mdn
1	Buyout-nonUS	2633	12.00	15475	11975	70.34	13.75	0.26	1.00	6202	276	2402	645	294
2	Buyout-US	2705	13.94	15173	10237	80.96	16.63	0.17	1.00	8320	610	2997	807	377
3	Biotech - nonUS	1166	13.22	3618	1530	9.98	3.25	1.00	0.26	659	245	283	1382	1139
4	Biotech - US CA/MA	1115	16.36	3484	836	22.47	11.99	1.00	0.21	1366	643	624	1392	1119
5	Biotech - US non CA/MA	1116	16.41	3219	956	13.55	5.70	1.00	0.21	995	405	521	1431	1102
6	Comm/Media- nonUS	1905	12.36	5875	3171	13.35	3.60	0.62	0.32	967	258	437	1180	947
7	Comm/Media - US CA/MA	1939	14.52	6827	1930	20.29	10.63	0.60	0.24	2941	648	2044	1380	1036
8	Comm/Media - US non CA/MA	2082	14.43	6750	2400	26.61	7.43	0.55	0.26	2459	533	1442	1371	1056
9	Computer- nonUS	2744	11.40	14172	8050	7.27	2.66	0.39	0.31	2128	463	1069	1286	1058
10	Computer - US CA/MA	3163	13.19	18910	5908	14.51	8.00	0.42	0.25	7453	1421	5239	1420	1069
11	Computer - US non CA/MA	3203	13.07	17102	6132	11.72	5.63	0.40	0.25	5962	870	4083	1446	1102
12	Medical - nonUS	1284	13.74	4020	2050	10.49	3.09	1.00	0.27	792	252	298	1296	1076
13	Medical - US CA/MA	1354	16.38	5168	1351	17.60	9.09	1.00	0.21	1911	598	1150	1568	1259
14	Medical - US non CA/MA	1639	15.76	6305	2042	14.42	5.25	1.00	0.23	2246	635	1215	1596	1247
15	non High Tech - nonUS	2833	11.66	22901	16787	16.39	2.53	0.44	0.31	2219	551	509	1249	915
16	non High Tech - US CA/MA	1759	15.42	5769	2421	16.56	4.58	0.36	0.24	1392	317	777	1804	1310
17	non High Tech - US non CA/MA	2425	14.56	12443	6317	15.45	3.21	0.37	0.25	3448	583	1902	1690	1219
18	Semiconductors - nonUS	1263	13.16	3850	2071	8.99	2.44	1.00	0.30	612	186	256	1405	1158
19	Semiconductors - US CA/MA	1499	15.85	4276	1175	17.77	9.28	1.00	0.24	1773	486	1086	1641	1322
20	Semiconductors - US non CA/MA	1240	16.60	2699	861	14.22	5.62	1.00	0.23	952	227	574	1637	1281
	TOTAL	39067	13.82	178036	88200	21.74	5.79	0.56	0.35	54797	10207	28908	1268	913

Table 2: Sample statistics - VC firm and VC fund. This table provides mean (median) and standard deviation of characteristics of VC firms (separately for VCs with 1 fund and multiple funds) 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=9895)		VCs with fund=1 (N=6245)		VCs with fund>1 (N=3650)		VC funds (N=20940)	
	Mean (Median)	Std. Dev	Mean (Median)	Std. Dev	Mean (Median)	Std. Dev	Mean (Median)	Std. Dev
# Styles	3.95 (3.00)	3.60	2.36 (2.00)	1.98	6.67 (6.00)	4.08	3.54 (3.00)	3.00
Styles/yr	1.77 (1.33)	1.22	1.33 (1.00)	0.62	2.50 (2.00)	1.59	1.71 (1.33)	1.04
# Industries	2.66 (2.00)	1.66	1.92 (1.00)	1.22	3.92 (4.00)	1.55	2.53 (2.00)	1.54
# Portfolio Geog	1.66 (1.00)	0.77	1.37 (1.00)	0.60	2.15 (2.00)	0.77	1.60 (1.00)	0.72
# Funds	2.12 (1.00)	2.69	1.00 (1.00)	0.00	4.03 (3.00)	3.71		
# Porfolio Cos	17.93 (5.00)	65.54	4.78 (2.00)	9.39	40.42 (19.00)	103.40	10.24 (4.00)	34.39
# Rounds	44.92 (6.00)	174.91	7.94 (3.00)	20.46	108.19 (38.00)	275.49	21.23 (6.00)	68.97
VC Age	9.67 (7.00)	11.25	7.05 (4.00)	11.07	14.13 (12.00)	10.10	6.51 (5.00)	6.90
Indept VC	0.60 (1.00)	0.49	0.57 (1.00)	0.49	0.65 (1.00)	0.48	0.65 (1.00)	0.48
VC Firm CA/MA	0.16 0.00	0.37	0.14 0.00	0.34	0.21 0.00	0.41	0.21 0.00	0.41
Early Stage Cos	0.32 (0.24)	0.34	0.32 (0.17)	0.38	0.31 (0.29)	0.25	0.28 (0.18)	0.32
Synd Rds	0.66 (0.80)	0.36	0.66 (0.89)	0.40	0.67 (0.75)	0.27	0.68 (0.84)	0.36
Style HHI (invt amt)	0.57 (0.52)	0.35	0.63 (0.68)	0.38	0.45 (0.39)	0.26	0.58 (0.54)	0.35
Style HHI (# cos)	0.57 (0.50)	0.33	0.69 (0.68)	0.32	0.37 (0.29)	0.23	0.40 (0.24)	0.38
Indus HHI (# cos)	0.63 (0.56)	0.30	0.73 (1.00)	0.29	0.46 (0.41)	0.21	0.63 (0.56)	0.30
Geog HHI (# cos)	0.80 (1.00)	0.25	0.86 (1.00)	0.23	0.69 (0.68)	0.24	0.80 (1.00)	0.26

Table 3: 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 1-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-US, 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.

	Q0			Q1			Q2			Q3			Q4			Test of Mean Equality	
# Unique VCs	2846			2799			3257			3651			4369				
	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	0.000	0.002	0.007	0.004	0.009	0.033	0.021	0.034	0.307	0.205	0.273	***	***
# Styles	1.157	1.000	0.471	2.669	2.000	2.396	3.891	3.000	3.045	3.554	3.000	2.653	2.662	2.000	1.968		***
# Funds	1.135	1.000	0.429	1.828	1.000	1.505	2.232	2.000	1.807	1.929	1.000	1.497	1.503	1.000	1.074	***	***
# Portfolio Cos	1.852	1.000	1.928	6.326	3.000	11.570	10.043	5.000	23.761	7.569	4.000	13.016	4.613	3.000	5.947	***	***
# Rounds	2.650	2.000	3.042	10.901	5.000	20.371	16.352	8.000	39.635	11.596	6.000	19.574	6.426	4.000	9.938	***	***
# Industries	1.188	1.000	0.486	2.085	2.000	1.332	2.725	2.000	1.560	2.583	2.000	1.451	2.140	2.000	1.260	***	***
# Portfolio Geog	1.072	1.000	0.276	1.456	1.000	0.641	1.704	2.000	0.716	1.670	2.000	0.704	1.474	1.000	0.629	**	***
Indept VC	0.619	1.000	0.486	0.636	1.000	0.481	0.677	1.000	0.468	0.653	1.000	0.476	0.616	1.000	0.486	***	
FI VC	0.162	0.000	0.368	0.149	0.000	0.356	0.130	0.000	0.336	0.134	0.000	0.341	0.147	0.000	0.354		***
CA/MA VC	0.134	0.000	0.341	0.264	0.000	0.441	0.310	0.000	0.463	0.259	0.000	0.438	0.211	0.000	0.408	***	***
US/non-US VC	0.750	1.000	0.433	0.933	1.000	0.250	0.953	1.000	0.212	0.921	1.000	0.270	0.856	1.000	0.351	***	***
VC Age	1.817	1.946	0.942	2.258	2.303	0.759	2.225	2.303	0.778	2.005	2.079	0.841	1.728	1.792	0.957	***	***
IPO Rate	0.036	0.000	0.100	0.063	0.034	0.100	0.060	0.036	0.086	0.054	0.029	0.085	0.050	0.013	0.096	***	***
Early Stage Focus	0.168	0.014	0.221	0.266	0.275	0.177	0.291	0.309	0.163	0.264	0.268	0.164	0.198	0.182	0.168	***	***
Synd Experience	0.436	0.486	0.249	0.522	0.589	0.181	0.550	0.606	0.160	0.547	0.606	0.170	0.526	0.626	0.215	*	***
Style HHI	0.523	0.577	0.186	0.310	0.278	0.150	0.265	0.225	0.138	0.278	0.241	0.144	0.378	0.318	0.192	***	***
% Funds Invested	0.295	0.203	0.256	0.563	0.693	0.201	0.568	0.693	0.194	0.505	0.624	0.221	0.355	0.310	0.257	***	***
New Fund Yr	0.111	0.000	0.315	0.156	0.000	0.363	0.198	0.000	0.399	0.195	0.000	0.396	0.179	0.000	0.384	***	***

Table 4: 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 1-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)-(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	-0.252***	-0.323***	-0.290***	-0.270***	-0.285***	-0.437***	-0.370***
	(0.01)	(0.01)	(0.03)	(0.03)	(0.03)	(0.08)	(0.08)
Independent VC	0.008						
	(0.02)						
Fin Inst VC	0.018						
	(0.03)						
US/non-US VC	0.262***						
	(0.04)						
CA/MA VC	0.071***						
	(0.02)						
Early Stage Focus			-2.528***	-2.285***	-2.506***	-2.604***	-2.346***
			(0.10)	(0.12)	(0.10)	(0.22)	(0.24)
IPO Rate			-0.055	-0.055	-0.049	-0.021	-0.006
			(0.09)	(0.09)	(0.09)	(0.10)	(0.10)
Synd Experience			0.191**	0.117	0.193**	0.416**	0.442**
			(0.09)	(0.10)	(0.09)	(0.20)	(0.20)
Style HHI			-0.263***	-0.833***	-0.252***	-0.396*	-1.044***
			(0.09)	(0.10)	(0.08)	(0.21)	(0.24)
% Funds Invested				-1.044***			-1.106***
				(0.06)			(0.10)
New Fund Yr					0.095***		0.052***
					(0.02)		(0.02)
Herding						0.024	0.036
						(0.02)	(0.03)
Constant	2.376***	2.870***	3.092***	3.595***	3.057***	3.880***	4.442***
	(0.04)	(0.03)	(0.10)	(0.10)	(0.10)	(0.28)	(0.29)
Observations	40,616	40,616	40,606	33,058	40,596	23,799	20,736
Number of firm_id	6,721	6,721	6,717	4,715	6,716	4,341	3,417
Year FE	NO	NO	YES	YES	YES	YES	YES
Firm FE	NO	YES	YES	YES	YES	YES	YES
Adj R^2	.	0.030	0.061	0.080	0.062	0.025	0.039

Table 5: 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 5-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. Signifiance 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	1071 (622)	1190 (925)	987 (487)	1140 (625)
1	1156 (899)	1106 (929)	1274 (1016)	961 (619)
2	1192 (901)	1032 (820)	1325 (1035)	1006 (608)
3	1215 (899)	1081 (854)	1343 (1028)	1052 (627)
4	1251 (940)	1100 (868)	1363 (1073)	1141 (681)
Total	1197 (903)	1071 (860)	1320 (1032)	1029 (629)
Q1 - Q4	***	–	***	***

Table 6: 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 5-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	1064 (614)	1170 (862)	1017 (587)	1086 (565)	1085 (636)	1232 (934)	925 (219)	1245 (710)
1	1149 (892)	1084 (901)	1269 (1016)	967 (614)	1199 (947)	1268 (1127)	1303 (1016)	920 (655)
2	1158 (864)	987 (762)	1295 (1010)	987 (589)	1334 (1044)	1217 (1058)	1445 (1122)	1107 (706)
3	1153 (839)	1025 (799)	1267 (975)	1029 (584)	1337 (1011)	1178 (964)	1480 (1131)	1115 (732)
4	1189 (863)	1040 (763)	1310 (1029)	1082 (658)	1313 (1003)	1157 (989)	1412 (1115)	1220 (730)
Total	1157 (864)	1026 (803)	1280 (1003)	1003 (603)	1310 (1004)	1191 (1013)	1423 (1101)	1120 (713)
Q1 - Q4	**	*	**	**	***	**	***	***
Panel B:	Herders				Contrarians			
0	1012 (549)	1145 (907)	932 (364)	1079 (563)	1338 (1141)	1347 (1008)	1264 (1157)	1422 (1009)
1	1159 (898)	1109 (941)	1283 (1027)	935 (579)	1113 (906)	1075 (916)	1137 (935)	1105 (865)
2	1209 (910)	1049 (835)	1352 (1051)	993 (585)	998 (788)	842 (685)	1001 (804)	1160 (900)
3	1231 (907)	1094 (870)	1360 (1034)	1067 (628)	1088 (846)	979 (763)	1201 (983)	933 (622)
4	1271 (950)	1113 (888)	1385 (1087)	1164 (686)	1120 (856)	1021 (687)	1216 (998)	1015 (681)
Total	1210 (908)	1083 (873)	1338 (1042)	1023 (608)	1079 (840)	967 (757)	1131 (924)	1077 (790)
Q1 - Q4	***	–	***	***	–	–	*	*

Table 7: VC Firm and Drift - Cox. This table reports 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. Exits include IPO, M&A or buyouts. Observations are at the VC firm - investment round level. The key variable of interest is lagged Drift Qtle, which is based on annual drift averaged over the last 5-year window (3-year window in specification (4)). While specifications (1)-(4) are based on the full sample, specification (5) uses investments until year 2005 and specification (6) only uses a VC's first-time investment in a portfolio company. 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.

	Full Sample				Year ≤ 2005	First Invt
	(1)	(2)	(3)	(4)	(5)	(6)
Lagged 5-year Drift Qrtl	0.975**	0.963***	0.971**		0.982	0.987*
	0.01	0.01	0.01		0.01	0.01
Lagged 3-year Drift Qrtl				0.980**		
				0.01		
VC Age			1.04	1.031	1.027	1.002
			0.03	0.02	0.03	0.01
Early Stage (Dummy)		0.766***	0.766***	0.753***	0.782***	0.791***
		0.02	0.02	0.02	0.02	0.02
Syndication (Dummy)		1.441***	1.442***	1.479***	1.497***	1.510***
		0.04	0.04	0.04	0.05	0.03
Independent VC		1.193***	1.193***	1.169***	1.192***	1.169***
		0.04	0.04	0.04	0.05	0.02
Fin Inst VC		1.106**	1.099*	1.083*	1.142**	1.022
		0.05	0.05	0.05	0.06	0.03
US/non-US VC		1.056	1.049	1.071	1.026	1.112*
		0.08	0.08	0.07	0.1	0.06
CA/MA VC		1.012	1.01	1.028	1.022	1.047***
		0.03	0.03	0.02	0.03	0.02
Style HHI		0.618***	0.664***	0.725***	0.643***	0.740***
		0.08	0.09	0.08	0.09	0.05
Synd Experience		1.588***	1.627***	1.623***	1.595***	1.398***
		0.18	0.19	0.16	0.21	0.09
Early Stage Focus		0.613***	0.614***	0.607***	0.677***	0.463***
		0.06	0.06	0.05	0.07	0.03
IPO Rate		1.270***	1.262***	1.254***	1.219**	1.389***
		0.11	0.11	0.1	0.11	0.08
Observations	2,69,245	2,69,244	2,69,244	3,29,498	1,81,133	86,055
Year FE	YES	YES	YES	YES	YES	YES
Style FE	YES	YES	YES	YES	YES	YES
Pseudo R^2	0.009	0.011	0.011	0.01	0.011	0.016

Table 8: VC Firm and Drift - Probit. This table reports estimates of a probit model, where the dependent variable is 1 if there is a successful exit within 10 years of the investment round, 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 Qtle, which is based on annual drift averaged over the last 5-year window (3-year window in specification (4)). While specifications (1)-(4) are based on the full sample, specification (5) uses investments until year 2005 and specification (6) only uses a VC's first-time investment in a portfolio company. 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.

	Full Sample				Year $\leq$ 2005	First Invt
	(1)	(2)	(3)	(4)	(5)	(6)
Lagged 5-year Drift Qrtl	-0.019**	-0.028***	-0.027***		-0.021**	-0.015***
	-0.01	-0.01	-0.01		-0.01	(0.01)
Lagged 3-year Drift Qrtl				-0.024***		
				0.01		
VC Age			0.005	0.009	-0.01	-0.017
			0.02	0.02	0.02	(0.01)
Early Stage (Dummy)		-0.183***	-0.183***	-0.195***	-0.166***	-0.154***
		0.02	0.02	0.02	0.02	(0.02)
Syndication (Dummy)		0.287***	0.287***	0.299***	0.337***	0.288***
		0.02	0.02	0.02	0.02	(0.01)
Independent VC		0.150***	0.150***	0.137***	0.156***	0.139***
		0.03	0.03	0.02	0.03	(0.01)
Fin Inst VC		0.074**	0.074**	0.066**	0.107***	0.030
		0.04	0.04	0.03	0.04	(0.02)
US/non-US VC		-0.016	-0.017	-0.001	0.034	0.036
		0.05	0.05	0.04	0.08	(0.03)
CA/MA VC		0.005	0.005	0.018	0.018	0.039***
		0.02	0.02	0.02	0.02	(0.01)
Style HHI		-0.225**	-0.216**	-0.170**	-0.303***	-0.135**
		0.1	0.1	0.09	0.12	(0.05)
Synd Experience		0.363***	0.366***	0.375***	0.397***	0.296***
		0.08	0.08	0.07	0.1	(0.04)
Early Stage Focus		-0.418***	-0.418***	-0.433***	-0.342***	-0.616***
		0.07	0.07	0.06	0.09	(0.05)
IPO Rate		0.300***	0.299***	0.288***	0.211**	0.324***
		0.08	0.08	0.07	0.09	(0.05)
Constant	-1.119***	-1.390***	-1.410***	-1.472***	-0.466***	-1.185***
	0.06	0.09	0.11	0.09	0.15	(0.07)
Observations	2,71,935	2,71,934	2,71,934	3,32,530	1,81,868	87,875
Year FE	YES	YES	YES	YES	YES	YES
Style FE	YES	YES	YES	YES	YES	YES
Pseudo R^2	0.114	0.125	0.125	0.119	0.082	0.143

Table 9: Success through next round financing or exit. Specifications (1)-(3) report the estimates of a Cox proportional hazards model, where the dependent variable is the number of days from financing to the earliest of the next financing round, exit or March 16, 2011. Specifications (4)-(6) report the estimates of a probit model in which the dependent variable is 1.0 if there is a successful exit (IPO, M&A, or buyout) or financing round 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 Qtle, which is based on annual drift averaged over the last 5-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		
	Round1	Round2	Round3	Round1	Round2	Round3
	(1)	(2)	(3)	(4)	(5)	(6)
Lagged Drift Quartile	0.956***	0.987	0.984	-0.042***	-0.035*	-0.042**
	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)
VC Age	0.924**	0.935*	1.024	-0.086**	-0.105**	0.021
	(0.03)	(0.04)	(0.03)	(0.04)	(0.05)	(0.04)
Early Stage (Dummy)	1.468***	1.247***	1.283***	0.364***	0.181***	0.185***
	(0.05)	(0.04)	(0.05)	(0.04)	(0.05)	(0.05)
Syndication (Dummy)	1.528***	1.228***	1.289***	0.387***	0.312***	0.379***
	(0.05)	(0.05)	(0.05)	(0.03)	(0.05)	(0.05)
Independent VC	1.205***	1.190***	1.032	0.204***	0.224***	0.023
	(0.05)	(0.06)	(0.05)	(0.05)	(0.06)	(0.06)
Fin Inst VC	0.956	0.962	0.949	-0.017	-0.001	-0.048
	(0.06)	(0.07)	(0.05)	(0.06)	(0.08)	(0.07)
US/non-US VC	1.355***	1.336***	1.106	0.202***	0.137*	0.046
	(0.10)	(0.12)	(0.17)	(0.05)	(0.08)	(0.14)
CA/MA VC	1.079*	1.042	0.996	0.103**	0.107***	0.048
	(0.04)	(0.03)	(0.03)	(0.04)	(0.04)	(0.04)
Style HHI	0.790	0.602**	0.654***	-0.055	-0.225	-0.555***
	(0.12)	(0.12)	(0.10)	(0.14)	(0.21)	(0.19)
Synd Experience	1.459***	1.904***	1.301*	0.268***	0.722***	0.303*
	(0.16)	(0.36)	(0.18)	(0.10)	(0.17)	(0.16)
Early Stage Focus	1.629***	1.894***	1.433***	0.228*	0.701***	0.193
	(0.19)	(0.23)	(0.17)	(0.13)	(0.14)	(0.15)
IPO Rate	0.786**	0.761**	0.727**	-0.008	-0.073	-0.289
	(0.08)	(0.10)	(0.11)	(0.11)	(0.16)	(0.19)
Constant				-1.498***	-2.037***	-1.410***
				(0.17)	(0.22)	(0.27)
Observations	71,111	49,349	38,699	73,065	49,737	38,874
Year FE	YES	YES	YES	YES	YES	YES
Style FE	YES	YES	YES	YES	YES	YES
Pseudo R^2	0.023	0.015	0.007	0.215	0.223	0.195

Table 10: VC Firm Heterogeneity. Specifications (1)-(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)-(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 Qtle, which is based on annual drift averaged over the last 5-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	1.011	0.958***	1.036	0.962***	0.003	-0.037***	0.023	-0.035***
	0.02	0.01	0.02	0.01	0.01	0.01	0.02	(0.01)
VC Age	0.964	1.059	1.108**	1.029	-0.052	0.019	0.068*	-0.009
	0.1	0.05	0.06	0.03	0.08	0.03	0.04	(0.02)
Early Stage (Dummy)	0.809***	0.747***	0.752***	0.768***	-0.150***	-0.200***	-0.195***	-0.180***
	0.04	0.02	0.06	0.02	0.04	0.03	0.05	(0.02)
Syndication (Dummy)	1.418***	1.443***	1.526***	1.433***	0.273***	0.290***	0.304***	0.284***
	0.07	0.05	0.11	0.05	0.03	0.03	0.05	(0.02)
Independent VC	1.143***	1.212***	1.11	1.204***	0.107***	0.167***	0.098*	0.157***
	0.05	0.06	0.09	0.05	0.04	0.03	0.05	(0.03)
Fin Inst VC	1.205**	1.068	0.949	1.107*	0.124**	0.062	-0.011	0.077**
	0.09	0.06	0.09	0.06	0.06	0.04	0.07	(0.04)
US/non-US VC	0.815**	1.351***	0.957	1.083	-0.167**	0.141**	-0.02	-0.006
	0.08	0.15	0.15	0.09	0.07	0.07	0.12	(0.06)
CA/MA VC	1.083**	0.982	0.954	1.018	0.061*	-0.016	-0.044	0.012
	0.04	0.03	0.07	0.03	0.03	0.02	0.05	(0.02)
Style HHI	1.365*	0.488***	1.111	0.634***	0.259**	-0.395***	0.056	-0.251**
	0.23	0.08	0.27	0.09	0.13	0.12	0.18	(0.11)
Synd Experience	1.744***	1.483***	2.363***	1.527***	0.337***	0.333***	0.672***	0.310***
	0.27	0.21	0.54	0.2	0.11	0.1	0.16	(0.09)
Early Stage Focus	0.645***	0.577***	0.869	0.589***	-0.405***	-0.462***	-0.13	-0.453***
	0.09	0.07	0.2	0.06	0.1	0.09	0.16	(0.08)
IPO Rate	1.403**	1.204*	1.371	1.222**	0.364***	0.262***	0.318*	0.281***
	0.2	0.12	0.27	0.11	0.12	0.09	0.16	(0.09)
Constant					-1.396***	-1.519***	-2.247***	-1.257***
					0.25	0.15	0.25	(0.12)
Observations	70,168	1,99,076	36,764	2,32,202	70,784	2,01,150	37,029	234,623
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	0.013	0.02	0.01	0.109	0.134	0.146	0.118

Table 11: Performance of pre-drift portfolio. Specifications (1)-(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)-(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 2 alternative time frames - VC's annual drift in the first year ahead and annual drift averaged over the first 3 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	3 year	1 year	3 year
	(1)	(2)	(3)	(4)
Drift Qtl	1.001	1.010*	-0.005	0.008*
	(0.01)	(0.01)	(0.00)	(0.00)
Portfolio Age	1.018**	1.018***	0.013*	0.013**
	(0.01)	(0.01)	(0.01)	(0.01)
Drift Qtl x Portfolio Age	1.005	1.005**	0.003	0.004*
	(0.00)	(0.00)	(0.00)	(0.00)
VC Age	1.028***	1.025***	0.018***	0.016***
	(0.01)	(0.01)	(0.01)	(0.01)
Early Stage (Dummy)	0.761***	0.762***	-0.187***	-0.184***
	(0.01)	(0.01)	(0.01)	(0.01)
Syndication (Dummy)	1.536***	1.560***	0.320***	0.343***
	(0.02)	(0.02)	(0.01)	(0.01)
Independent VC	1.138***	1.134***	0.114***	0.113***
	(0.02)	(0.02)	(0.01)	(0.01)
Fin Inst VC	1.087***	1.091***	0.070***	0.073***
	(0.02)	(0.02)	(0.01)	(0.01)
US/non-US VC	1.148***	1.154***	0.055***	0.076***
	(0.04)	(0.04)	(0.02)	(0.02)
CA/MA VC	1.060***	1.059***	0.047***	0.048***
	(0.01)	(0.01)	(0.01)	(0.01)
Style HHI	0.870***	0.855***	-0.077**	-0.093***
	(0.04)	(0.04)	(0.03)	(0.03)
Synd Experience	1.461***	1.486***	0.296***	0.320***
	(0.06)	(0.06)	(0.03)	(0.03)
Early Stage Focus	0.640***	0.666***	-0.364***	-0.325***
	(0.03)	(0.03)	(0.03)	(0.04)
IPO Rate	1.380***	1.358***	0.316***	0.295***
	(0.06)	(0.06)	(0.04)	(0.04)
Constant			-1.289***	-0.965***
			(0.04)	(0.04)
Observations	242,944	216,813	245,110	218,343
Year FE	YES	YES	YES	YES
Style FE	YES	YES	YES	YES
Pseudo R^2	0.011	0.011	0.103	0.090

Table 12: VC Firm Performance -Alternative Explanations. This table presents results for two alternative tests - Granger causality (columns 1 and 2) and Matching model (columns 3 and 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 based on a matching procedure. The dependent variable is the number of days from financing to the earlier of exit (i.e., IPO, M&A, or buyout) or March16, 2011. 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. In column (3)((4)), the treatment group comprises of VCs with above median (top quartile) lagged 5-year drift (excluding zero drift), while the control group has below median (bottom quartile) 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. Each of the 2 models includes controls used in Table 7 and are defined in Appendix B. ***, **, and * denote significance at the 1%, 5% and 10% levels, respectively.

	Granger Test: OLS		Matching Model: Cox	
	Performance	Drift Quartile	Above/Below Median	Top/Bottom Quartile
	(1)	(2)	(3)	(4)
Lagged Performance	0.514***	0.619		
	(0.03)	(0.55)		
Lagged Drift Qtl	-0.001***	0.008		
	(0.00)	(0.01)		
Treated			0.896***	0.781***
			(0.01)	(0.03)
VC Age	0.007	-1.077***	1.077***	1.214***
	(0.00)	(0.20)	(0.02)	(0.04)
Early Stage (Dummy)			0.726***	0.689***
			(0.01)	(0.03)
Syndication (Dummy)			1.191***	1.002
			(0.02)	(0.04)
Independent VC			1.186***	1.533***
			(0.03)	(0.11)
Fin Inst VC			0.994	1.382***
			(0.04)	(0.12)
US/non-US VC			1.001	1.703**
			(0.12)	(0.38)
CA/MA VC			1.035**	0.855***
			(0.02)	(0.04)
Style HHI	-0.029*	-0.432	1.130	0.465***
	(0.02)	(0.55)	(0.09)	(0.08)
Synd Experience	0.012	0.112	1.983***	1.140
	(0.01)	(0.43)	(0.14)	(0.15)
Early Stage Focus	0.027**	-3.193***	0.740***	1.194
	(0.01)	(0.38)	(0.05)	(0.19)
IPO Rate			1.923***	1.277
			(0.16)	(0.21)
Constant	-0.001	6.014***		
	(0.02)	(0.68)		
Observations	9,874	9,874	79,170	14,357
Year FE	YES	YES	YES	YES
Firm FE	YES	YES		
Style FE	NO	NO	YES	YES
Adj R^2 / Pseudo R^2	0.916	0.199	0.014	0.027

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