HARVARD | BUSINESS | SCHOOL

# The Persistent Effect of Initial Success: Evidence from Venture Capital

Ramana Nanda
Sampsa Samila
Olav Sorenson

Working Paper 17-065

# The Persistent Effect of Initial Success: Evidence from Venture Capital

Ramana Nanda
Harvard Business School

Sampsa Samila
IESE Business School

Olav Sorenson
Yale School of Management

**Working Paper 17-065**

# The Persistent Effect of Initial Success: Evidence from Venture Capital*

RAMANA NANDA
Harvard Business School

SAMPSA SAMILA
IESE Business School

OLAV SORENSON
Yale School of Management

June 3, 2019

**Abstract:** We use investment-level data to study performance persistence in venture capital (VC). Consistent with prior studies, we find that each additional IPO among a VC firm's first ten investments predicts as much as an 8% higher IPO rate on its subsequent investments, though this effect erodes with time. In exploring its sources, we document several additional facts: successful outcomes stem in large part from investing in the right places at the right times; VC firms do not persist in their ability to choose the right places and times to invest; but early success does lead to investing in later rounds and in larger syndicates. This pattern of results seems most consistent with the idea that initial success improves access to deal flow. That preferential access raises the quality of subsequent investments, perpetuating performance differences in initial investments.

**Keywords:** venture capital, performance, monitoring, selection, status
**JEL Classification**: G24, M13

*RNanda@hbs.edu; ssamila@iese.edu; olav.sorenson@yale.edu. We thank Shai Bernstein, Michael Ewens, Joan Farre-Mensa, Will Goetzmann, Arthur Korteweg, Christos Makridis, Aksel Mjøs, David Robinson, Antoinette Schoar, Chris Stanton, Joel Waldfogel, Ayako Yasuda, and seminar participants at Aalto University, Boston University, the Chinese University of Hong Kong, Copenhagen Business School, ESMT, ESSEC, IE, IESE, London Business School, the National University of Singapore, the NBER Summer Institute, the University of Luxembourg, the University of Minnesota, and the VATT Institute for Economic Research for helpful comments on earlier versions of this paper. We gratefully acknowledge financial support from the Division of Research and Faculty Development at HBS, the Centre for Law and Business at the National University of Singapore, and the Yale School of Management.

# I. Introduction

One of the distinctive features of private equity as an asset class has been long-term persistence in the relative performance of private equity partnerships. Kaplan and Schoar (2005), for example, found correlations of nearly 0.5 between the returns of one fund and the next within a given private equity firm. Among venture capital (VC) funds, they report even higher levels of persistence, with correlations approaching 0.7 (see also, Phalippou and Gottschalg, 2009; Robinson and Sensoy, 2013; Harris et al., 2014; Ewens and Rhodes-Kropf, 2015; Korteweg and Sørensen, 2017). By contrast, persistence has been almost non-existent among asset managers operating in the public equity markets, such as mutual funds and hedge funds (for reviews, see Ferson, 2010; Wermers, 2011).

The most common interpretation of this persistence has been that private equity fund managers differ in their quality. Some managers, for example, may have a stronger ability to distinguish better investments from worse ones. Or, they may differ in the degrees to which they add value post-investment—for instance, by providing strategic advice to their portfolio companies or by helping them to recruit able executives. Consistent with this interpretation, even within venture capital partnerships, Ewens and Rhodes-Kropf (2015) reported large and persistent differences in investment performance across the individual partners of those funds.

This inference of quality differences across private equity investors, however, has relied on indirect evidence. Although Ewens and Rhodes-Kropf (2015) documented persistence at the level of the individual partner, they did not attempt to decompose the sources of that individual-level persistence. Fund-level studies, moreover, have had limited ability to account for investment-level factors that influence performance. Persistence might, for example, occur simply because managers focus their investments in particular regions and industries (Sorenson and Stuart, 2001). If those segments differ in terms of their positions in long-run cycles or in their levels of competition among private equity firms (e.g., Gompers and Lerner, 2000), then one could observe serial correlation due to inertia in the contexts in which firms invest rather than because some venture capitalists prove better than others at selecting, monitoring or advising their portfolio companies.

To gain greater insight into the sources of persistence, we shift the unit of analysis to the individual investment, similar to Ewens and Rhodes-Kropf (2015). But whereas they do so to estimate persistence at the partner level, we do so, in large part, to decompose the extent to which persistence stems from specific target companies versus from investing in particular industries and regions at particular points in time. Examining persistence in performance at the individual investment level also allows us to include all investors over an extended period of time, as opposed to considering only the subset of firms and time periods for which fund-level returns have been available.

We focus our analysis on the venture capital segment of private equity for two reasons. First, it has had the highest levels of performance persistence (Kaplan and Schoar, 2005; Harris et al., 2014). Second, our shift in unit of analysis requires an investment-level performance measure. Although information on investment-level – as opposed to fund-level – returns has been available for select subsets of investors, one can determine for *all* startups whether they went public or were acquired. Since these forms of investment exits produce nearly all of the positive returns in venture capital (Cumming and MacIntosh, 2003; Cochrane, 2005), the rates of these events within a particular VC fund correlate highly with fund returns (Phalippou and Gottschalg, 2009).

Consistent with prior studies of returns at the fund-level, we find high levels of performance persistence at the investment-level across VC firms. For example, a 10 percentage point higher IPO rate among a VC firm's first ten investments – that is, one additional IPO – predicts a more than 1.6 percentage point higher IPO rate for all subsequent investments by that firm, relative to a VC firm with one fewer IPO among its first 10 investments. Given that fewer than one in five investments in our sample resulted in an IPO, that amounts to an 8% higher likelihood of a public offering over the baseline.

Year-state-industry-stage intercepts at the investment level absorb roughly half of this gross persistence. In other words, differences in where, when, and how venture capital firms invest account for much of the overall persistence in performance across VC firms. But even among VC firms investing in the same stages in the same industries in the same states in the same years, a 10 percentage point higher IPO rate among a VC firm's first ten investments predicts a roughly 4.3% higher IPO rate for the firm's subsequent investments.

The strength of this persistence in success rates nevertheless attenuates over time. Some of this attenuation stems from attrition: VC firms with few IPOs or exits among their initial investments presumably find it difficult to raise a subsequent fund (Kaplan and Schoar, 2005). Long-term convergence in performance across VC firms nevertheless accounts for most of the attenuation. Using a number of different estimation techniques, our investment-level results reveal that venture capital performance exhibits mean reversion (for parallel results at the fund level, see Harris et al., 2014), just as one finds in other asset classes.

But performance differences still persist for long periods of time, on the order of a decade or more. What might account for that persistence? Analyzing performance at the investment level allows us to document a number of additional facts that provide insight into the probable source of the persistence. Initial success, for example, appears to stem in large part from investing in the right places at the right times. Indeed, our analyses reveal that the average IPO and exit rates for all investments made by *other* VC firms in the same year-state-industry-stage segments as the focal VC firm's initial investments strongly predict the observed success rates for the focal VC firm's initial investments. Initial success therefore stems not so much from choosing the right companies or from nurturing them but from investing in the right places at the right times.

Interestingly, initial success, itself, rather than some underlying characteristic of the VC firms appears to account even for the apparent within-segment persistence. Regressions using the average rates of success among other VC firms as an instrument for a focal VC firm's initial success – thereby purging the focal VC firm's unobserved ability in choosing and cultivating specific investments from the estimates – generated as large estimates of persistence as the naïve linear regressions. Although venture capitalists add value to startups through the provision of capital and through mentoring and monitoring (e.g., Hellmann and Puri, 2002; Bernstein et al., 2016), differences across venture capitalists in their ability to select and nurture specific companies appears to play little if any role in accounting for performance persistence.

VC firms may nevertheless differ in their ability to select investments based not on identifying specific startups but on spotting emerging trends and technologies. In other words, VC firms may vary in their aptitude for choosing attractive segments. But we find no evidence that venture capitalists persist in their selection of attractive segments. VC firms that had invested initially in attractive industries and regions continue to invest in them and those segments often continue to experience above-average exit rates. But when choosing industries and regions in which they had not previously invested, VC firms that had enjoyed initial success displayed no better ability than those that had not in selecting promising segments.

Initial success does, however, lead to changes in how venture capitalists invest. VC firms enjoying early success began to invest more and in larger syndicates. They became more central in the community, allowing them access to a larger selection of deals (Sorenson and Stuart, 2001). VC firms with higher levels of initial success also shifted their investments away from the first round of financing, where assessing the potential of a startup proves most difficult. Firms without access to syndicated rounds may need to focus more on early stages to "get into" promising startups, while those with access have the luxury of investing later, after some of the uncertainty surrounding the startup's prospects has been resolved. Adjusting for these differences eliminates most of the remaining performance persistence within a particular region, industry, investment stage, and year.

This pattern of results appears most consistent with performance persistence in venture capital arising from differential access to deal flow. Venture capital operates as a two-sided market. Offering the best price or the first bid does not guarantee an investment. Entrepreneurs can often choose among competing investors. Venture capitalists similarly have a say in selecting their syndicate partners. To the extent that entrepreneurs and other venture capitalists *believe* that VC firms differ in their ability to add value to firms, they prefer partners perceived as more able. Hsu (2004), in fact, found that entrepreneurs accept lower valuations and less attractive terms from more prestigious VC firms when choosing between offers. Prominent VC firms also gain access to a wider and better range of investment opportunities through syndicate partners who want to co-invest with them (Sorenson and Stuart, 2001; Hochberg et al., 2007).

Despite their beliefs about the importance of these quality differences, entrepreneurs and other venture capitalists have little on which to base their assessments of VC firm quality (Korteweg and Sørensen, 2017). Even *ex post* they cannot determine whether another VC firm might have generated more value for a particular venture. In such situations, initial differences in success – even due to chance events – could lead others to perceive a venture capitalist as higher quality, allowing that investor to access attractive deals. Even with no unusual ability to select investments or to nurture them to success, this access advantage allows successful VC firms to invest in more promising startups, thereby perpetuating their initial success.

Our results connect to several strands of the finance literature. Most directly, they advance the literature examining persistence in the performance of venture capital firms. Our investment-level analyses suggest that initial success matters for the long-run success of VC firms, but that these differences attenuate over time and converge to a long-run average across all VC firms. Although these early differences in performance appear to depend on being in the right place at the right time, they become self-reinforcing as entrepreneurs and others interpret early success as evidence of differences in quality, giving successful VC firms preferential access to and terms in investments. This fact may help to explain why persistence has been documented in private equity but not among mutual funds or hedge funds, as firms investing in public debt and equities need not compete for access to deals. It may also explain why persistence among buyout funds has declined as that niche has become more crowded (Harris et al., 2014; Braun et al., 2017).

Interestingly, even if persistence emerges from access advantages rather than from differences in ability, investors in the asset class – the limited partners – would still prefer to invest in the historically-successful firms, especially in terms of performance net of the industries, regions, and stages in which they invested. Persistence due to where venture capitalists invest might simply reflect differences in the underlying risks associated with the VC firms' portfolios, the betas. But preferential access to deal flow could not only raise the expected returns of funds but also reduce their riskiness. Not surprisingly then, VC firms that have enjoyed success in their earlier funds raise larger funds and raise them more frequently (Gompers et al., 1998; Kaplan and Schoar, 2005).

More broadly, our results contribute to a recent literature on how initial differences, even if largely due to exogenous events, can have long-lasting consequences. Oyer (2008), Kahn (2010), Oreopoulos et al. (2012) and others, for example, have found that graduating during a recession can lead individuals to pursue different career paths, with those entering the labor market during these downturns never reaching the income trajectories of their peers who entered during better economic times. Schoar and Zuo (2017) have similarly demonstrated that CEOs who began their careers in recessions lead smaller firms and manage them more conservatively, in terms of investing less in capital expenditures and research and development and in terms of more aggressively avoiding taxes and managing costs. Our results point to a similar sort of long-term effect associated with VC firms being in the right place at the right time. In part, initial differences in success lead VC firms to pursue different investing paths, moving away from the first round and into larger, syndicated investments. But in part, these initial differences create *beliefs* about the ability of the venture capitalists that become self-confirming as investors, entrepreneurs, and others act on them.

# II. Data

We analyze data drawn from the VentureXpert database maintained by Thomson Reuters, which includes round-level information on venture capital investments around the world. VentureXpert has unique investor- and portfolio company-identifiers that allow us to trace the outcomes of individual portfolio companies and to construct the entire investment histories of nearly all VC firms. Although no data source offers complete coverage of all venture investments, Kaplan and Lerner (2017) noted that VentureXpert has better coverage than the primary alternatives at the level of individual investment rounds.[1]

We limit our analysis to investments made between 1961 and 2008. Two factors dictated our choice of starting year: On the one hand, since our core analysis correlates the success of a VC firm's *initial* investments with success in the same VC firm's subsequent investments, a later start date, such as 1980, would exclude several prominent investors, such as Kleiner-Perkins and Sequoia. On the other hand, the earliest information on investments might have been collected retrospectively and therefore open to survival bias. Kaplan and Lerner (2017) reported that the firm that initiated the VentureXpert survey and database, which Thomson Reuters eventually acquired, began operations in 1961. Information prior to that year would have been collected retrospectively, so we exclude VC firms that began investing prior to 1961 from the analysis. The results nevertheless remain unchanged if we restrict the sample to VC firms that began investing after 1980, and Table 3 further demonstrates that our results remain robust over shorter sub-periods.

Our choice of ending year similarly balances the long time required for a venture to achieve a successful exit with the smaller samples arising from earlier end dates. Although our download of the data includes information through 2016, we limit the analysis to investments

[1]VentureXpert under reports the proportion of companies that have failed (leaving them coded as ongoing concerns), but this fact should not bias our results as we focus only on successful exits, through IPOs and through trade sales. VentureXpert also misses some investments (Kaplan et al., 2002). Through extensive comparison of the data to other sources, however, we have determined that VentureXpert misses no more than about 10% of the relevant deals. Even if not random, such a low level of missing observations should not meaningfully influence our results.

made by 2008 so that we have sufficient time to observe whether those portfolio companies went public or were acquired. That is, we include outcomes observed through 2016, for all investments made in the 1961 to 2008 period.

Within this date range, we restrict our focus to firms headquartered in and investing in the United States. We also limit the analysis to firms involved in venture capital investing. VentureXpert includes the entire spectrum of private equity firms, from early stage venture investors to those engaged in leveraged buyouts (LBOs). As noted above, our focus on performance at the investment level requires an investment-level performance measure. For those engaged in venture capital investing, exits – whether through IPOs or through trade sales – provide a good measure of investment-level performance. But for firms engaged in other forms of private equity, such as distressed debt and LBOs, these outcomes have less relevance. We therefore limit the sample (i) to VC firms classified as private partnerships, (ii) to funds classified as venture capital, and (iii) to investments in the four investment stages related to venture capital (seed, early, expansion, and later).

Because many follow-on investments – additional investments made by a VC firm in one of its existing portfolio companies – occur almost *de facto* if the target company has another investment round, we limit our analysis to the initial investments by particular VC firms in specific startup companies. In other words, a portfolio company can appear in our sample multiple times, once for each VC firm that invested in it. Any given VC firm will also appear many times in our sample, once for each portfolio company in which it has invested. But, if a VC firm invests in the same portfolio company across multiple rounds, only the first investment by that VC firm – which might not represent the first round of investment in the portfolio company – appears in our sample. This restriction also prevents us from counting the same successful outcome more than once for any particular investor.

Table 1 provides descriptive statistics for our sample. On average, 20% of the investments made by VC firms went to companies that eventually went public (i.e. had an IPO) and 51% went to companies that experienced either an IPO or a trade sale, allowing the investors to "exit" (sell) their equity positions.[2] These represent the two most profitable outcomes for VC firms. Using hand-collected information on 246 investments in Canada and the United States, for example, Cumming and MacIntosh (2003) reported that investments that resulted in IPOs had average gross returns of more than 400% in the United States while investments that ended in trade sales had average gross returns of 143%.[3] By contrast, write-offs, the single most common outcome, usually resulted in a near-total loss of the original investment. Given the bimodal nature of these outcomes, it has become common for researchers to treat IPOs and acquisitions (trade sales) as successful events and all other outcomes as unsuccessful (e.g., Cochrane, 2005; Hochberg et al., 2007). Phalippou and Gottschalg (2009), moreover, reported that the proportion of target companies that had a successful exit in a fund has a very high correlation to the ratio of distributed funds to funds paid in by the limited partners, a common measure of returns.

# III. Persistence

## A. *Investment-Level Persistence*

We begin by documenting persistence in the performance of venture capital investors at the investment level. Our approach involves assessing the strength of association between the success of a VC firm's prior investments and its success in subsequent investments. An alternative approach would treat performance persistence essentially as an invariant property of the firm, similar to a firm-specific alpha. Korteweg and Sørensen (2017), for example, decomposed performance persistence into that associated with the firm and that associated

[2]Note that successful startups attract more venture capital investors. Thus, while 14% of startups in our sample experience an IPO and 43% have either an IPO or are acquired, the average *investment* has higher rates of success. Those success rates still exceed those typically reported at the investment level. The disparity emerges because VC firms with fewer than 11 portfolio companies – not included in our sample – have lower IPO and exit rates than those with more than 10 portfolio companies.

[3]Although one might worry that VC firms would attempt to embellish their apparent success by disguising unsuccessful investments as acquisitions, Puri and Zarutskie (2012) found no evidence that VC firms pursued such a strategy. Other exit events, such as a buy back by management, could also result in positive returns, but they represent relatively rare outcomes.

with the period of the investment. Their approach has advantages for estimating the signal-to-noise ratio in fund performance (and consequently also the extent to which investors may have the ability to identify better-performing firms). But their approach also has disadvantages. First, it essentially assumes that firm-level advantages remain constant over time. Second, it offers less flexibility for exploring the sources of these firm-level differences.

Our core analysis estimates a series of linear probability models with fixed effects:

$$Y_{vi} = \beta_0 + \beta_1 \bar{Y}_v^{i-10} + \eta_{ysjg}^i + \epsilon_{vi}, \tag{1}$$

where $Y_{vi}$ refers to the dichotomous outcome – either an IPO or any exit – of the investment made by VC firm $v$ in the $i$th startup company in which it invested. We report these results in Table 2. Our main predictor of interest is $\bar{Y}_v^{i-10}$, the share of VC firm $v$'s ten investments prior to its investment in startup $i$ that resulted in the outcome $Y$. The choice of 10 prior investments is somewhat arbitrary, but all of the results presented in Tables 2 through 10 remain robust to using 3, 5, 7, 10, or 15 prior investments to measure past success. The $\eta_{ysjg}^i$ represents the fixed effects included in the regression related to the context of investment $i$. Our most stringent fixed effects control for the year×state×industry×stage of investment $i$, in other words, comparing VC firm $v$'s investment in startup $i$ to other investments in the same year-state-industry-stage segments as the focal investment. We report standard errors clustered at both the level of the VC firm and at the level of the startup company.

Column (1) of Table 2 shows a positive and statistically significant association between the share of a VC firm's prior 10 investments that succeeded and the probability that the focal investment will succeed. Panel A, for example, reports that every additional IPO among the previous ten investments – a 10 percentage point increase in the rate – corresponded to a 2.53 percentage point higher IPO rate for the next investment (about a 14% increase over the baseline IPO rate). Consistent with prior research at the fund level, we find persistence in performance across VC firms at the deal level.

Although this persistence appears lower than that found in prior studies based on returns

– Kaplan and Schoar (2005), for example, reported correlations of 0.69 (PME) and 0.57 (IRR) between one VC fund and the next, and Diller and Kaserer (2009) found similar levels of persistence for funds investing in Europe – our estimations differ in at least three important respects from those calculated in prior research. First, aggregation to the fund level probably reduces the noisiness of the performance measures, resulting in larger correlations. Second, our focus on initial investments in target companies means that any differentials associated with some VC firms "doubling down" more effectively than others, or systematically being better at abandoning worse performing investments, would not appear in our estimates.[4] Third, despite including only VC firms that invested in at least 11 companies, our sample has more than twice as many VC firms as any of these earlier studies, in part because our study covers a longer period, in part because the database has fewer missing values for target company exits than for fund returns.[5]

This simple serial correlation points to persistence in performance, but it might stem from a variety of factors, some of which would have little to do with the ability or quality of the venture capitalists. For example, returns and average IPO and exit rates might vary over time, across industries and regions, and by investment stage. Sorenson and Stuart (2001, 2008) found that VC firms had a strong tendency to invest in companies located close to their offices, to focus on a narrow range of industries, and to invest in particular stages of target company maturity, even after accounting for the supply of high-quality investments available in any particular quarter. If returns and success rates do differ across industries, regions, or investment stages, then persistence might emerge as an artifact of these consistent investing styles rather than because some VC firms enjoy better performance for a particular

[4] Many practitioners see the ability to "pull the plug" as one of the most important differences between the best venture capitalists and the average ones. Consistent with this idea, Guler (2007) found that highly regarded VC firms renewed their investments in companies at lower rates than others. This factor may therefore account for some of the higher performance persistence in studies examining fund returns.

[5] The VentureXpert data used both here and by Kaplan and Schoar (2005) have a much higher proportion of missing data for fund returns than for the success of portfolio companies. If only the more successful funds reported their returns, that could have led to an upward bias in the serial correlations reported by Kaplan and Schoar (2005). Kaplan and Schoar (2005) nevertheless provided extensive evidence that any selection in the reporting of returns appeared relatively uncorrelated with performance and therefore should not have biased their estimates of persistence.

sort of investment. Examining success at the level of the individual investment allows us to adjust for these potential differences due to investing focus.[6]

Column (2) of Table 2 reveals that a large share of the persistence observed in Column (1) stems from differences in the kinds of investments made. Column (2) includes year×state×industry×stage intercepts. These fine-grained fixed effects absorb roughly half of the persistence observed in the models accounting only for vintage. Even after adjusting for these fine-grained differences in kinds of investments, however, the proportion of IPOs (and of exits) in the previous ten investments by a VC firm still correlates strongly with the success of its next investment.

Columns (3) and (4) repeat the estimations in Columns (1) and (2) but with the addition of VC-firm fixed effects. Instead of comparing performance across firms, these regressions therefore examine how the success of a specific VC firm's prior 10 investments relate to the success of its next one. Interestingly, the coefficients switch signs. For any given VC firm, greater success in its prior 10 investments predicts a *lower* likelihood of success in its next investment. In other words, while we find persistence in performance *across* VC firms, we find evidence of mean-reversion in performance *within* VC firms. Harris et al. (2014) similarly found regression to the mean at the fund level when estimating performance persistence with firm-level fixed effects.

Venture capital as an industry has evolved and matured over the past 60 years. Table 3 nevertheless reveals that these patterns have been fairly stable across the history of the industry. The columns estimate performance persistence across and within VC firms for investments made before 1990, from 1985-1995, from 1990-2000, from 1995-2005, and from 2000-2008. Panels A and B report the results without VC fixed effects while Panels C and D present the results with them. Looking across the columns, one can see that the pattern of performance persistence across VC firms but mean reversion within VC firms has been highly consistent over time.

[6]Kaplan and Schoar (2005) adjusted for industry and stage differences but their focus on the fund as the unit of analysis required them to allocate the entire fund to a single industry and stage.

The results in Tables 2 and 3 document that mean reversion exists, but they do not necessarily imply that differences in the performance across VC firms erode to zero over time. To test this possibility more explicitly, Table 4 shifts to examining how the success of the *initial* 10 investments by VC firms relates to performance differences in the subsequent investments of those firms. We again estimate Equation (1), but replace our key explanatory variable – the share of successful outcomes in the previous 10 investments – with the share of successful outcomes in the *initial* 10 investments:

$$Y_{vi} = \beta_0 + \beta_1 \bar{Y}_v^{10} + \eta_{ysjg}^i + \epsilon_{vi}, \tag{2}$$

Note that our key explanatory variable, $\bar{Y}_v^{10}$ now remains constant across all investments by a particular VC firm. We therefore can no longer include VC-firm fixed effects. This approach nevertheless has the advantage of allowing us to study the duration of performance persistence in a more transparent manner.

Column (1) of Table 4 reports the results from regressions that only include year fixed effects. The coefficients are statistically significant and economically meaningful. Panel A indicates that every additional IPO among the first ten investments – a 10 percentage point increase in the rate – corresponded to a 1.5 percentage point higher IPO rate among all subsequent investments, an 8% difference relative to the average IPO rate. Similarly, Panel B implies that every additional exit among the same ten investments predicts a 1.8 percentage point higher exit rate (a 3.6% difference relative to the average). Column (2) adds year×state×industry×stage fixed effects. Even after adjusting for these fine-grained differences in kinds of investments, the proportion of IPOs (or exits) in the first ten investments by a VC firm still correlates strongly with the success of that firm's subsequent investments. Column (2) of Panel A, for example, implies that every additional IPO among the first ten investments predicts a 0.8 percentage point higher IPO rate among all subsequent investments, a 4.2% increase over the average IPO rate.

### *B. Time Path of Persistence*

Columns (3)-(5) of Table 4 investigate the duration of this persistence. Column (3) examines the 11th to the 30th target companies financed by a VC firm, Column (4) the 31st to the 60th companies, and Column (5) the 61st to the 100th companies. As with Column (2), all of the models incorporate year×state×industry×stage fixed effects. Panel A reports the results for IPOs only and Panel B for all exits. The extent to which success in the first ten investments predicts success in subsequent investments declines with experience. The point estimates suggest little, if any, persistence beyond the 60th portfolio company, implying long-term convergence to a common mean.

Selection offers one potential explanation for this attenuation in performance persistence. In other words, perhaps those with less success in their initial investments found it difficult to raise subsequent funds and therefore left the sample (Kaplan and Schoar, 2005). Learning offers a second potential explanation, where those with the worst performance improve with experience. Kempf et al. (2014), for example, found that learning-by-doing occurs even among mutual fund managers investing in public equities, and in venture capital, Sørensen (2007) found positive associations between investing experience and the rates at which portfolio companies had successful exits.

To assess this possibility more directly, Table 5 reports estimates of the relationship between the cumulative (logged) number of investments made by a VC firm prior to a focal investment and the success of that investment, in terms of the probability of an IPO (Panel A) and the probability of exit (Panel B). In Column (1), both panels show positive relationships between cumulative investing experience and expected success. In Panel A, for example, a doubling in experience corresponds to a 0.6 percentage point increase in the rate of IPOs associated with future investments, a 3% rise over the base rate. To account for the effects of selection, the second column introduces VC firm fixed effects, which again flips the sign of the coefficient: success rates appear to *decline* with experience.

Column (3) reports mixed models, where we allow each individual VC firm to have a different learning rate as well as a different base level of success. In other words, we allow these variables to have random coefficients. The base level of success refers to the intercept—that is, the expected performance for VC firms with no investing experience. It therefore effectively captures initial performance differences. In these mixed models, experience, on average, has an estimated coefficient close to zero. But it varies substantially across firms (see the standard deviation of the estimated experience coefficient), meaning that many VC firms do better with investing experience and many others do worse. Interestingly, the correlation between these estimated firm-specific learning coefficients and those of the firm-specific intercepts ranges from $-0.9$ to $-0.94$ across the various models, meaning that the firms with the highest initial performance declined the most over time while those with the lowest initial performance improved the most.

Consistent with the results in Tables 2 and 3, this decline in performance for those who had high initial success and improvement in performance for those who had lower initial success points to a mean-reverting process. Figure 1 reveals that this mean reversion appears even in the unadjusted data. Each dot on this plot represents the entire history of one VC firm in our sample. The x-axis depicts the total number of startups that the VC firm backed during our sample period, while the y-axis reports the proportion of those startup companies that had either an IPO (upper panel) or any exit (lower panel). Apart from one or two outliers, the graph illustrates strong convergence to the mean: VC firms with larger numbers of investments converge to the industry average success rate.

# IV. Sources of Persistence

Despite the convergence in performance over time, VC firms that enjoyed higher initial success continued to see higher subsequent success until they invested in more than 60 companies. Since the average fund in our sample invests in about 18 portfolio companies (median = 12), our results imply that the advantages of success in the first fund persist well into the third or fourth fund.

We explored three potential mechanisms that might account for this persistence. (1) VC firms may differ in their ability to select promising startups or promising sectors. (2) Even if they do not differ in their ability to select the right investments, some venture capitalists may prove better than others at monitoring their portfolio companies and at mentoring founding teams to success. (3) Even if VC firms do not differ meaningfully in their ability to select startups or to mentor and monitor portfolio companies, some venture capitalists may have preferential access to deals, allowing them to invest in the most attractive startups and potentially to gain better terms in those deals.

**Selection:** Venture capitalists spend a great deal of time screening and doing due diligence on potential investments, trying to understand which ones have the greatest potential for growth and profit. These efforts appear effective: Research, for example, has found that VC-backed firms patent at higher rates, operate more efficiently, grow faster, survive longer, and more commonly experience profitable exits than seemingly similar firms that did not receive venture capital financing (Hellmann and Puri, 2000; Engel and Keilbach, 2007; Chemmanur, 2010; Puri and Zarutskie, 2012). Some of these differences may reflect value added by the venture capitalist but some of it likely stems from the effective selection of promising startups (Gompers et al., forthcoming). VC firms, moreover, may vary in this selection ability.

**Monitoring:** A substantial body of research also suggests that VC firms add value post-investment to their portfolio companies in a variety of ways. Hellmann and Puri (2002), for example, found that companies that received investments from VC firms adopted more professional management practices earlier in their lives. Bottazzi et al. (2008) reported that more active VC firms appeared to increase the odds of a successful exit more than less active ones. Bernstein et al. (2016), meanwhile, found that, when VC firms could monitor and advise their portfolio companies more closely, those companies went public at higher rates. Given the numerous ways in which VC firms can add value post-investment, it would not seem surprising if some VC firms proved better at these activities than others.

**Access:** A third factor involves preferential access to deal flow. Venture capitalists select portfolio companies but entrepreneurs often also have a choice of investors. The venture capitalists already invested in a startup, moreover, have substantial influence over who gets invited to invest in subsequent investment rounds for a promising prospect (Sorenson and Stuart, 2008). When startups have multiple suitors, venture capitalists with better reputations will more likely win a deal when they bid the same price. In fact, entrepreneurs often prefer them even when they offer a *lower* price (Hsu, 2004). Presumably, the entrepreneurs and existing investors believe it in their own interest to bring prominent venture capitalists into the deal, either because they believe that these investors have acumen or connections that could increase the value of the startup or because they believe that an investment from a prominent investor will signal to others the quality of the startup (Cong and Xiao, 2017).

We investigate these mechanisms in three steps. We begin by considering whether performance persistence stems from the better performance of the specific targets selected by successful VC firms, which could arise either because these firms can better select promising investments or because they can advise them more ably. We then explore whether some VC firms appear better able to select the right industries, regions, or times to invest. Finally, we examine the relationship between initial success and a variety of variables measuring investment behavior that should relate to access to deal flow.

## *A. Target-Specific Persistence*

Before delving into the additional analyses, note that the patterns reported in Section III already suggest that differences in the ability to select specific startups or in the ability to mentor and monitor them to success may not matter much in producing performance persistence. The value of these activities should only accrue to the specific companies in which a venture capital firm actually invests. One might also expect these abilities either to remain relatively stable over time or perhaps to improve with experience. But neither of those patterns play out in data. Where and when VC firms invest accounts for more than half of the overall persistence. And, rather than improving with experience, VC firm performance exhibits mean reversion.

One of the difficulties inherent in trying to determine whether differences in ability might account for performance persistence stems from the fact that one cannot readily assess investor ability independently from the success of their investments. We therefore adopted an indirect approach, estimating the extent to which one could predict early success on the basis of the average success of *other* investors in the same sorts of investments, and whether that average success for a particular kind of investment, in turn, predicted persistence in investment success.

To see why this approach gives us insight into this question, note that if some venture capital firms simply have a better ability to choose more promising companies or to nurture them to successful exits, then they should succeed at higher rates than their peers investing in similar sorts of companies. But if common segment-specific factors account for initial success, then the performance of any particular VC firm should correlate highly with that of other VC firms investing in the same industries, regions, and stages at the same times.

We therefore shift to using the success of peers investing in the same year-state-industry-stage segments as the focal VC firm did in its initial 10 investments as the key explanatory variable. This shift should eliminate from the persistence estimates the effects of any initial success that stems from the focal VC firm's ability to select or nurture specific startups. We estimated:

$$Y_{vi} = \beta_0 + \beta_1 \bar{Y}_{-v}^{10} + \eta_{ysjg}^{i} + \epsilon_{vi}, \tag{3}$$

where, as above, $Y_{vi}$ refers to the dichotomous outcome – either an IPO or any exit – of the investment made by VC firm $v$ in the $i$th startup company in which it invested. Our main variable of interest, $\bar{Y}_{-v}^{10}$ now refers to the mean outcome of all *other* startup companies that received venture capital investments in the same year-state-industry-stage segments as the focal VC firm's first ten investments, but that did not include the focal VC as an investor. As before, $\eta_{ysjg}^{i}$ represents the fixed effects related to the focal investment by VC $v$ in startup $i$. In other words, Equation 3 estimates the same model as Equation 2, but where we replace the share of the focal VC firm's initial investments that resulted in an IPO or acquisition with the share of all other investments in the same cells (not backed by the focal VC firm).

Table 6a reports the results of these models. The results in both Panel A and Panel B reveal strong positive correlations between the success of the focal investment and the average success experienced by other VC firms in these segments. The magnitudes imply that a VC firm whose initial 10 investments occurred in segments with a 10 percentage point higher IPO rate of *other* startups (not backed by that VC) had a 4% higher chance of an IPO for all its subsequent investments, after controlling for the fine-grained fixed effects of the year-state-industry-stage segments for each of its subsequent investments. Given the similarity of this magnitude to that seen in Table 4, our results suggest that the early success of VC firms depends almost entirely on having been "in the right place at the right time"—that is, investing in industries and in regions that did particularly well in a given year. Moreover, the results in Table 6a document the same decline in persistence over subsequent investments as seen in Table 4.

Table 6b reports a parallel set of models but where we use the success of other startups – those not funded by the focal VC firms but in the same initial segments in which the focal VC firms invested – as an instrument for the initial success of the VC firm. Table 6a, in other words, provides the reduced form version of the IV estimation in Table 6b. The first stage of this instrumental variable regression is:

$$\bar{Y}_{v}^{10} = \beta_0 + \beta_1 \bar{Y}_{-v}^{10} + \xi_v, \tag{4}$$

where $\bar{Y}_{v}^{10}$ denotes the share of VC firm $v$'s first ten investments that resulted in the outcome in question, either an IPO or any exit, and $\bar{Y}^{10}_{-v}$ refers to the mean outcome of all *other* startup companies that received venture capital investments in the same year-state-industry-stage segments as the focal VC firm's first ten investments. The coefficient $\beta_1$ therefore captures initial success driven not by the focal firm's choices and activities but by factors common to the contexts in which the VC firm has been investing.

The first stages reveal a strong positive partial correlation between the success of the focal investor and that of other VC firms who invested in the same fine-grained year-state-industry-stage segments, on the order of 0.5.[7] The instrumented results reveal patterns consistent with, though larger in magnitude than, those in Table 6a.[8] The fact that the IV regression can account for all of the within-segment persistence suggests that initial success itself – due to investing initially in the right places at the right times – explains even the differences in subsequent success across VC firms within particular industries and regions.

In our IV strategy, the exclusion restriction requires that, after controlling for these stringent fixed effects $\eta^i_{ysjg}$, the average success of *other* portfolio companies in the same segments as the focal VC firm's *initial* investments does not influence the success of the focal VC firm's *subsequent* investments, except through the effect that the success predicted by it has on the focal VC firm – for example, by enhancing the focal VC firm's reputation (which might, in turn, have advantages in terms of preferential access to deals). The fine-grained fixed effects should address most concerns regarding the exclusion restriction but one might still worry that some residual correlations could arise: For example, perhaps high quality VC firms have a tendency, in their initial investments, to cluster in certain segments.

Figure 2 explores the extent to which the IV result depends sensitively on the exclusion restriction. To determine whether a small-to-modest violation of this exclusion restriction

[7] The Kleibergen-Paap Wald rk $F$-statistic (Kleibergen and Paap, 2006) assesses the strength of the first stage. It has the benefit of being robust to non-*i.i.d.* errors and thus suitable for clustered standard errors (as used here). Across all of the regressions except one, this $F$-statistic has a value higher than the benchmark of roughly 16 for the instrument to have sufficient strength to eliminate at least 90% of the bias in the naïve regressions (Stock and Yogo, 2005).

[8] The IV regression may yield larger magnitude results because it reduces downward bias due to measurement error.

would threaten this result, we implemented the "local-to-zero" (LTZ) approach, proposed by Conley et al. (2012). In essence, the exclusion restriction assumes that the coefficient for the instrument in the second stage has a value of zero ($\gamma = 0$). The LTZ method relaxes this assumption by allowing one to treat $\gamma$ as though it comes from a distribution ($\gamma \sim U(0, \delta)$). To establish a range of values for $\delta$, it seems reasonable to assume that the coefficient $\gamma$ for the instrument in the second-stage regression should not exceed that obtained in the reduced form regression. In other words, adding the endogenous variable should not increase the coefficient of the instrument, given that the instrument, the endogenous variable, and the dependent variable all have positive pairwise correlations. Given that the coefficients for the instrument in the reduced form estimations range from 0.10 to 0.11 (see Table 7A), we explore values for $\delta$ up to 0.12. Even at quite high values of $\delta$ – cases that would involve substantial violations of the exclusion restriction – the IV produces point estimates equal to or larger than the OLS estimates (the red dot-dash lines). This result therefore does not appear sensitive to potential violations of the exclusion restriction.

## *B. Segment Selection*

The analysis above runs counter to the view that some VC firms have a better ability to select specific companies or have more aptitude in cultivating their success (even if venture capitalists on average play an important role in selecting and governing startups). VC firms may nevertheless differ in their ability to select investments at a more macro level. Perhaps some venture capitalists can foresee the industries and regions about to emerge as hotspots. If so, then being in the right place at the right time may depend not just on chance but also on the ability to anticipate these emerging trends.

We explored this issue by examining whether VC firms exhibited persistence in choosing attractive segments. We measured the attractiveness of a year-state-industry-stage segment as above (in defining the instrumental variable); that is, for each investment, we calculated the attractiveness of the segment as the average IPO rate (or exit rate) experienced by all startup companies in the same year-state-industry-stage receiving an investment from *another* VC firm. We regressed this measure of segment attractiveness on the average segment attractiveness of the first ten investments in which the VC firm invested. We estimated:

$$\bar{Y}^{i}_{-v} = \beta_0 + \beta_1 \bar{Y}^{10}_{-v} + \phi_y + \xi_{vi}, \tag{5}$$

where $\bar{Y}^{i}_{-v}$ represents the attractiveness of the year-state-industry-stage segment in which the VC firm $v$ invested in startup company $i$ and $\bar{Y}^{10}_{-v}$ denotes the average attractiveness of the segments of the first ten investments made by VC firm $v$. The $\phi_y$ specify fixed effects for the year in which VC firm $v$ made the investment in startup company $i$.

Table 7 reports the results of these models. Panel A treats only IPOs as a successful outcome while Panel B includes all exits. The first column examines the extent to which VC firms continue to invest in attractive segments when they invest in the same segments as they had initially invested (i.e. when they invest in companies in the same industries, regions, and stages as their first 10 portfolio companies). The coefficient suggests a fairly high degree of persistence. But note that this estimate essentially captures serial correlation in the performance of particular segments. Given that the segment fixed effects absorb such a large proportion of the raw persistence (in Tables 2 and 4), one would probably expect some persistence in the performance of particular segments.

That persistence, however, might stem from factors that all investors could easily spot (Gompers and Lerner, 2000). It took little special insight, for example, to understand that Internet-related businesses seemed a good place to invest in the late-1990's. To assess whether persistence in the performance of sectors might stem from factors that all VC firms could observe, Column (2) introduces a number of control variables to account for these factors.[9]

[9] These models adjust for the popularity of the segment with nine measures: (i) the count of startup companies, in the segment, in which the focal VC firm did not invest; (ii) the average number of VC firms investing per round in these other startups; (iii) the average size, in 2017 dollars, of VC investments in them; (iv) the average number of rounds these other startups had received; (v) the number of central VC firms investing in these startups; (vi) IPOs and (vii) acquisitions in the same state-industry segment among startup companies that received their last investment in the previous five years; and (viii) IPOs and (ix) acquisitions in the same industry among startup companies that received their last investment in the previous five years.

Their inclusion reduces the serial correlation in continuing to invest in attractive segments by more than half.

But even that persistence in investing in attractive segments could stem from inertia in where venture capitalists invest combined with serial correlation in the performance of those segments. It does not point to an ability to spot trends in those segments. Columns (3)-(7) therefore examine only cases in which the VC firm invested in state-industry-stages in which it had not invested in its first ten investments. In other words, did VC firms that invested in attractive segments in their initial investments appear able to select attractive segments in the future? In Column (3), even without accounting for observable factors that might signal the attractiveness of a segment, VC firms demonstrated no consistent ability to choose attractive segments. After adjusting for these factors in Column (4), moreover, the point estimates for persistence in selecting sectors end up being close to zero.

## *C. Investing Behavior*

We turn finally to examining preferential access to deal flow. The difficulty with examining this potential mechanism stems from the fact that our data do not allow us to see who had the opportunity to invest in a particular target company or who would have liked to have invested but who could not get into the deal. We therefore explored how the characteristics of later investments correlated with initial success, controlling for the characteristics of the initial investments. In other words, we examined how VC firms changed in their investing behavior in response to initial success.

We have one observation per later investment (i.e. the 11th and subsequent target companies). The dependent variables reflect the characteristics of those investments or of the VC firm at the time of that investment – round of the investment, the syndication of the investment, the amount of the investment, and the centrality of the focal VC firm in the syndication network – and the level of initial success enjoyed by the VC firm again serves as the primary explanatory variable of interest. We estimated:

$$C_{vi} = \beta_0 + \beta_1 \bar{Y}_v^{10} + \bar{C}_v^{10} + \phi_y + \epsilon_{vi}, \tag{6}$$

where $C_{vi}$ refers to the characteristic of interest for VC firm $v$ at the time of the investment in target company $i$, $\bar{C}_{v10}$ denotes the average value of the characteristic in question across the first ten investments made by the VC firm $v$, and $\phi_y$ represents fixed effects for the year of the investment.

Table 8 first considers the probability of investing as part of a syndicate and the average size of those syndicates. Columns (1) and (2) examine whether the investment round involved more than one investor. Initial success appeared to lead to more syndicated investments. Each additional initial exit corresponded to a 0.9 to 1 percentage point increase in the probability of syndication. Given the roughly 12% baseline probability of a solo investment, this effect amounts to a 7% to 8% decline in the probability of a solo investment for each initial exit. Columns (3) and (4) then explore whether initial success also corresponded to investing in larger syndicates. It did, with each additional initial exit predicting a roughly 4% increase in the number of co-investors in subsequent investment rounds. Columns (5) and (6) finally consider whether initial success led to firms becoming more central in the co-investment network.[10] These models reveal the largest correlates of initial success, with a 10 percentage point higher success rate among the initial five or ten investments predicting an 8% to 14% increase in centrality. We should note that all of these changes hold in models where we instrument initial success using the same instrument as in Table 6b. These changes therefore appear to stem from initial success itself rather than from unobserved factors related to both early success and investing strategies.

Table 9 considers the investment round and investment size of the VC firm's initial

[10] We use the standard eigenvector centrality measure pioneered by Bonacich (1987)—this measures weights the sum of connections a VC firm has with other firms according to the centrality of those VC firms. Not only has prior research on the industry generally used eigenvector centrality (Sorenson and Stuart, 2001) but this centrality measure appears most strongly associated with fund performance (Hochberg et al., 2007).

investments in companies. As a startup matures, more information becomes available about its chances of success. Investors can therefore more easily discriminate the wheat from the chaff, the companies with the highest potential from the also-rans. Columns (1) and (2) consider only whether the first investment by the focal VC firm occurred in the first round of investing in the target company (by any venture investor). All of the models suggest that VC firms reduced the proportion of investments made in the first round in response to initial success. Each additional initial exit predicted a 0.7 to 0.8 percentage point drop in the probability of a first round investment. Columns (3) and (4), then, consider whether initial success led to larger investments.[11] Initial success predicted larger future investments, with each additional initial exit corresponding to a 5.6% increase in the amount invested per syndicate participant.

But do these changes in investing behavior account for performance persistence? Table 10 examines the extent to which the positive long-term effects on performance associated with initial success depend on these mechanisms, by adjusting for them in our persistence models. Panel A reports the results for only IPOs while Panel B considers both IPOs and trade sales as successful forms of exit. Overall, these changes appear to account for 57% to 74% of the persistence remaining after adjusting for investing focus (i.e. after including the year×state×industry×stage fixed effects). Access to deal flow therefore would appear to explain most of the residual persistence in performance.

# V. Discussion

To understand better what channels might account for persistence in the performance of venture capital firms, we examine how the performance of VC firms' investments – in terms of having successful exits, either through IPOs or trade sales – depend on their initial success. Although the performance of VC firms converges with increasing numbers of investments,

[11]VentureXpert only records the total amount invested in a round and the number of investors in the round but not how much each individual participant invested. We therefore can only estimate the average size of these investments.

we find that initial success predicts future success for as many as 50 subsequent investments. We find that both initial and future success depend in large part on being in the right places at the right times but also that VC firms do not appear to persist in their ability to select those attractive segments. We further find that differences in the selection or nurturing of specific portfolio companies appear to contribute little to explaining this persistence. VC firms enjoying early success did, however, shift their investments to later stages and to syndicated investments. Initial success also allowed these firms to move into more central positions in the co-investment network.

The picture that emerges then is one where initial success gives the firms enjoying it preferential access to deals. Both entrepreneurs and other VC firms want to partner with them. Successful VC firms therefore get to see more deals, particularly in later stages, when it becomes easier to predict which companies might have successful outcomes. Even if venture capitalists do not differ in their abilities to identify more promising ventures (but they all have some ability to distinguish the entrepreneurs and startups with better odds of success), this access advantage could perpetuate differences in initial success over extended periods of time.

Although this conclusion may seem at odds with the usual interpretation of persistence in the finance literature, it seems consistent with the perspectives offered by many practitioners. Chris Dixon, a prominent partner at Andreessen Horowitz (a16z), for example, notes that: "The popular view of venture investing is that it is about picking good companies, because that's what's important with public equities. But you can't apply the logic of public equity markets, where by definition anyone can invest in any stock. Success in VC is probably 10% about picking, and 90% about sourcing the right deals and having entrepreneurs choose your firm as a partner." (Eisenmann and Kind, 2014, p. 8)

An open question concerns whether these access advantages accrue at the level of the VC firm or the level of the individual venture capitalist. Although our data do not include information on which partners led these deals, Ewens and Rhodes-Kropf (2015) provided convincing evidence that most of the persistence in performance occurs at the level of the individual rather than at the level of the VC firm. Given the importance that entrepreneurs often place on having board representation from specific partners at these firms and the fact that the underlying social relationships in the venture capital community connect individuals rather than firms, partners within VC firms probably vary considerably in their personal access to deal flow. They probably also carry these access advantages with them if they move to another VC firm or decide to start their own funds. That movement of individuals across firms may therefore contribute to the dissipation of persistence over time at the firm level (Ewens and Rhodes-Kropf, 2015). It also means that some VC firms, those founded by partners with strong reputations in the industry, may have access advantages from day one, thereby contributing to their initial success, in an almost self-confirming prophecy.

Although our results suggest that VC firms do not differ in their *relative* ability to select and govern startups, they do not imply that VC firms do not create value on average. Our findings seem entirely consistent with the long literature documenting the many ways in which VC firms can increase the value of the firms in which they invest. We would also note that our analysis cannot say anything about whether ability or access to deal flow might drive performance persistence on the intensive margin of returns. Some investors, for example, might become good at experimentation—investing in a large number of firms and doubling down or abandoning investments in a way that leads to better overall returns.

Our results also seem relevant to the debate on the extent to which the horse (the business idea) or the jockey (the team) contributes to the success of a venture. Kaplan et al. (2009), studying the evolution of fifty firms from business plans to successful exits, found that the business ideas remained relatively stable even though the management teams did not. They therefore argued that investors should place more weight on the business idea than on the management team. Our results would appear to add some additional weight to this horse side of the scale. To the extent that performance, in large part, depends on investing in the right industries and regions at the right times, it has less to do with the specific venture –

and therefore with any particular team – and more to do with a particular investing space (the business).

But jockeys may still matter. Note that the importance of the access channel to performance depends on the idea that many investors can see that these companies have strong chances of success. What signals or creates that potential remains an open question. Investors – surprisingly, given the apparent importance of the business idea to success – appear to weight teams more heavily than business ideas when choosing early-stage investments (Gompers et al., forthcoming; Berstein et al., 2017). Perhaps the characteristics of founding teams account for that potential success that many investors can see. If so, it could help to explain both why so many investors focus on founding teams in their choices and on why access would matter to gaining entry into those promising deals.

The importance of access to deals for performance in venture capital could also help to explain why persistence appears in venture capital but not in most other asset classes, such as mutual funds and hedge funds. For investors primarily purchasing and selling public securities, access depends only on price. When multiple firms perceive an opportunity they therefore compete away the returns associated with it. But, in venture capital, access often depends on more than price. It operates as a two-sided market. Because entrepreneurs and other investors believe that they might benefit from affiliating with prominent investors – who they believe have the ability to create more value for them – they willingly accept lower prices from these individuals and firms, allowing them to earn rents on their reputations.

Because this mechanism depends to some extent on the supply of capital exceeding the demand for it, at least for the most promising deals, it also implies that the returns to past success – and the prestige associated with it – should become more pronounced during periods when venture capital becomes plentiful. Indeed, consistent with this expectation, Shi et al. (2017), exploring the temporal sensitivity of the results in Hochberg et al. (2007), found that VC firms central in the co-investment network only enjoyed greater success during booms. During busts, central firms performed no better than more peripheral ones.

Even though these differences do not emerge from heterogeneity in the abilities of VC firms, investors in venture capital, limited partners, can potentially still invest in them to earn excess returns. Whether they can do so, however, depends in large part on whether investors have enough information about the performance of previous funds at the time that they must decide whether to invest in future ones. Phalippou (2010), for example, notes that a large share of the correlation in returns across funds stems from investments made within only a few years of one another, when the outcomes of the earlier ones might not yet have been apparent. Our results, nevertheless, suggest that at least a small portion of the performance persistence associated with early success lasts long enough for investors to react to it—if only they can discern the signal from the noise (Korteweg and Sørensen, 2017).

# REFERENCES


Bernstein, Shai, Xavier Giroud, and Richard Townsend, 2016, The impact of venture capital monitoring, *Journal of Finance* 71, 1591–1622.

Berstein, Shai, Arthur Korteweg, and Kevin Laws, 2017, Attracting early stage investors: Evidence from a randomized field experiment, *Journal of Finance* 72, 509–538.

Bonacich, Phillip, 1987, Power and centrality - a family of measures, *American Journal of Sociology* 92, 1170–1182.

Bottazzi, Laura, Marco Da Rin, and Thomas Hellmann, 2008, Who are the active investors? Evidence from venture capital, *Journal of Financial Economics* 89, 488–512.

Braun, Reiner, Tim Jenkinson, and Ingo Stoff, 2017, How persistent is private equity performance? Evidence from deal-level data, *Journal of Financial Economics* 123, 273–291.

Chemmanur, Thomas J., 2010, How does venture capital financing improve efficiency in private firms? A look beneath the surface, *Review of Financial Studies* 24, 4037–4090.

Cochrane, John H, 2005, The risk and return of venture capital, *Journal of Financial Economics* 75, 3–52.

Cong, Lin William, and Yizhou Xiao, 2017, Persistent blessings of luck, Working paper, University of Chicago.

Conley, Timothy G., Christian B. Hansen, and Peter E. Rossi, 2012, Plausibly exogenous, *The Review of Economics and Statistics* 94, 260–272.

Cumming, Douglas J., and Jeffrey G. MacIntosh, 2003, A cross-country comparison of full and partial venture capital exits, *Journal of Banking and Finance* 27, 511–548.

Diller, Christian, and Christoph Kaserer, 2009, What drives private equity returns? – Fund inflows, skilled GPs, and/or risk?, *European Financial Management* 15, 643–675.

Eisenmann, Thomas, and Liz Kind, 2014, Andeessen horowitz, Case 9-814-060.

Engel, Dirk, and Max Keilbach, 2007, Firm-level implications of early stage venture capital investment - an empirical investigation, *Journal of Empirical Finance* 14, 150–167.

Ewens, Michael, and Matthew Rhodes-Kropf, 2015, Is a VC partnership greater than the sum of its partners?, *Journal of Finance* 70, 1081–1113.

Ferson, Wayne, 2010, Investment performance evaluation, *Annual Review of Financial Economics* 2, 207–234.

Gompers, Paul, Will Gornall, Steven N. Kaplan, and Ilya A. Strebulaev, forthcoming, How do venture capitalists make decisions?, *Journal of Financial Economics* .

Gompers, Paul, and Josh Lerner, 2000, Money chasing deals? The impact of fund inflows on private equity valuation, *Journal of Financial Economics* 55, 281–325.

Gompers, Paul, Josh Lerner, Margaret M. Blair, and Thomas Hellmann, 1998, What drives venture capital fundraising?, *Brookings Papers on Economic Activity* 149–204.

Guler, Isin, 2007, Throwing good money after bad? Political and institutional influences on sequential decision making in the venture capital industry, *Administrative Science Quarterly* 52, 248–285.

Harris, Robert S., Tim Jenkinson, Steven N. Kaplan, and Ruediger Stucke, 2014, Has persistence persisted in private equity? Evidence from buyout and venture capital funds, Working Paper, University of Virginia.

Hellmann, Thomas F., and Manju Puri, 2000, The interaction between product market and financing strategy: The role of venture capital, *Review of Financial Studies* 13, 959–984.

Hellmann, Thomas F., and Manju Puri, 2002, Venture capital and the professionalization of start-up firms: Empirical evidence, *Journal of Finance* 57, 169–197.

Hochberg, Yael V., Alexander Ljungqvist, and Yang Lu, 2007, Whom you know matters: Venture capital networks and investment performance, *Journal of Finance* 62, 251–301.

Hsu, David H., 2004, What do entrepreneurs pay for venture capital affiliation?, *Journal of Finance* 59, 1805–1844.

Kahn, Lisa B., 2010, The long-term labor market consequences of graduating from college in a bad economy, *Labour Economics* 17, 303–316.

Kaplan, Steven N., and Josh Lerner, 2017, *Measuring Entrepreneurial Businesses: Current Knowledge and Challenges*, chapter Venture capital data: Opportunities and challenges (University of Chicago Press, Chicago).

Kaplan, Steven N., and Antoinette Schoar, 2005, Private equity performance: Returns, persistence, and capital flows, *Journal of Finance* 60, 1791–1823.

Kaplan, Steven N., Berk Sensoy, and Per Stromberg, 2009, Should investors bet on the jockey or the horse? evidence from the evolution of firms from early business plans to public companies, *Journal of Finance* 64, 75–115.

Kaplan, Steven N., Per Stromberg, and Berk A. Sensoy, 2002, How well do venture capital databases reflect actual investments?, http://dx.doi.org/10.2139/ssrn.939073.

Kempf, Elisabeth, Alberto Manconi, and Oliver Spalt, 2014, Learning by doing: The value of experience and the origins of skill for mutual fund managers, Working paper, Tilburg University.

Kleibergen, Frank, and Richard Paap, 2006, Generalized reduced rank tests using the singular value decomposition, *Journal of Econometrics* 133, 97–126.

Korteweg, Arthur, and Morten Sørensen, 2017, Skill and luck in private equity performance, *Journal of Financial Economics* 124, 535–562.

Oreopoulos, Philip, Till van Wachter, and Andrew Heisz, 2012, The short- and long-term career effects of graduating in a recession, *American Economic Journal: Applied Economics* 4, 1–29.

Oyer, Paul, 2008, The making of an investment banker: Stock market shocks, career choice, and lifetime income, *Journal of Finance* 63, 2601–2628.

Phalippou, Ludovic, 2010, Venture capital funds: Flow-performance relationship and performance persistence, *Journal of Banking and Finance* 34, 568–577.

Phalippou, Ludovic, and Oliver Gottschalg, 2009, The performance of private equity firms, *Review of Financial Studies* 22, 1747–1776.

Puri, Manju, and Rebecca Zarutskie, 2012, On the life cycle dynamics of venture-capital and non-venture-capital-financed firms, *Journal of Finance* 67, 2247–2293.

Robinson, David, and Berk Sensoy, 2013, Do private equity fund managers earn their fees? Compensation, ownership, and cash flow performance, *Review of Financial Studies* 26, 2760–2797.

Schoar, Antoinette, and Luo Zuo, 2017, Shaped by booms and busts: How the economy impacts ceo careers and management styles, *Review of Financial Studies* 30, 1425–1456.

Shi, Yuan, David Waguespack, and Olav Sorenson, 2017, Temporal issues in replication: The stability of centrality-based advantage, *Sociological Science* 4, 107–122.

Sørensen, Morten, 2007, How smart is smart money? A two-sided matching model of venture capital, *Journal of Finance* 62, 2725–2762.

Sorenson, Olav, and Toby E. Stuart, 2001, Syndication networks and the spatial distribution of venture capital investments, *American Journal of Sociology* 106, 1546–1588.

Sorenson, Olav, and Toby E. Stuart, 2008, Bringing the context back in: Settings and the search for syndicate partners in venture capital investing, *Administrative Science Quarterly* 53, 266–294.

Stock, James H., and Motohiro Yogo, 2005, Testing for weak instruments in linear IV regression, in D. W. K. Andrews, and J. H. Stock, eds., *Identification and Inference for Econometric Models: Essays in Honor of Thomas Rothenberg*, 80–108 (Cambridge University Press, Cambridge).

Wermers, Russ, 2011, Performance measurement of mutual funds, hedge funds, and institutional accounts, *Annual Review of Financial Economics* 3, 537–574.

Figure 1: VC Experience and Performance.

Notes: In both panels, each dot represents the entire history of a single venture capital (VC) firm in the sample and the horizontal axis counts the total number of startup companies in which the VC firm invested. In the upper panel, the vertical axis is the proportion of IPOs in all of the startup companies in which the VC invested. In the lower panel, the vertical axis is the proportion of exits, IPOs or acquisitions, in all of the startup companies in which the VC invested.

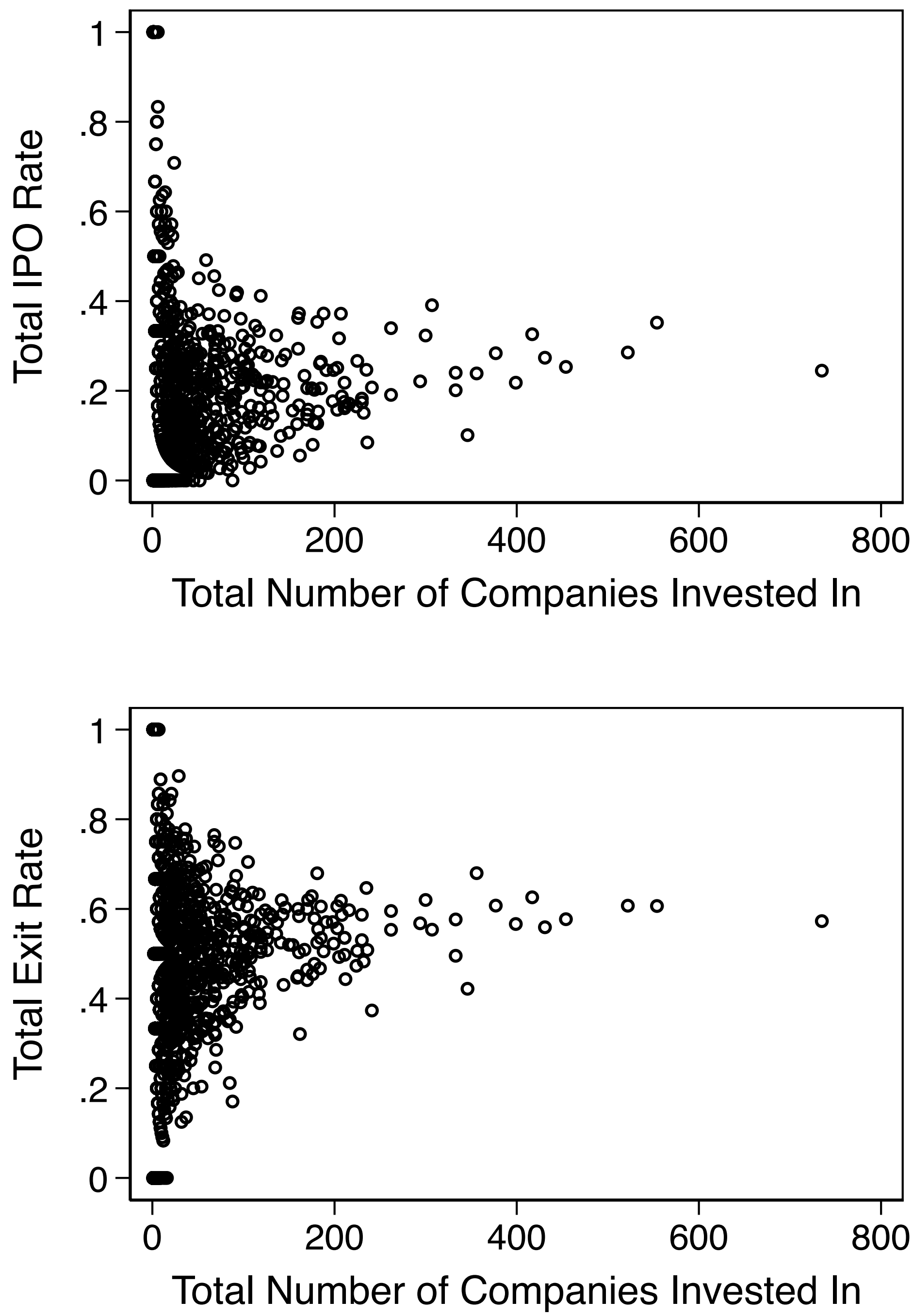
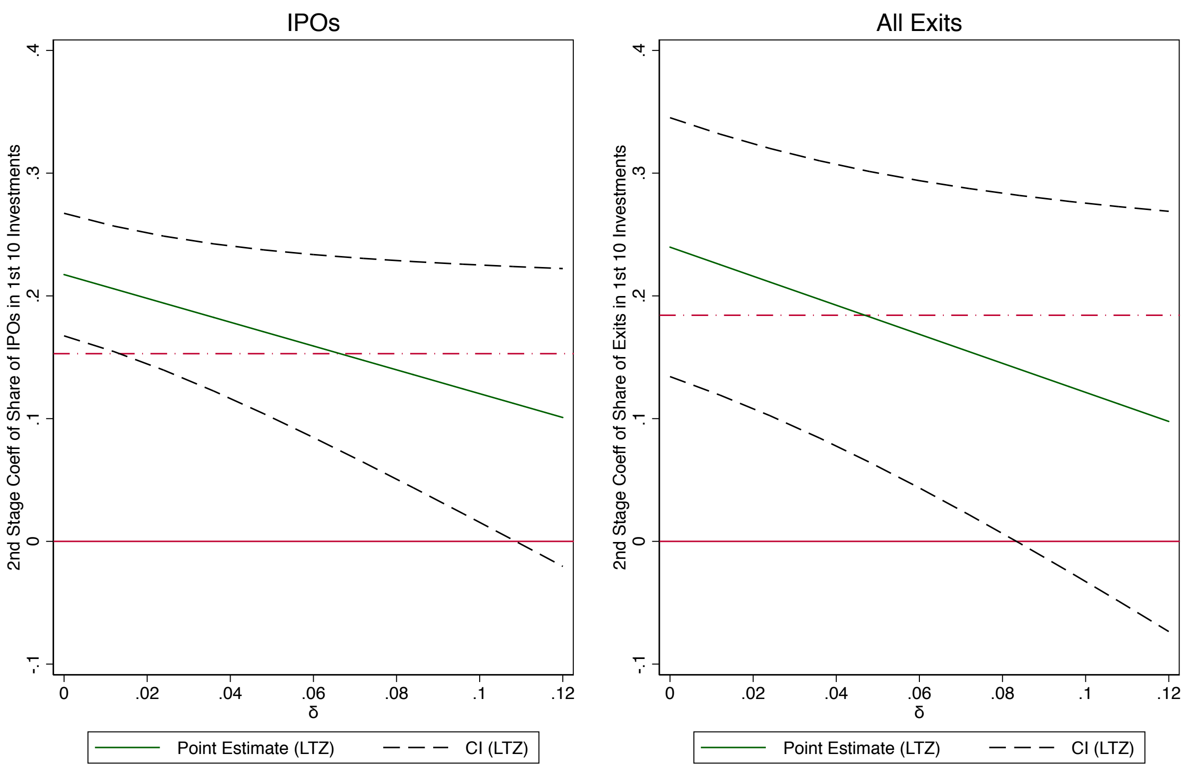


Figure 2: Plausible Exogeneity.

Notes: This figure replicates the estimation of Table 6b using the "local-to-zero" (LTZ) method of Conley et al. (2012). The graphs correspond to Model 1 of Table 6b. The parameter $\gamma$, representing the effect of the instrument in the second stage, has the assumed distribution $\gamma \sim U(0, \delta)$ (normal approximation). The solid line represents the point estimate of the second stage coefficient for the endogenous variable and the dotted lines the 90% confidence intervals. The dash-dot line denotes the OLS estimate from Model 1 of Table 4.



# Table 1: Descriptive Statistics

This table reports descriptive statistics on the sample used for the analysis. The sample is drawn from the VentureXpert database of Thomson-Reuters and consists of venture capital (VC) firms based in the United States and their investments in U.S.-based startups. The data covers the period from 1961 to 2008 and includes only VC firms who made their first investment in 1961 or later and who invested in at least 11 startups between 1961 and 2008. All outcomes are measured as of the end of 2016. When a VC firm invests in multiple rounds for a given startup, only the first investment by the VC firm in that startup enters the sample. Only VC firms classified as private partnerships and funds classified as venture capital are included and only first investments in stages classified as 'seed', 'early', 'expansion', and 'later' are included. Descriptive statistics are reported separately for the first ten investments (used to determine the VC's level of initial success --- the key regressor in the analysis) and for all subsequent investments--- which form the basis of the estimation sample.

| | *Full Sample* | *First 10 investments* | *Subsequent investments* |
|---|---|---|---|
| Number of VC firms making an investment | 895 | 895 | 895 |
| Number of unique startups receiving an investment | 19,802 | 6,809 | 17,492 |
| Number of VC-startup pairs, corresponding to the initial investments by a VC in a given startup | 46,013 | 8,950 | 37,063 |
| Probability that initial investment has an IPO | 19.7% | 22.4% | 19.0% |
| Probability that initial investment has an Exit | 51.0% | 48.9% | 51.5% |
| Proportion of unique startups that had an IPO | 13.7% | 18.5% | 13.8% |
| Proportion of unique startups that had an Exit | 42.8% | 47.0% | 44.3% |

## Table 2: Performance Persistence in Proximate Investments

This table reports the results of OLS regressions studying performance persistence at the deal-level. The sample consists of the first investment made by a venture capital (VC) firm in a target company, starting with the eleventh company in which the VC firm invested. The dependent variable is an indicator for whether the target company had an IPO (Panel A) or any exit, that is, an IPO or a trade sale (Panel B). Standard errors are clustered by VC firm and startup company. Columns (1) and (3) include Year fixed effects, noted below as Y. Columns (2) and (4) include Year x State x Industry x Stage fixed effects, noted below as YSIG. Columns (3) and (4) further include VC firm fixed effects. *, ** and *** refer to significance at 0.1, 0.05 and 0.01 respectively.

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| *Panel A: IPOs* | *Without VC fixed effects* | | *With VC fixed effects* | |
| Share of previous 10 investments with IPO | 0.253*** | 0.117*** | -0.010 | -0.036* |
| | (0.022) | (0.018) | (0.020) | (0.019) |
| Additional Fixed Effects | Y | YSIG | Y | YSIG |
| Number of Observations | 37,063 | 37,063 | 37,063 | 37,063 |
| Number of VC firms | 895 | 895 | 895 | 895 |
| *Panel B: All Exits* | *Without VC fixed effects* | | *With VC fixed effects* | |
| Share of previous 10 investments with an Exit | 0.251*** | 0.145*** | -0.064*** | -0.083*** |
| | (0.018) | (0.017) | (0.020) | (0.019) |
| Additional Fixed Effects | Y | YSIG | Y | YSIG |
| Number of Observations | 37,063 | 37,063 | 37,063 | 37,063 |
| Number of VC firms | 895 | 895 | 895 | 895 |

## Table 3: Performance Persistence in Proximate Investments - different time periods

This table reports the results of OLS regressions studying performance persistence at the deal-level. The sample consists of the first investment made by a venture capital (VC) firm in a target company, starting with the eleventh company in which the VC firm invested. The dependent variable is an indicator for whether the target company had an IPO (Panel A and C) or any exit, that is, an IPO or a trade sale (Panel B and D). Each column is a different subsample time period. Standard errors are clustered by VC firm and startup company. All columns include Year x State x Industry x Stage fixed effects, noted below as YSIG. *, ** and *** refer to significance at 0.1, 0.05 and 0.01 respectively.

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| | Before 1990 | 1985-1995 | 1990-2000 | 1995-2005 | 2000-2008 |
| *Panel A* | *IPOs without VC fixed effects* | | | | |
| Share of previous 10 investments with IPO | 0.060 | 0.094*** | 0.130*** | 0.129*** | 0.094*** |
| | (0.043) | (0.036) | (0.027) | (0.023) | (0.021) |
| *Panel B* | *All Exits without VC fixed effects* | | | | |
| Share of previous 10 investments with an Exit | 0.071* | 0.104*** | 0.162*** | 0.153*** | 0.143*** |
| | (0.038) | (0.034) | (0.027) | (0.021) | (0.023) |
| *Panel C* | *IPOs with VC fixed effects* | | | | |
| Share of previous 10 investments with an Exit | -0.148*** | -0.147*** | -0.070*** | -0.040 | -0.129*** |
| | (0.047) | (0.045) | (0.030) | (0.026) | (0.029) |
| *Panel D* | *All Exits with VC fixed effects* | | | | |
| Share of previous 10 investments with an Exit | -0.167*** | -0.175*** | -0.158*** | -0.121*** | -0.216*** |
| | (0.045) | (0.042) | (0.033) | (0.025) | (0.030) |
| Additional Fixed Effects | YSIG | YSIG | YSIG | YSIG | YSIG |
| Number of Observations | 8,057 | 8,264 | 16,096 | 21,074 | 17,965 |
| Number of VC firms | 254 | 296 | 566 | 734 | 785 |

# Table 4: Performance Persistence of Initial Investments

This table reports the results of OLS regressions studying performance persistence at the deal-level. The sample consists of the first investment made by a venture capital (VC) firm in a target company, starting with the eleventh company in which the VC firm invested. The dependent variable is an indicator for whether the target company had an IPO (Panel A) or any exit, that is, an IPO or a trade sale (Panel B). Standard errors are clustered by VC firm and startup company. Column (1) includes Year fixed effects, noted below as Y. Columns (2) - (5) include Year x State x Industry x Stage fixed effects, noted below as YSIG. *, ** and *** refer to significance at 0.1, 0.05 and 0.01 respectively.

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| | | | *Panel A: IPOs* | | |
| | All subsequent investments | All subsequent investments | Investments 11-30 | Investments 31-60 | Investments 61-100 |
| Share of first 10 investments with IPO | 0.153*** | 0.079*** | 0.073*** | 0.047* | 0.025 |
| | (0.016) | (0.013) | (0.025) | (0.026) | (0.036) |
| Fixed Effects | Y | YSIG | YSIG | YSIG | YSIG |
| Number of Observations | 37,063 | 37,063 | 12,207 | 8,717 | 6,174 |
| Number of VC firms | 895 | 895 | 895 | 399 | 208 |
| | | | *Panel B: All Exits* | | |
| | All subsequent investments | All subsequent investments | Investments 11-30 | Investments 31-60 | Investments 61-100 |
| Share of first 10 investments with an Exit | 0.184*** | 0.084*** | 0.155*** | 0.120*** | 0.059 |
| | (0.024) | (0.021) | (0.031) | (0.039) | (0.048) |
| Fixed Effects | Y | YSIG | YSIG | YSIG | YSIG |
| Number of Observations | 37,063 | 37,063 | 12,207 | 8,717 | 6,174 |
| Number of VC firms | 895 | 895 | 895 | 399 | 208 |

## Table 5: VC Firm Experience and Performance

This table reports the results of OLS regressions studying the relationship between investing experience and performance. The sample consists of the first investment made by a venture capital (VC) firm in a startup company. The dependent variable is a dummy variable indicating whether the startup company in question had an IPO in Panel A or any exit in Panel B. All estimations include either Year (=Y) or Year x State x Industry x Stage fixed effects, noted below as YSIG. Column (2) further includes VC firm fixed effects. Models 3 is a mixed model where the cumulative number of investments by the VC and the constant have random coefficients. The standard deviations of the random coefficients and the estimated correlations are reported below. Standard errors are clustered by VC firm and startup company in columns (1) and (2), and by VC firm in column (3). Note the number of observations are higher than those in other tables as this table also includes investments from VC firms that invested in fewer than 11 companies. *, ** and *** refer to significance at 0.1, 0.05 and 0.01 respectively.

| | (1) | (2) | (3) |
|---|---|---|---|
| *Panel A: IPOs* | | | |
| | OLS | VC FE | Mixed |
| Cumulative Num of investments | 0.006*** | -0.014*** | -0.005** |
| | (0.002) | (0.004) | (0.002) |
| Constant | | | 1.106*** |
| | | | (0.034) |
| stdev(Cumulative Num of investments) | | | 0.032*** |
| | | | (0.004) |
| stdev(Constant) | | | 0.150*** |
| | | | (0.010) |
| corr(Cum Num of Investments, Constant) | | | -0.944*** |
| | | | (0.013) |
| stdev(Residual) | | | 0.360*** |
| | | | (0.004) |
| Fixed Effects | YSIG | YSIG | Y |
| Number of Observations | 46,013 | 46,013 | 46,013 |
| Number of VC firms | 895 | 895 | 895 |
| *Panel B: All Exits* | | | |
| | OLS | VC FE | Mixed |
| Cumulative Num of investments | 0.009*** | -0.015*** | -0.001 |
| | (0.003) | (0.005) | (0.003) |
| Constant | | | 1.136*** |
| | | | (0.044) |
| stdev(Cumulative Num of investments) | | | 0.034*** |
| | | | (0.003) |
| stdev(Constant) | | | 0.164*** |
| | | | (0.010) |
| corr(Cum Num of Investments, Constant) | | | -0.885*** |
| | | | (0.026) |
| stdev(Residual) | | | 0.484*** |
| | | | (0.001) |
| Fixed Effects | YSIG | YSIG | Y |
| Number of Observations | 46,013 | 46,013 | 46,013 |
| Number of VC firms | 895 | 895 | 895 |

## Table 6a: Studying performance persistence by *excluding* focal VC's initial investments

This table reports the results of regressions where the sample consists of the first investment made by a venture capital (VC) firm in a target company, starting with the eleventh company in which the VC firm invested. The dependent variable is an indicator for whether the target company had an IPO (Panel A ) or any exit (Panels B). The key regressor is the relevant success outcome (IPO or Exit) for all *other* starups in the YSIG segments as the focal VC firm's initial 10 investments -- that is, excluding any company backed made by the focal VC firm in the YSIG segments of its first 10 investments. This measure captures the degree to which contextual factors in that segment - rather than the focal VC firm's ability to select and govern specific companies - were responsible for the success experienced by the focal VC firms initial 10 investments. Standard errors are clustered by VC firm and startup company. All estimations include either Year fixed effects, noted below as Y, or Year x State x Industry x Stage fixed effects, noted below as YSIG. *, ** and *** refer to significance at 0.1, 0.05 and 0.01 respectively.

*Panel A: IPOs*

| | *(1)* | *(2)* | *(3)* | *(4)* | *(5)* |
|---|---|---|---|---|---|
| | *All subsequent investments* | *All subsequent investments* | *11-30* | *31-60* | *61-100* |
| IPO Rate for other startups (not backed by focal VC) in same YSIG as initial investment | 0.112*** | 0.073*** | 0.070*** | 0.016 | 0.052 |
| | (0.022) | (0.016) | (0.041) | (0.039) | (0.044) |
| Fixed Effects | Y | YSIG | YSIG | YSIG | YSIG |
| Number of Observations | 37,006 | 37,006 | 12,187 | 8,687 | 6,167 |

*Panel B: All Exits*

| | *All subsequent* | *All subsequent investments* | *11-30* | *31-60* | *61-100* |
|---|---|---|---|---|---|
| Exit Rate for other startups (not backed by focal VC) in same YSIG as initial investment | 0.101*** | 0.055*** | 0.121*** | 0.062 | -0.032 |
| | (0.031) | (0.025) | (0.049) | (0.053) | (0.056) |
| Fixed Effects | Y | YSIG | YSIG | YSIG | YSIG |
| Number of Observations | 37,006 | 37,006 | 12,187 | 8,687 | 6,167 |

## Table 6b: Studying performance persistence by *excluding* focal VC's initial investments - - Instrumental Variable estimations

This table reports the results of regressions where the sample consists of the first investment made by VC firm in a target company, starting with the eleventh company in which the VC firm invested. The dependent for IV regressions is an indicator for whether the target company had an IPO (Panel A) or any exit (Panel B). IV regressions use the relevant success outcome (IPO or Exit) for all *other* starups in the YSIG cells as the focal VC firm's initial 10 investments as an instrument for the success of the focal VC firm's initial 10 investments. The coefficient on the first stage regression and the related F-statistic are reported below the respective IV coefficients. All estimations include either Year fixed effects, noted below as Y, or Year x State x Industry x Stage fixed effects, noted below as YSIG. *, ** and *** refer to significance at 0.1, 0.05 and 0.01 respectively.

*Panel A: IPOs*

| | *(1)* | *(2)* | *(3)* | *(4)* | *(5)* |
|---|---|---|---|---|---|
| | *IV: All* | *IV: All* | *IV: 11-30* | *IV: 31-60* | *IV: 61-100* |
| Share of first 10 investments with IPO | 0.217*** | 0.139*** | 0.147* | 0.041 | 0.179 |
| | (0.031) | (0.027) | (0.085) | (0.097) | (0.160) |
| | *First Stage* | *First Stage* | *First Stage* | *First Stage* | *First Stage* |
| IPO Rate for *other* startups in same YSIG as VC's initial 10 investments | 0.517*** | 0.527*** | 0.480*** | 0.394*** | 0.288*** |
| | (0.087) | (0.077) | (0.069) | (0.093) | (0.102) |
| Kleibergen-Paap Wald rk F-statistic | 35.445 | 47.08 | 47.941 | 17.944 | 7.946 |
| Fixed Effects | Y | YSIG | YSIG | YSIG | YSIG |
| Number of Observations | 37,063 | 37,063 | 12,207 | 8,717 | 6,174 |

*Panel B: All Exits*

| | *IV: All* | *IV: All* | *IV: 11-30* | *IV: 31-60* | *IV: 61-100* |
|---|---|---|---|---|---|
| Share of first 10 investments with an Exit | 0.240*** | 0.127*** | 0.230** | 0.135 | -0.065 |
| | (0.064) | (0.058) | (0.095) | (0.113) | (0.116) |
| | *First Stage* | *First Stage* | *First Stage* | *First Stage* | *First Stage* |
| IPO Rate for *other* startups in same YSIG as VC's initial 10 investments | 0.423*** | 0.429*** | 0.526*** | 0.456*** | 0.495*** |
| | (0.076) | (0.074) | (0.060) | (0.072) | (0.088) |
| Kleibergen-Paap Wald rk F-statistic | 31.28 | 33.62 | 75.777 | 40.19 | 31.842 |
| Fixed Effects | Y | YSIG | YSIG | YSIG | YSIG |
| Number of Observations | 37,063 | 37,063 | 12,207 | 8,717 | 6,174 |

## Table 7: Persistence in Segment Selection

This table reports the results of OLS regressions studying the degree to which VC firms can consistently select 'good' segments Panel A considers IPOs and Panel B considers all exits. The dependent variable in Panel A is the IPO rate among companies that received VC investment in the same year-state-industry-stage segment in which the focal VC firm invested, but excluding all companies in which the focal VC firm ever invested. The dependent variable in Panel B is constructed similarly but includes all exits. All models include Year fixed effects, noted below as Y. Columns (1) and (2) consider State-Industry-Stage investments corresponding to the initial 10 investmental made by the focal VC firm. Models 3-7 look at the mirror image of these, and exclude any State-Industry-Stage segments in which the VC firm had invested in its first investments. Standard errors are clustered by VC firm and by year-state-industry-stage segments *, ** and *** refer to significance at 0.1, 0.05 and 0.01 respectively.

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
|---|---|---|---|---|---|---|---|
| *Panel A IPOs* | | | | | | | |
| | *Investments in Initial Sectors* | *Investments in Initial Sectors* | *Investments in New Sectors* | *Investments in New Sectors* | *11-30 that were in new sectors* | *31-60 that were in new sectors* | *61-100 that were in new sectors* |
| IPO Rate for other startups in same YSIG as initial investments | 0.119** | 0.053** | 0.014 | 0.006 | 0.036 | 0.027 | -0.037* |
| | (0.029) | (0.023) | (0.012) | (0.008) | (0.022) | (0.026) | (0.021) |
| Fixed Effects | Y | Y | Y | Y | Y | Y | Y |
| Controls for attractiveness of the segment | No | Yes | No | Yes | Yes | Yes | Yes |
| Number of Observations | 5,647 | 5,647 | 27,388 | 27,388 | 8,122 | 6,185 | 4,665 |
| Number of VC firms | 693 | 693 | 875 | 875 | 875 | 393 | 207 |
| *Panel B: All Exits* | | | | | | | |
| | *Investments in Initial Sectors* | *Investments in Initial Sectors* | *Investments in New Sectors* | *Investments in New Sectors* | *11-30 that were in new sectors* | *31-60 that were in new sectors* | *61-100 that were in new sectors* |
| Exit Rate for other startups in same YSIG as initial investments | 0.130** | 0.073** | 0.022 | -0.001 | 0.001 | 0.015 | 0.009 |
| | (0.028) | (0.024) | (0.014) | (0.010) | (0.025) | (0.020) | (0.019) |
| Fixed Effects | Y | Y | Y | Y | Y | Y | Y |
| Controls for attractiveness of the segment | No | Yes | No | Yes | Yes | Yes | Yes |
| Number of Observations | 5,647 | 5,647 | 27,388 | 27,388 | 8,122 | 6,185 | 4,665 |
| Number of VC firms | 693 | 693 | 875 | 875 | 875 | 393 | 207 |

## Table 8: Change in Syndication and Network Centrality based on Initial Success

This table reports the results of OLS regressions where the sample consists of the first investment made by a venture capital (VC) firm in a target company, starting with the eleventh company in which the VC firm invested and including all subsequent 'first investments'. The dependent variable in columns (1) and (2) is an indicator for whether the initial investment by the focal VC firm was syndicated with another VC firm. The dependent variable in columns (3) and (4) is the log of the syndicate size of the VC firm's first investment in a company. The dependent variable in columns (5) and (6) is the Eigenvector Centrality of the VC firm. Standard errors are clustered by VC firm and startup company. *, ** and *** refer to significance at 0.1, 0.05 and 0.01 respectively.

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | *Round is Syndicated* | *Round is Syndicated* | *Syndicate Size* | *Syndicate Size* | *Network Centrality* | *Network Centrality* |
| Share of first 10 investments with IPO | 0.109*** | | 0.195*** | | 0.077*** | |
| | (0.020) | | (0.051) | | (0.012) | |
| Share of first 10 investments with an Exit | | 0.095*** | | 0.262*** | | 0.046*** |
| | | (0.023) | | (0.052) | | (0.010) |
| Share of first 10 investments that were syndicated | 0.234*** | 0.222*** | | | | |
| | (0.039) | (0.040) | | | | |
| Average syndicate size of first 10 investments | | | 0.253*** | 0.247*** | | |
| | | | (0.030) | (0.029) | | |
| Eigenvector Centrality at 10th investment | | | | | 0.219*** | 0.275*** |
| | | | | | (0.059) | (0.066) |
| Fixed Effects | Y | Y | Y | Y | Y | Y |
| Number of Observations | 37,063 | 37,063 | 37,063 | 37,063 | 37,063 | 37,063 |
| Number of VC firms | 895 | 895 | 895 | 895 | 895 | 895 |

## Table 9: Change in Round and Size of First Investments based on Initial Success

This table reports the results of OLS regressions where the sample consists of the first investment made by a venture capital (VC) firm in a target company, starting with the eleventh company in which the VC firm invested. The dependent variable in columns (1) and (2) is an indicator for whether the initial investment by the focal VC firm occurred in the first round of financing for the company. The dependent variable in columns (3) and (4) is the log of the round size (in dollars) in which the VC firm's first invested in the company. Standard errors are clustered by VC firm and startup company. *, ** and *** refer to significance at 0.1, 0.05 and 0.01 respectively.

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | *First investment is in Round 1* | *First investment is in Round 1* | *Size of first investment* | *Size of first investment* |
| Share of first 10 investments with IPO | -0.072** | | 0.800*** | |
| | (0.036) | | (0.081) | |
| Share of first 10 investments with an Exit | | -0.058* | | 0.433*** |
| | | (0.034) | | (0.094) |
| Share of first 10 investments that were Round 1 | 0.344*** | 0.341*** | | |
| | (0.031) | (0.031) | | |
| Average size of first 10 investments | | | 0.306*** | 0.248*** |
| | | | (0.038) | (0.041) |
| Fixed Effects | Y | Y | Y | Y |
| Number of Observations | 37,063 | 37,063 | 36,243 | 36,243 |
| Number of VC firms | 895 | 895 | 892 | 892 |

## Table 10: Persistence of Initial Success Controlling for Changes in Investing Behavior

This table reports the results of OLS regressions studying performance persistence at the deal-level. The sample consists of the first investment made by a venture capital (VC) firm in a target company, starting with the eleventh company in which the VC firm invested. The dependent variable is an indicator for whether the target company had an IPO (Panel A) or any exit (Panel B). Standard errors are clustered by VC firm and startup company. Control variables correspond to the round number, round size, syndicate size in the given round and eigenvector centrality of the VC at the time of the given round. All estimations include Year x State x Industry x Stage fixed effects, noted below as YSIG. *, ** and *** refer to significance at 0.1, 0.05 and 0.01 respectively.

| | (1) | (2) |
|---|---|---|
| *Panel A: IPOs* | | |
| Share of first 10 investments with IPO | 0.079*** | 0.034*** |
| | (0.014) | (0.013) |
| Round number (log) | | 0.011 |
| | | (0.008) |
| Round size (log) | | 0.035*** |
| | | (0.003) |
| Syndicate size (log) | | 0.053*** |
| | | (0.006) |
| Eigenvector Centrality | | 0.198*** |
| | | (0.071) |
| Fixed Effects | YSIG | YSIG |
| Number of Observations | 37,063 | 36,243 |
| Number of VC firms | 895 | 892 |
| *Panel B: All Exits* | | |
| Share of first 10 investments with an Exit | 0.084*** | 0.022 |
| | (0.021) | (0.018) |
| Round number (log) | | 0.034*** |
| | | (0.010) |
| Round size (log) | | 0.050*** |
| | | (0.005) |
| Syndicate size (log) | | 0.085*** |
| | | (0.008) |
| Eigenvector Centrality | | 0.383*** |
| | | (0.090) |
| Fixed Effects | YSIG | YSIG |
| Number of Observations | 37,063 | 36,243 |
| Number of VC firms | 895 | 892 |