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
National University of Singapore

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
NUS Business School
National University of Singapore

Olav Sorenson
Yale School of Management

January 16, 2017

Abstract: We used data on individual investments in the portfolios of venture capital firms to study persistence in their performance. Each additional IPO among a VC's first five investments predicted a 13% higher IPO rate for its subsequent 50 investments. Roughly half of this performance persistence stemmed from investment "styles"—investing in particular regions and industries. We found no evidence of performance persistence stemming from a differential ability to select or govern portfolio companies. Rather, our results suggest that early success in venture investing yields better deal flow in subsequent investments, thereby perpetuating differences in the outcomes of initial investments.

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

*RNanda@hbs.edu; sampsa.samila@nus.edu.sg; olav.sorenson@yale.edu. We thank Shai Bernstein, Michael Ewens, Joan Farre-Mensa, Will Goetzmann, Arthur Korteweg, Christos Makridis, David Robinson, Antoinette Schoar, Chris Stanton, and participants at Aalto University, the Chinese University of Hong Kong, Copenhagen Business School, ESSEC, National University of Singapore, NBER Summer Institute, the VATT Institute for Economic Research, and the University of Luxembourg 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 NUS, and the Yale School of Management.

I. Introduction

One of the more distinctive features of private equity as an asset class is the long-term persistence in the relative performance of private equity investors. For example, Kaplan and Schoar (2005) 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 reported even higher levels of persistence, with correlations approaching 0.7 (see also, Phalippou and Gottschalg, 2009; Robinson and Sensoy, 2013; Korteweg and Sørensen, 2016). 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 managers differ in their quality. Some managers, for example, may have greater ability to distinguish better investments from worse ones. They may also differ substantially in the degree to which they add value post-investment—for instance, by providing strategic advice to their portfolio companies or by helping them to recruit high-quality executives.

But these studies of persistence in private equity performance have generally been done at the fund level.[1] Although that focus has been entirely appropriate in terms of estimating the magnitudes of the serial correlations in returns and in understanding variance in investable performance, fund-level aggregation has some disadvantages for disentangling the sources of persistence. It 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 might observe persistence due simply to the fact that managers have consistent investing styles over time.

To gain greater insight into the sources of persistence, we shift the unit of analysis to the individual investment. Doing so allows us to control for differences in the average

[1]For an exception, see Ewens and Rhodes-Kropf (2015), which examined persistence in the investing success of individual VC partners.

performance of investments at particular points in time, and in particular industries and regions. It also allows us to examine persistence in performance within funds.

We focus our analysis on the venture capital segment of private equity for two reasons. First, VC has exhibited the highest levels of persistence within private equity (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 generally not been available for private equity across a wide cross-section of firms, one can determine whether individual VC-backed companies 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 fund correlate highly with fund returns (Phalippou and Gottschalg, 2009).

Consistent with prior studies of returns at the fund-level, we found high levels of persistence in performance at the individual-level of analysis. A 20 percentage point higher IPO rate among the first five investments – that is, one additional IPO – for example, corresponded to a more than two percentage point higher IPO rate for the VC firm across all subsequent investments. Given that less than one in six investments in our sample resulted in an IPO, that implies a 12.7% higher likelihood of a public offering over the baseline.

Roughly half of this gross persistence stemmed from investing styles. State-industry-year-investment stage intercepts at the investment level absorbed 46% to 56% of this gross persistence. But even within these tightly controlled cells, initial success still predicted long-term performance: a 20 percentage point higher IPO rate among the first five investments corresponded to a roughly 7% higher subsequent IPO rate, even within a particular region and industry and investment stage in a particular year. These differences attenuate with time, but, on average, success in the first five or ten investments predicted better performance for at least the next 50 investments made by a VC firm.

A natural explanation for this persistence in outcomes is that venture capitalists differ in their (unobserved) ability—for example in their aptitude for selecting the best startups and in their ability to mentor them to successful outcomes. We found little evidence that such systematic differences across venture capitalists can account for the persistence in our setting. For example, the average IPO and exit rates for all investments made by *other* VC firms in the same state-industry-year cells as the focal VC firm's first five or ten investments strongly predicted the observed success rates for the focal VC firm's initial investments. In other words, initial success stemmed largely from investing in the right place at the right time, rather than from selecting or nurturing specific investments. In fact, 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 from the estimates – generated as large estimates of persistence as the naïve linear regressions.[2]

Perhaps, then, differences in success in venture capital stem not so much from selecting and nurturing individual companies but from spotting trends, in terms of industries and regions about to emerge as hotspots? Here again, however, we found no evidence for inherent differences in the ability to choose the right sectors. VC firms that selected state-industry-year-investment stages with high average success rates for their first five or ten investments exhibited no ability to choose similarly-attractive industries and regions for their subsequent investments. We also found that investment success for VC firms did not improve with experience. In models with VC firm fixed effects included, success appeared to *decline* with the cumulative number of investments. Mixed coefficient models, however, revealed that this pattern emerged from a strong negative correlation – on the order of -0.9 – between initial success and the slope of the relationship between experience and success. In other words, VC firms that had less initial success did better over time while those that initially did well declined in their subsequent performance. With experience, VC firms tended to converge to the average exit rates for the industry as a whole, suggesting a mean-reverting process.

The picture that emerges from these results is that variation in initial success among VC

[2]We would note that since our results are about relative performance differences, we do not claim that venture capitalists do not add value. Rather, any *differences* across venture capitalists in the the value they add plays no discernible role in increasing the odds of a successful outcome for a startup.

firms stems from the unanticipated success of startups in particular industries and regions rather than from the systematic ability of some venture capitalists to select better investments, to nurture them more effectively, or to choose the right times and places to invest on a consistent basis. Yet, this initial success appears consequential as it leads to persistence in outcomes over an extended period of time.

To understand how random variation in initial performance might lead to longer-term persistence, we explored whether initial success might give VC firms better access to deal flow in their subsequent investments. To the extent that entrepreneurs believe that VC firms differ in their ability to nurture firms, entrepreneurs would prefer investments from firms perceived as more able if they have multiple offers. But entrepreneurs have little on which to base their assessments of VC firm quality; even *ex post* they cannot determine whether another VC firm might have generated more value for them. Entrepreneurs may then rely on early success – and the associated prestige of the firms enjoying it – as a signal of quality. Consistent with this idea, Hsu (2004) found that entrepreneurs preferred investments from higher-status VC firms, even if they offered less attractive terms, and high-status VC firms have been found to have access to a wider range of investments (Sorenson and Stuart, 2001) and to enjoy higher average returns (Hochberg et al., 2007).

We report a number of results consistent with this access channel. First, we found that VC firms that enjoyed higher levels of initial success shifted their investments away from the initial round, where assessing the potential of a venture proves most difficult. A 20 percentage point increase in the number of IPOs in the first five investments corresponded to a roughly 2% reduction in the proportion of future investments made in the first round. Second, these same VC firms also invested in more and larger syndicated rounds. The same 20 percentage point increase in the number of IPOs among the initial investments predicted a 4% larger average syndicate size across all future investments. Finally, initial success also led to more central positions within the industry. A 20 percentage point increase in the number of IPOs in the first five investments corresponded to a roughly 19% higher centrality score. Adjusting for these differences eliminated one-half to three-quarters of the residual performance persistence within a particular region and industry and investment stage in a particular year. The "access" channel therefore appears to account for most of the persistence in our context that was not due to investing styles.

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. Although most of these early differences in performance appear to emerge by chance, they become self-reinforcing as entrepreneurs and others interpret them as evidence of differences in quality, giving successful VC firms preferential access to and terms in investments. Venture capitalists certainly do add value to startups through the provision of capital and through mentoring and monitoring (e.g., Kortum and Lerner, 2000; Hellmann and Puri, 2002; Bernstein et al., 2016), but the persistent differences in performance *across* VC firms appear to stem more from firms that have become known for their past success having better access to future sought-after deals than from the better ability of those firms to select and nurture startups to success. This fact may also help to explain why persistence exists 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.

Interestingly, even if persistence emerges from access advantages rather than from innate differences in ability, investors in the asset class – the limited partners – would still prefer to invest in the most 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 risk factors in the VC firms' portfolios, the betas. But preferential access to deal flow could not only raise the expected returns of funds but also reduce the uncertainty associated with them. 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 in economics and finance that finds that initial differences, even if largely due to chance events, can have long-lasting effects on outcomes. Oyer (2008), Kahn (2010), Oreopoulos et al. (2012) and others, for example, have documented 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 (forthcoming) have similarly demonstrated that CEOs who began their careers during downturns 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 managing costs and avoiding taxes. Our results point to a similar sort of long-term effect due to random initial differences. In part, these 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, they appear to stem from initial differences in success creating *beliefs* about ability that persist as investors, entrepreneurs, and others act on those beliefs.

II. Data

We analyze data drawn from the VentureXpert database maintained by Thomson Reuters, which includes round-level information on venture capital investments across 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 (2015) note that VentureXpert has better coverage than the primary alternatives at the level of individual investment rounds.[3]

We began by limiting the analysis to investments made between 1961 and 2006. Two factors dictated our choice of starting year: On the one hand, since our core analysis cor-

[3] Although VentureXpert under reports the proportion of companies that have failed (leaving them coded as ongoing concerns), this fact should not bias our results as we focus only on successful exits, through IPOs and through trade sales.

relates the success of a VC's *initial* investments with success in the same VC's subsequent investments, a later start date, such as 1980, would require us to omit a number of prominent VC investors, such as Kleiner-Perkins and Sequoia (which began their investing before 1980). On the other hand, the earliest information on investments might have been collected retrospectively and therefore open to survival bias. Kaplan and Lerner (2015) reported that the firm that initiated the VentureXpert survey and database, which Thomson Reuters later acquired, began collecting information in 1961. Given that information prior to that year would have been collected retrospectively, we excluded VC firms that began investing prior to 1961 from the analysis.[4] We should note, however, that the results remain the same even if we restrict the sample to only VC firms who began investing after 1980.

Our choice of ending year similarly balanced 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 2014, we limited the analysis to investments made by 2006 so that we would have sufficient time to observe whether those portfolio companies went public or were acquired. We nevertheless included all outcomes observed through 2014, for all investments made in the 1961 to 2006 period.

Within this date range, we restricted our focus to firms headquartered in and investing in the United States. We also limited 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 primarily in leveraged buyouts (LBOs). As noted above, our focus on performance at the investment level required 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 investment, such as distressed debt and LBOs, these outcomes seem less relevant. We therefore limited the sample (i) to VC firms classified as private partnerships,

[4]The first documented VC firm, American Research and Development Corporation, began investing in 1946. However, since most of the prominent players in venture capital emerged in the 1970s or later, this restriction does not exclude any of the elite firms.

(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 limited our analysis to the initial investments by particular VC firms in specific startup companies.[5] 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 porfolio 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 – 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 I provides descriptive statistics for our sample. On average, 15% of the portfolio companies in which VC firms had invested eventually went public (i.e. had an IPO) and 45% of those companies experienced either an IPO or a trade sale, allowing the VC firms to "exit" their investments (i.e. sell their equity positions).[6] These represent the two most profitable outcomes for VC investors. 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%.[7] By contrast, write-offs, the single most common outcome, generally 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

[5]VC firms often invest in all subsequent rounds *pro rata* to their initial investment, in part to protect the value of their equity position and in part because they become emotionally attached to their investments (Guler, 2007).

[6]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.

[7]Although other exit events, such as a buy back by management, could also result in positive returns, they represent relatively rare outcomes.

all other outcomes as unsuccessful (e.g., Cochrane, 2005; Hochberg et al., 2007). Phalippou and Gottschalg (2009), moreover, demonstrated that the proportion of target companies that have 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. Performance Persistence in Venture Capital

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 in its initial investments to its success in all of its 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 (2016), for example, decompose performance persistence into that associated with the firm and that associated with the period of the investment. Their approach has some advantages for estimating the signal-to-noise ratio in fund performance (and consequently in the extent to which investors may have the ability to identify correctly better-performing firms.) But that approach has at least one important disadvantage with respect to our primary interest here: It essentially assumes that the average firm-level advantage remains stable over time. But factors such as learning and reputation, discussed further and explored below, emerge over time.

Figure 1 depicts the relationship between initial success – in a VC firm's first five investments – with the success of subsequent investments. As one can see, success in the first five investments strongly predicts subsequent success, whether one uses only investments that culminated in IPOs or those that led to either IPOs or trade sales as the measure of success (hereafter we refer to this combination of IPOs and trade sales simply as "exits"). For example, a VC firm that experienced three IPOs in its first five investments had about twice the IPO rate in its subsequent investments as a VC firm that had only one IPO among its first five portfolio companies.

The associated partial correlations between performance in the first five or ten investments and that of subsequent investments range from roughly 0.12 to 0.19 (see Table II). Although this persistence appears far 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 – these correlations differ in at least three important respects from those calculated in prior research. First, our correlations include *all* subsequent investments, not just those made in the subsequent fund. When we focus on the more proximate future investments (see Table III), the serial correlation in success rises, though never to the levels observed by Kaplan and Schoar (2005). Second, our focus on initial investments 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. [8] Third, our sample includes nearly twice as many VC firms as these earlier studies, in part because our sample covers a longer period, and in part because the database has fewer missing values for target company exits than for fund returns.[9]

Although this simple serial correlation suggests persistence in performance, it might emerge from a variety of factors, some of which could have little to do with the ability or quality of the VC firms. 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

[8]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 high status VC firms renewed their investments in companies at lower rates than others. This factor may therefore account for some of the higher persistence in studies of fund returns relative to our results here.

[9]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 also could have led to an upward bias in the serial correlations reported by Kaplan and Schoar (2005) relative to the population of funds as a whole. Kaplan and Schoar (2005) nevertheless provided extensive evidence that any selection on who reported returns appeared relatively uncorrelated with performance and therefore should not have biased their estimates of persistence.

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 type of investment. Examining success at the level of the individual investment allows us to account for these potential differences due to investing styles.[10]

To account for these differences, we therefore estimated a series of linear probability models with fixed effects:

$$Y_{vi} = \beta_0 + \beta_1 \bar{Y}_{v5(10)} + \eta_{ysjg} + \epsilon_{vi}, \tag{1}$$

where Y_{vi} refers to the dichotomous outcome – either an IPO or any exit – of the investment made by VC firm v in the ith startup company in which it invested. Our main variable of interest is $\bar{Y}_{v5(10)}$, the share of VC v's first five (or ten) investments that resulted in the outcome Y. The η_{ysjg} represents the fixed effects included in the regression. The odd-numbered models in Table II include only fixed effects for the year of the investment. But the more restrictive even-numbered models have year-state-industry-stage fixed effects. In other words, among investments made in the same year in the same state in the same industry and at the same stage, do VC firms vary in their performance depending on the rates of success that they enjoyed in their first five or ten investments? We report standard errors clustered at the level of the VC firm and at the level of the startup company, as we have repeated observations of the same startup company if more than one VC firm invested in it.[11]

Models 1 and 3 adjust only for the year (vintage) of the investment. These models all reveal relatively high levels of persistence. For example, Model 1 of Panel A indicates that every additional IPO among the first five investments – a 20 percentage point increase in

[10] Kaplan and Schoar (2005) did adjust for industry and stage differences but their focus on the fund as the unit of analysis required them to allocate all investments within a fund to a single industry and stage.

[11] We estimated these models using the REGHDFE package in Stata (Correia, 2014).

the rate – corresponded to a 2.4 percentage point higher IPO rate among all subsequent investments, a 13% difference relative to the average IPO rate. Similarly, Model 1 of Panel B implies that every additional exit among the same five investments predicted a 2.6 percentage point higher exit rate (a 5% difference relative to the average). Models incorporating information also on the success of the second five investments (Model 3) found even higher levels of persistence.

A large share of this persistence, however, appears to stem from differences in the kinds of investments made by firms. Models 2 and 4 introduce the year-state-industry-stage fixed effects. In each of the models, these fixed effects absorb roughly half (46% to 56%) 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 (or exits) in the first five (or ten) investments by a VC firm still correlates strongly with the success of that firm's subsequent investments. Model 2 of Panel A, for example, implies that every additional IPO among the first five investments predicts a 1.3 percentage point higher IPO rate among all subsequent investments.

Table III then investigates the duration of this persistence. Models 1 and 4 look at the 11th to the 30th investments made by a VC firm, Models 2 and 5, the 31st to the 60th investments, and Models 3 and 6, the 61st to the 100th investments. Models 1, 2, and 3 include only year fixed effects while Models 4, 5, and 6 incorporate year-state-industry-stage fixed effects. Panel A reports the results for IPOs only and Panel B for all exits. Whether IPOs or all exits and whether including only year fixed effects or the more fine-grained bins, the estimates consistently reveal a decline over time in the extent to which success in the first ten investments predicted success in subsequent investments. But, even in the models with year-state-industry-stage fixed effects, VC firms that enjoyed higher initial success continued to experience higher subsequent success until at least their 60th investment.[12] If an average fund has roughly ten portfolio companies, these results would imply that the advantages of

[12]Because the sample size shrinks as we consider later investments, the standard errors also become larger. These estimates therefore represent a conservative test of the duration of persistence.

early success persist into at least the sixth fund.

IV. Sources of Persistence

Given that the persistence appears to be more than just a matter of investing styles, we next explored potential mechanisms that might account for this persistence.

A. Innate differences

Target selection and nurturing: 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. In fact, venture capitalists themselves perceive the ability to select the right companies as the primary factor in determining differences in their success (Gompers et al., 2016). These efforts also 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).

A substantial body of research has also found 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 closer to the time of founding. Bottazzi et al. (2008) reported that more active VC firms appeared to increase the odds of a successful exit more than less active ones. And Bernstein et al. (2016) further found that, when VC firms monitored and advised their portfolio companies more closely, those companies, in turn, went public at higher rates. Given the importance of selection and the numerous ways in which VC firms can add value post-investment, it would not be surprising if some VC firms proved better at these activities than others.

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

Why does that approach give us insight into innate differences? If some venture capital firms simply have a better ability to choose more promising companies or to nurture them to successful outcomes, then they should succeed at higher rates than their peers investing in similar sorts of deals. Moreover, if we use the success of peers as an instrumental variable to predict initial success – in essence, removing the endogenous portion of initial success that might stem from unobserved differences across VC firms – then the instrumented initial success variable should exhibit no (or much lower) persistence.

We therefore created a variable that captures the success of others who invested in the same times and places as the focal VC firm's initial investments. Specifically, for each of the initial investments, we calculated the average IPO and exit rates across all startups – except for the focal initial investments themselves – in the same year-state-industry-stage sectors as these initial investments. We then estimated:

$$\bar{Y}_{v5(10)} = \beta_0 + \beta_1 \bar{Y}^{ysjg}_{-v5(10)} + \xi_v, \tag{2}$$

where $\bar{Y}_{v5(10)}$ denotes the share of VC firm v's first five (or first ten) investments that resulted in the outcome under question, either an IPO or any exit, and $\bar{Y}^{ysjg}_{-v5(10)}$ refers to the mean outcome of all *other* startup companies that received venture capital investments in the same year-state-industry-stage cells as the focal VC firm's first five (or first ten) investments. The coefficient β_1 therefore captures success driven not by the focal firm's choices and activities but by factors common to the context in which the VC firm has been investing.

Table IV reports the results of these models. Panel A estimates the effects on IPO rates while Panel B estimates them on all exits. Models 1 and 2 consider only the first five investments of the focal VC firm while Models 3 and 4 consider the first ten investments. Given that this variable has one value per VC firm, Models 1 and 3 include only one observation per VC firm. But, as noted above, these models also serve as the first stage of an instrumental variable (IV) regression. Since the second stage of the IV regressino requires one observation for each subsequent investment made by the VC firm, Models 2 and 4 report these estimates at the investment level. Thus, for example, a firm that made investments in 50 target companies would appear either 45 times (i.e. the 6th to 50th investments) or 40 times (i.e. the 11th to the 50th investments).

All of the models reveal a strong positive 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 cells. In large part, then, early success depended simply 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.

Table V then estimates Equation 1 but uses $\bar{Y}^{ysjg}_{-v5(10)}$ as an instrumental variable for the initial success $\bar{Y}_{v5(10)}$ (as in Equation 2). Panel A estimates the effects for IPOs while Panel B does so for all exits. Models 1, 3, 5, and 7 replicate the results from Panel B of Table II. Models 2, 4, 6, and 8, meanwhile, report the results instrumenting for initial success.[13]

Interestingly, not only do the instrumented results for success also exhibit persistence but the estimated magnitude of the persistence increases by roughly 50% to 100% in the IV regressions, though the larger standard errors mean that one cannot reject the null that the IV regression produces equivalent estimates of effect sizes. Recall, however, that the expectation – if innate differences in either target selection or mentoring ability drove the

[13]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, with the exception of the first five investments using all exits – this F-statistic has a value close to or higher than the benchmark of roughly 16 for the instrument to have sufficient strength to eliminate 90% of the bias in the naïve regressions (Stock and Yogo, 2005).

results – had been to see *no*, or at least much less, persistence in the instrumented models.

This approach, however, depends on the idea that the average success of other investors in the same industries and regions does not in any way relate to the success of the focal investor (the exclusion restriction). One might nevertheless worry that some common factor could influence the selection both of industries and regions and of firms. If so, the most able VC firms might cluster in their investments, violating this assumption. We explored this possibility in two ways.

We began by plotting the success of year-state-industry-stage cells as a function of the prior success of the VC firms investing in them (Figure 2). Each point represents a year-state-industry-stage with at least two startup companies. The x-axis depicts the proportion of startups in that cell with a successful exit, either an IPO in the upper panel or any exit in the lower panel; the y-axis, meanwhile, corresponds to the past success rate – the proportion IPOs in the upper panel or the proportion all exits in the lower one – of all VC firms investing in that cell. Although the fitted lines reveal positive correlations between cell attractiveness and the past success of the VCs that invested in it, the relationship appears weak and VC firms of all observed performance levels invest in the most attractive cells. Any clustering of the most able firms in the same industries and regions, therefore, appears small.

To determine whether a small violation of the exclusion restriction might nonetheless influence our results, we implemented the "local-to-zero" (LTZ) approach, proposed by Conley et al. (2012), for examining the sensitivity of IV results to the exogeneity assumption. 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 γ as though it comes from a distribution ($\gamma \sim U(0, \delta)$). Figure 3 depicts the point estimates and confidence intervals around those estimates for the coefficient of interest in Model 6 (Table V) for a range of values for δ (the left panel corresponds to results for IPOs, the right to results for all exits). Even at quite high values of δ – cases that would involve moderately large violations of the exclusion restriction – the IV produced point estimates equal to or larger than the OLS estimates (the red dot-dash lines). Potential violations of the exclusion restriction therefore do not appear to drive the results. As noted above, the fact that persistence appeared no lower using the IV suggests that the value of initial success stemmed from the initial success itself, rather than from some unobserved factor related to both that initial success and future success.

Sector selection: Although the IV regression analysis largely eliminated the possibility that some VC firms had a better ability to select future winners or more aptitude in nurturing them to success, VC firms may still differ in their ability to select good investments at a more macro level. Perhaps some venture capitalists have an ability to choose 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 see these emerging trends.

We explored this issue by examining whether VC firms exhibited persistence in choosing attractive sectors. We measured the attractiveness of a year-state-industry-stage cell as above (in defining the instrumental variable); that is, for each investment, we calculated the attractiveness of the sector 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 sector attractiveness on the average quality of the first five (or ten) segments in which the VC firm invested. We included a fixed effect for the year of the investment; although VC firms can choose where to invest, they have less freedom to time their investments because of the limited life spans of their funds. Thus, we estimated:

$$\bar{Y}^{ysjg}_{-vi} = \beta_0 + \beta_1 \bar{Y}^{ysjg}_{-v5(10)} + \phi_y + \xi_{vi}, \tag{3}$$

where $\bar{Y}^{ysjg}_{-vi}$ represents the attractiveness of the year-state-industry-stage sector in which the VC firm v invested in startup company i and $\bar{Y}^{ysjg}_{-v5(10)}$ denotes the average attractiveness of the sectors of the first five (or ten) investments made by VC firm v. The ϕ_y specify fixed effects for the year in which VC firm v made the investment in startup company i.

Table VI reports the results of these models. Panel A treats only IPOs as a successful outcome while Panel B includes all exits. Models 1-3 focus on the first five investments and Models 4-6 on the first ten investments. Starting with Models 1 and 3, we see a strong positive correlation, consistent with the idea that VC firms exhibit persistence in selecting the right segments in which to invest. This relationship may, however, simply stem from the VC firm investing in the same sectors (inertia) combined with persistence in the performance of those sectors. Hence, in Models 2 and 5, we excluded all state-industry-stage sectors in which the focal VC firm had invested in its first five (Model 2) or ten (Model 4) investments. This restriction eliminated most of the persistence.

The remaining persistence, moreover, may stem from the fact that all investors can easily observe some trends (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-1990s. Models 3 and 6 therefore adjust for the popularity of the segment with eight 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 2015 dollars, of VC investments in them; (iv) the average eigenvector centrality of the VC firms investing in these other startups; (v) IPOs and (vi) acquisitions in the same state-industry sector among startup companies that received their last investment in the previous five years; and (vii) IPOs and (viii) acquisitions in the same industry among startup companies that received their last investment in the previous five years. The inclusion of these controls entirely erased the serial correlation between the attractiveness of the sectors in which VC firms placed their initial investments and the attractiveness of the sectors to which they allocated their subsequent investments.

B. Learning

Another potential explanation for the persistence of initial success could involve learning-by-doing. Initial success, even if not indicative of innate differences, could reflect learning or could give venture capitalists leeway with their investors to get better at the trade. Although to a certain extent each potential investment represents a unique opportunity, VC firms may learn to understand the industry or business model better over time. Kempf et al. (2014), for example, found that learning-by-doing even appears to occur among mutual fund managers. Managers with more experience investing in a particular industry earned higher abnormal returns in it, in large part because they appeared better at anticipating earnings surprises. Within the venture capital industry, Sørensen (2007) used the number of investments that a VC firm had made as a proxy for its quality and found positive associations between this experience and the rates at which portfolio companies had successful exits. We therefore examined whether VC firms appeared to improve in their outcomes with experience.

Table VII explores this relationship. Models 1 and 4 estimate the simple relationship between the (logged) number of investments made and the success of those investments in terms of the proportion IPOs (Panel A) and in terms of the proportion overall exits (Panel B). Model 1 only adjusts for annual differences in average performance while Model 4 includes fixed effects for the fine-grained year-state-industry-stage segments. All four coefficients show positive relationships between the number of investments made and the expected success of future investments, though the effect sizes appear quite small. In Model 4 (Panel A), for example, a doubling in investing experience corresponded to a 0.4 percentage point increase in the rate of IPOs associated with future investments, a 2% rise over the base rate. Of course, given that every deal represents a unique company, one would probably only expect modest rates of improvement with experience.

But this "learning" effect might also stem simply from survival. If the most successful VC firms survive longer and therefore invest in more companies, then one might see a positive relationship between the number of investments made and the odds of success even if learning does not occur at the firm level. We therefore introduced VC firm-level fixed effects in Models 2 and 5. Surprisingly, after the introduction of these fixed effects, the coefficient on experience flips sign: success rates appear to *decline* with experience.

To investigate this puzzling result more closely, Models 3 and 6 then estimate mixed models, where we allowed each individual VC firm to have a different learning rate as well as a different base level of success. In other words, we allowed these variables to have random coefficients. In these mixed models, experience, on average, has an estimated coefficient close to zero. But it varies substantially (see the standard deviation of the estimated experience coefficient), meaning that many VC firms appeared to get better over time and many others appeared to get worse. Interestingly, however, the correlation between these estimated firm-specific learning coefficients and those of the firm-specific intercepts ranged from -0.88 to -0.95 across the various models, meaning that those firms with the highest average performance declined over time while those with the lowest average performance improved.

This decline in performance for those who had high initial success and improvement in performance for those who had lower initial success, of course, points to a mean-reverting process. Figure 4 shows that a pattern consistent with 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 either had an IPO (upper panel) or any exit (lower panel). Apart from one or two outliers, the graph illustrates a pattern of strong convergence to the mean: the VC firms with the largest total number of investments converged to the industy average success rate.

Two additional points about this graph seem worth noting. First, the somewhat greater mass below the mean than above it suggests that those with below-mean average performance survived at lower rates. Second, performance differences across VC firms appear to decline, rather than increase, over time (if they increased, one would expect divergence rather than convergence in performance). Focusing on the persistence of initial performance differences therefore does not appear to miss performance heterogeneity that emerges later.

C. Access to Deal Flow

A third factor involves preferential access to deal flow. Such access might emerge through a couple of distinct channels. But both channels depend on the idea that potential partners face uncertainty about the quality of those with whom they work and that they interpret early success – and any prestige or reputation that it engenders – as a signal of higher quality.

One involves the entrepreneurs themselves. Those startups that have the highest potential likely have multiple suitors. One would generally expect that this competition would drive up the price of the target company's equity, effectively competing away any potential excess returns that investors might earn (Gompers and Lerner, 2000). But Hsu (2004) found that entrepreneurs accepted lower valuations from high status VC firms in these situations, presumably because they believed that these investors would better nurture their businesses or that they would offer them greater certification value. To the extent that early success translates into a reputation or status that entrepreneurs value, these better deal terms might then account for persistence in excess returns (Kaplan and Schoar, 2005).

Although those better terms would predict performance persistence on the intensive margin, the same process could generate persistence on the extensive margin. Imagine that several VC firms have an interest in a particularly promising company, the higher status VC firm may have an advantage in "getting the deal" relative to the less prominent one. Even if venture capitalists have no *differential* ability in identifying the most promising ventures, those with initial success can enjoy superior deal flow, as long as, on average, all venture capitalists have some ability to discern the more from the less promising investments.

The second stems from the importance of social relationships in the venture capital community. Because VC firms frequently invest in groups and because access to those syndicates often requires the acquiescence of the existing investors, who you know matters to deal flow. Sorenson and Stuart (2001) found that as VC firms gained experience and came to occupy more central positions in the industry, firms could invest at greater distances and in a wider range of industries. In essence, having a more expansive network of investing partners appeared to allow VC firms to consider a wider range of deals. Consistent with the idea that choosing from a larger set of investment options would lead to higher returns, Hochberg et al. (2007), in turn, found a positive relationship between centrality and the success rates of the investments made by VC firms. Thus, to the extent that early success means that a VC firm becomes more attractive as a co-investor, persistence might emerge from this expanded access to deal flow in much the same way as it could by providing preferential access to entrepreneurs.

To explore this channel, we investigated how the characteristics of later investments correlated with initial success, controlling for the characteristics of the initial investments. We have one observation per later investment (i.e., the 6th and subsequent, or the 11th and subsequent investments). The dependent variables are 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 primary explanatory variable of interest is the level of initial success enjoyed by the VC firm. In particular, we estimated:

$$C_{vi} = \beta_0 + \beta_1 \bar{Y}_{v5(10)} + \bar{C}_{v5(10)} + \phi_y + \epsilon_{vi}, \tag{4}$$

where C_{vi} refers to the characteristic of interest for VC firm v at the time of the investment in target company i, $\bar{C}_{v5}$ denotes the average value of the characteristic in question across the first five investments made by the VC firm v, and ϕ_y represents fixed effects for the year of the investment.

Table VIII first considers the investment round. As a startup company matures, more information becomes available about its chances of success. Hence, investors can more easily discriminate the wheat from the chaff, the companies with the highest potential from the also-rans. Models 1 and 2 consider only whether the investment occurred in the first round of investment in the target company. All of the models suggest that VC firms reduced the proportion of investments made in the first round with initial success. Each additional initial exit predicted a 0.7 to 1.1 percentage point drop in the probability of a first round investment. Models 3 and 4, then, consider whether initial success led to general movement toward later rounds. Here, however, one cannot distinguish the effects from zero.

We next explored the probability of investing as part of a syndicate and the average size of those syndicates (Table IX). Models 1 and 2 examine simply 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 1.9 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 14% decline in the probability of a solo investment for each initial exit. Models 3 and 4 then examine 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.

Table X finally examines whether initial success led to larger average investments and to firms becoming more central in the co-investment network. Models 1 and 2 report estimates of the effects on the size of the average investment made by a member of a syndicate in which the focal VC participated.[14] Initial success predicted larger future investments, with each additional initial exit corresponding to a 5.6% increase in the amount invested per participant in the syndicate.[15] Models 3 and 4 finally consider the changes in eigenvector centrality associated with initial success.[16] These models reveal the largest correlates of initial success, with a 20 percentage point higher success rate among the initial five or ten investments predicting a 12% to 22% increase in centrality.

[14]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 can therefore only estimate the average size of these investments.

[15]This effect may, however, stem in part from more successful VC firms being able to raise larger funds and therefore having more capital to invest in future target companies.

[16]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).

We should note that all of these changes hold in models where we instrument initial success using the same instrument as reported in the first stages in Table IV. These changes therefore appear to stem from initial success itself rather than from unobserved factors related to both early success and investing strategies.

But do these changes in position and investing behavior account for performance persistence? Table XI examines the extent to which the positive long-term effects of performance associated with initial success depends on these mechanisms, by adjusting for them in our persistence models. Models 1 through 4 include only year fixed effects while Models 5 through 8 incorporate the fine-grained year-state-industry-stage (YSIS) fixed effects. As in all of the tables, 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 48% to 71% of the persistence remaining after adjusting for investing styles (i.e. including the YSIS fixed effects). It therefore would appear that access to deal flow explains a large share of the residual persistence in performance.

Some may feel that the finding of Ewens and Rhodes-Kropf (2015) that persistence appears, perhaps even more strongly, at the level of the individual venture capitalist conflicts with this interpretation. But prestige and social networks, and consequently access to deal flow, could easily exist at the level of individual partners. It would simply require that entrepreneurs or other venture capital firms prefer certain individuals within a firm to others—for example, that they might prefer John Doerr, or some other partner with a storied history, to an associate. It does, however, imply that some of the small residual persistence still observed in our sample may stem from individuals who develop reputations at existing firms but who then found their own partnerships.

V. Discussion and conclusion

To understand better what channels might account for persistence in the performance of private equity firms, we examined how the performance of VC firms' investments – in terms of having successful exits, either through IPOs or trade sales – depended on their initial success. We found that long-term success depended strongly on initial success, that initial success depended primarily on investing in the right place at the right time, and that VC firms did not choose the right places and times at a rate higher than chance. We also found that VC firms did not appear to improve in performance with experience, but that VC firms enjoying early success did shift their investments to later stages and to syndicated investments. Initial success also led these firms to occupy more central positions in the co-investment network.

The picture that emerges then is one where persistent performance differences across VC firms stem from the fact that early success gives the firms enjoying it preferential access to deal flow. Both entrepreneurs and other VC firms want to partner with them. VC firms therefore get to see more deals, particularly in later stages, when it becomes easier to predict which companies might have successful outcomes. As noted above, even if VCs have no differential ability to identify more promising ventures (but on average have at least some ability to distinguish those with better odds of sucess), the access channel can perpetuate (random) differences in initial success over an extended period of time.

Although our results suggests that VC firms do not differ in their *relative* ability to select and govern startups, they are 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 status 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.

This access channel would nevertheless help to explain why persistence appears in private equity but not in most other settings, 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 private equity, 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 higher status 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 idea that the supply of capital exceeds the demand for it, at least for deals with less uncertainty, it also implies that the returns to status should become most 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 had higher success rates during booms. During busts, they appeared no different in their performance than less central VC firms.

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 would not necessarily have yet been realized. 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.

REFERENCES

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

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.

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.

Conley, T G, C B Hansen, and P E Rossi, 2012, Plausibly exogenous, *The Review of Economics and Statistics* 94, 260–272.

Correia, Sergio, 2014, REGHDFE: Stata module to perform linear or instrumental-variable regression absorbing any number of high-dimensional fixed effects, Statistical Software Components, Boston College Department of Economics.

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.

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, 2016, How do venture capitalists make decisions?, Working paper, Harvard Business School.

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, 2015, Venture capital data: Opportunities and challenges, Presented at the NBER-CRIW Conference on Measuring Entrepreneurial Businesses: Current Knowledge and Challenges.

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

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, 2016, Skill and luck in private equity performance, *Journal of Financial Economics* forthcoming.

Kortum, Samuel, and Josh Lerner, 2000, Assessing the impact of venture capital on innovation, *RAND Journal of Economics* 31, 674–92.

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, forthcoming, Shaped by booms and busts: How the economy impacts ceo careers and management styles, *Review of Financial Studies* .

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 Initial Success and Later Success.

Notes: The sample consists of one observation per venture capital firm. In the left panel, the horizontal axis divides the population of VC firms based on how many IPOs the first five startup companies in their portfolios had. The vertical axis is the proportion of IPOs among all the startup companies that the VC firms invested in later. In the right panel, the horizontal axis divides the population of VC firms based on how many exits, either IPOs or acquisitions, the first five startup companies in their portfolios had. The vertical axis is the proportion of exits among all the startup companies that the VC firms invested in later.

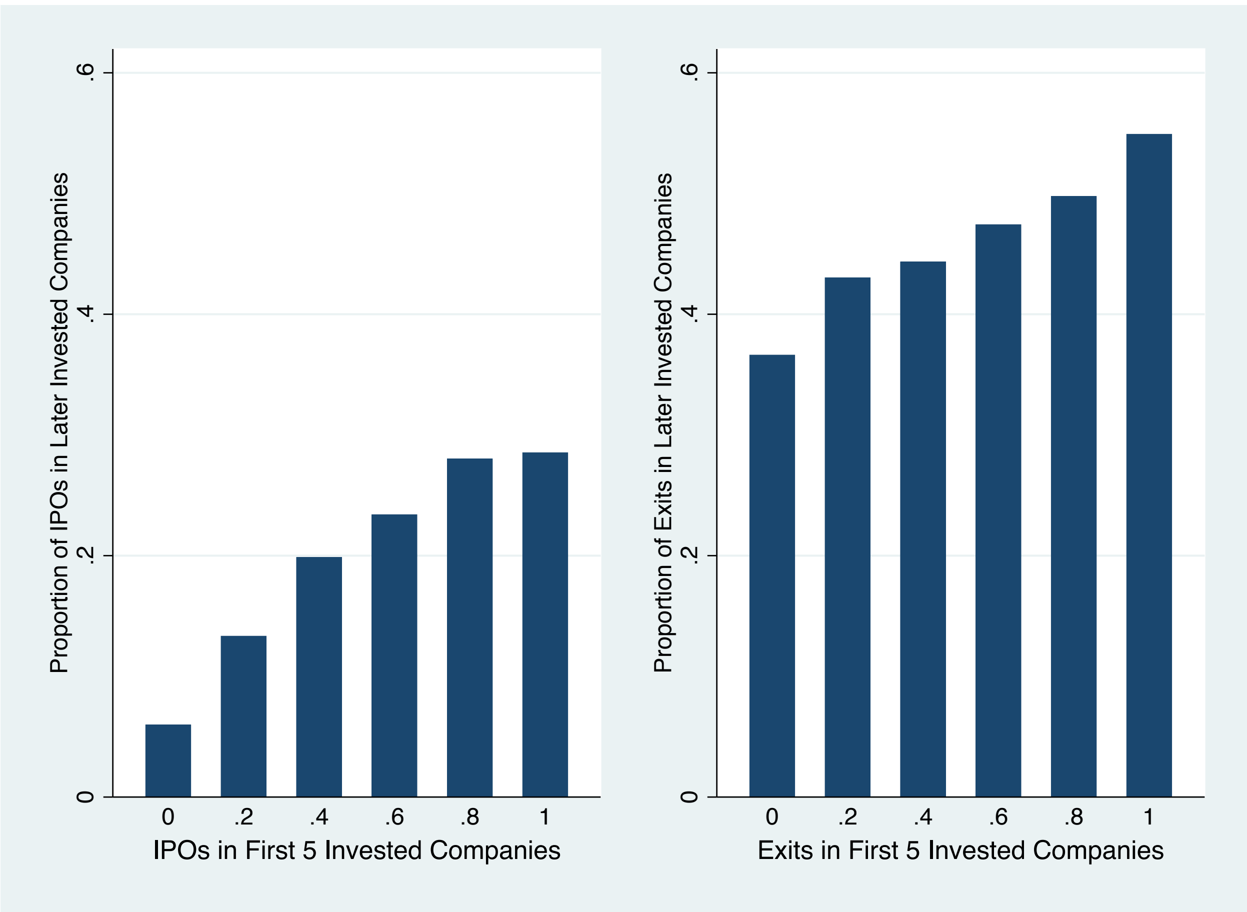

Figure 2: Sector Quality and VC Quality.

Notes: The sample consists of all year-state-industry-stage cells with at least two startup companies and each dot represents one VC firm that invested in the cell. The horizontal axis is the IPO rate (upper panel) or the exit rate (lower panel) across all startup companies in that cell. The vertical axis is the past success of the VC firms who invested in the cell, as IPOs in the upper panel and as all exits in the lower panel. The fitted line with confidence intervals shows the correlation between the average success of a cell and the past success rate of VC firms who invested in it.

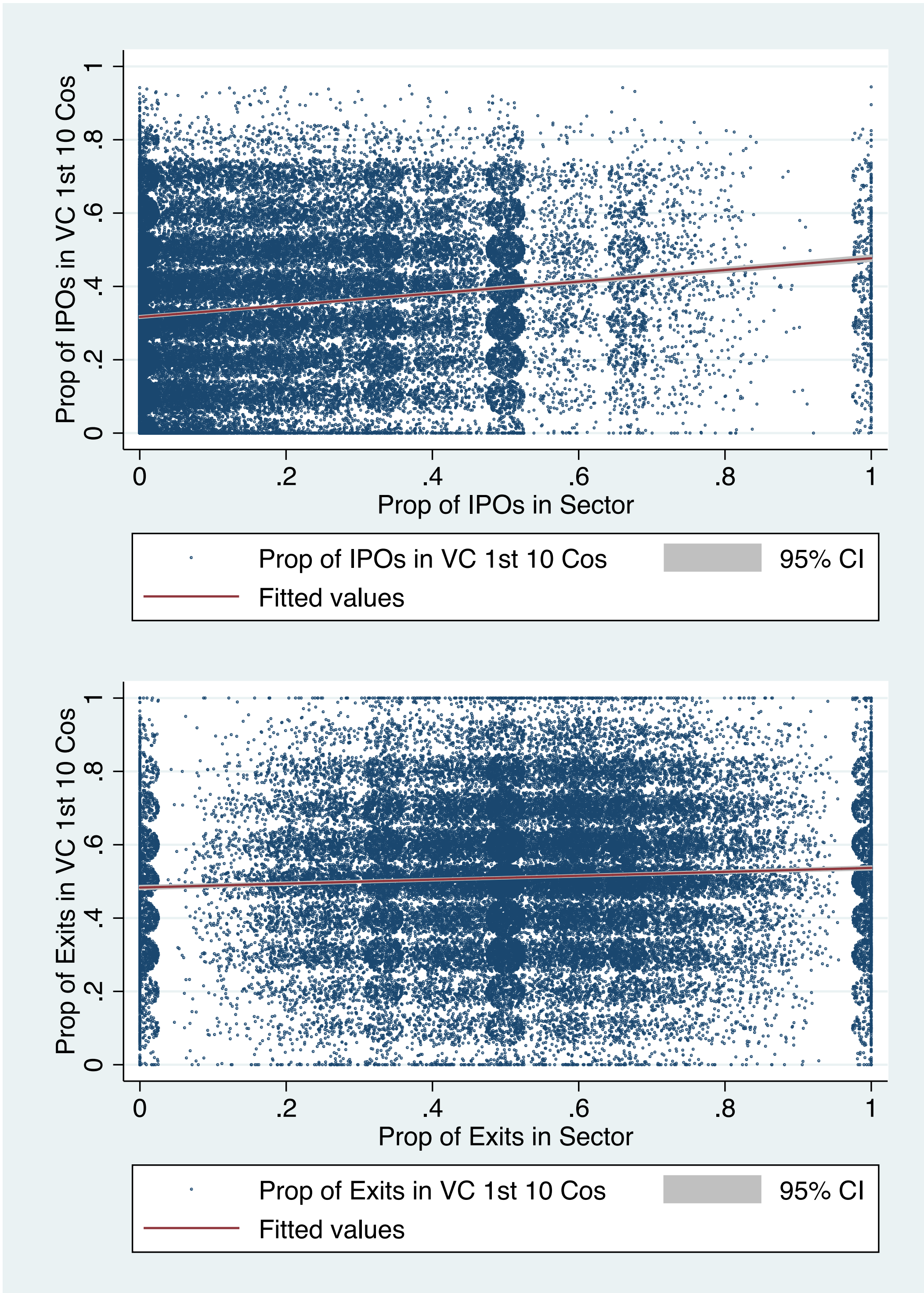

Figure 3: Plausible Exogeneity.

Notes: This figure replicates the estimation of Table V Model 6 using the "local-to-zero" (LTZ) method of Conley et al. (2012). The graph on the left corresponds to Panel A of Table V and the graph on the right to Panel B. The parameter γ, 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 5 of the same table.

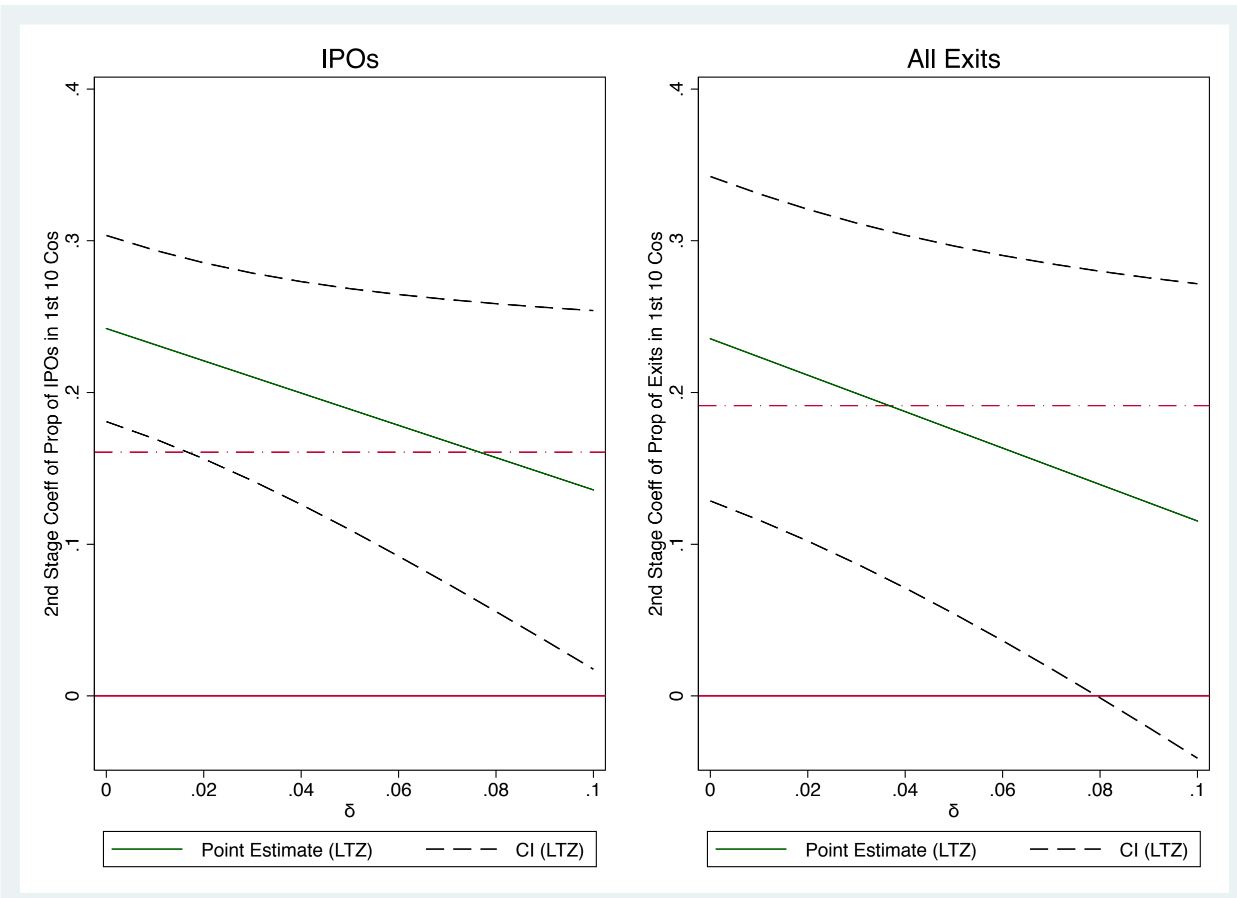

Figure 4: VC Experience and Performance.

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.

Table I: Summary Statistics

Notes: The data is from the VentureXpert database of Thomson-Reuters and the sample consists of venture capital (VC) firms based in the United States and their investments in startup companies based in the United States. Only VC firms classified as private partnerships and funds classified as venture capital are included. Only investments in stages classified as "seed", "early", "expansion", and "later" are included and only the first investment by a VC firm in a particular startup company. The data covers the period from 1961 to 2006 and includes only VC firms who made their first investment in 1961 or later.

Variable	**Mean**	**N**
Panel A: Startup Companies		
IPO	0.144	18474
Exit	0.421	18474
Panel B: VCs with at least six invested companies		
Prop of IPOs in 1st 5 Cos	0.216	1133
Prop of Exits in 1st 5 Cos	0.479	1133
Panel C: VCs with at least eleven invested companies		
Prop of IPOs in 1st 10 Cos	0.224	824
Prop of Exits in 1st 10 Cos	0.489	824

Table II: Persistence of Initial Success

Notes: The sample consists of the first investment made by a venture capital (VC) firm in a target company, starting with the sixth company (Models 1-2) or the eleventh company (Models 3-4) in which the VC firm invested. The dependent variable is an indicator variable for whether the target company had an IPO (Panel A) or an exit (Panel B), that is, an IPO or a trade sale. The independent variables measure the initial success of the VC firm by calculating the proportion of IPOs (or exits) in the first five (or ten) target companies in which the VC firm invested.

OLS regressions with standard errors clustered by VC firm and startup company. Fixed effects in regressions: Y = Year; YSIS = Year-State-Industry-Stage. Statistical significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

	(1)	(2)	(3)	(4)
Panel A: IPOs				
Prop of IPOs in 1st 5 Cos	0.120***	0.065***		
	(0.015)	(0.011)		
Prop of IPOs in 1st 10 Cos			0.161***	0.083***
			(0.017)	(0.014)
Sample Mean DV	0.189	0.191	0.190	0.192
R^2	0.099	0.445	0.101	0.444
Fixed Effects	Y	YSIS	Y	YSIS
VC Firms	1133	1108	824	811
Observations	38338	34314	33422	29600
Panel B: All Exits				
Prop of Exits in 1st 5 Cos	0.132***	0.059***		
	(0.019)	(0.015)		
Prop of Exits in 1st 10 Cos			0.191***	0.090***
			(0.024)	(0.021)
Sample Mean DV	0.508	0.521	0.515	0.527
R^2	0.033	0.343	0.035	0.338
Fixed Effects	Y	YSIS	Y	YSIS
VC Firms	1133	1108	824	811
Observations	38338	34314	33422	29600

Table III: Duration of Persistence

Notes: The sample consists of the first investment made by a venture capital (VC) firm in a target company starting with the 11th company in which the VC firm invested. Panel A codes only whether the target company had an IPO while Panel B considers both IPOs and trade sales as successful exits. The independent variables measure the proportion of IPOs (Panel A) or successful exits (Panel B) in the first ten companies in which the VC firm invested. Models 1 and 4 include only the 11th to the 30th target companies in which the VC firm invested, Models 2 and 4 the 31st to the 60th, and Models 3 and 6 the 61st to the 100th.

OLS regressions with standard errors clustered by VC firm and startup company. Fixed effects in regressions: Y = Year; YSIS = Year-State-Industry-Stage. Statistical significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

	(1) 11-30	(2) 31-60	(3) 61-100	(4) 11-30	(5) 31-60	(6) 61-100
Panel A: IPOs						
Prop of IPOs in 1st 10 Cos	0.215***	0.173***	0.107***	0.079***	0.046*	0.028
	(0.027)	(0.027)	(0.031)	(0.025)	(0.027)	(0.039)
Panel B: All Exits						
Prop of Exits in 1st 10 Cos	0.284***	0.200***	0.138***	0.176***	0.112***	0.072
	(0.028)	(0.035)	(0.036)	(0.032)	(0.039)	(0.050)
Fixed Effects	Y	Y	Y	YSIS	YSIS	YSIS
VC Firms	824	369	200	800	362	197
Observations	11072	8036	5654	8110	5566	3804

Table IV: Predicting Initial Success

Notes: Models 1 and 3 include one observation per venture capital (VC) firm. Models 2 and 4 one observation for every company the VC firm invested in starting with the 6th in Model 2 and the 11th in Model 4. In Panel A, the dependent variable is the proportion of IPOs in the first 5 target companies in which the VC firm invested in Models 1 and 2 and in the first 10 companies in Models 3 and 4. In Panel B, the dependent variable is the proportion of exits, including IPOs and trade sales, in the first 5 companies in which the VC firm invested in Models 1 and 2 and in the first ten companies in Models 3 and 4. The Models 2 and 4 with the full sample form the first stages for the two-stage least squares regressions in Table V.

The independent variables measure the average IPO or exit rate of all startup companies that received a round of VC investment in the same year-state-industry-stage sector as the first five or ten companies in which focal VC firm invested. The calculation excludes all startup companies in which the focal VC firm ever invested.

OLS regression with standard errors clustered by VC firm. Statistical significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

	(1) Firm	(2) Sample	(3) Firm	(4) Sample
Panel A: IPOs				
Avg IPO Rate in 1st 5 Cos' Yr-St-Ind-Stg	0.560***	0.344***		
	(0.043)	(0.074)		
Avg IPO Rate in 1st 10 Cos' Yr-St-Ind-Stg			0.748***	0.506***
			(0.054)	(0.088)
Constant	0.105***	0.243***	0.071***	0.189***
	(0.009)	(0.027)	(0.010)	(0.024)
R^2	0.186	0.083	0.307	0.182
VC Firms	1123	1123	823	823
Observations	1123	37697	823	33365
Panel B: All Exits				
Avg Exit Rate in 1st 5 Cos' Yr-St-Ind-Stg	0.321***	0.204***		
	(0.042)	(0.077)		
Avg Exit Rate in 1st 10 Cos' Yr-St-Ind-Stg			0.561***	0.456***
			(0.048)	(0.079)
Constant	0.339***	0.445***	0.239***	0.311***
	(0.020)	(0.039)	(0.022)	(0.036)
R^2	0.056	0.029	0.157	0.138
VC Firms	1123	1123	823	823
Observations	1123	37697	823	33365

Table V: Persistence of Initial Success: Instrumental Variables Regressions

Notes: The sample consists of the first investment made by a venture capital (VC) firm in a startup company, starting with the sixth company the VC firm invested in (Models 1-4) or the eleventh company the VC firm invested in (Models 5-8). Panel A considers whether the startup company had an IPO and Panel B considers whether the startup company had any exit, IPO or acquisition. The independent variables measure the initial success of the VC firm by calculating the proportion of IPOs or exits in the first five or ten startup companies in which the VC firm invested.

Models 1, 3, 5, and 7 replicate models from Panel B of Table II. Models 2, 4, 6, and 8 use the full sample regressions from Table IV as first stages in an instrumental variables 2SLS regression. The Kleibergen-Paap Wald rk F-statistic measures the strength of the first stage with 16 being a critical value for <10% bias.

OLS regression in Models 1, 3, 5, and 7 and 2SLS regression in Models 2, 4, 6, and 8 with standard errors clustered by VC firm and startup company. Fixed effects in regressions: Y = Year; YSIS = Year-State-Industry-Stage. Statistical significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

	(1) 5	(2) 5-IV	(3) 5	(4) 5-IV	(5) 10	(6) 10-IV	(7) 10	(8) 10-IV
Panel A: IPOs								
Prop of IPOs in 1st 5 Cos	0.120***	0.185***	0.065***	0.119***				
	(0.015)	(0.053)	(0.011)	(0.045)				
Prop of IPOs in 1st 10 Cos					0.161***	0.242***	0.083***	0.162***
					(0.017)	(0.038)	(0.014)	(0.035)
Kleibergen-Paap Wald rk F-stat		14.753		13.066		27.676		36.174
Fixed Effects	Y	Y	YSIS	YSIS	Y	Y	YSIS	YSIS
VC Firms	1133	1123	1108	1099	824	823	811	810
Observations	38338	37697	34314	33743	33422	33365	29600	29543
Panel B: All Exits								
Prop of Exits in 1st 5 Cos	0.132***	0.362**	0.059***	0.155				
	(0.019)	(0.144)	(0.015)	(0.098)				
Prop of Exits in 1st 10 Cos					0.191***	0.235***	0.090***	0.117**
					(0.024)	(0.065)	(0.021)	(0.058)
Kleibergen-Paap Wald rk F-stat		4.991		4.543		28.532		31.680
Fixed Effects	Y	Y	YSIS	YSIS	Y	Y	YSIS	YSIS
VC Firms	1133	1123	1108	1099	824	823	811	810
Observations	38338	37697	34314	33743	33422	33365	29600	29543

Table VI: Picking Good Sectors

Notes: The sample consists of the first investment made by a venture capital (VC) firm in a startup company, starting with the sixth company the VC firm invested in (Models 1-3) or the eleventh company the VC firm invested in (Models 4-6). 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 sector in which the focal VC invested, but excluding all companies in which the focal VC ever invested. The dependent variable in Panel B is constructed similarly but includes all exits, IPOs and acquisitions.

Models 1 and 4 show the basic results with the average IPO rate (Panel A) or exit rate (Panel B) among the first five (Model 1) or ten (Model 4) sectors in which the focal VC made investments, excluding any companies in which the focal VC ever invested. Models 2, 3, 5, and 6 exclude any State-Industry-Stage sector in which the VC firm had invested in its first five (Models 2-3) or ten (Models 5-6) investments. Models 3 and 6 add control variables for the general attractiveness of the sector.

OLS regression with standard errors clustered by VC firm and year-stage-industry-stage sector. Fixed effects in regressions: Y = Year. Statistical significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: IPOs						
Avg IPO Rate in 1st 5 Cos' Yr-St-Ind-Stg	0.009	−0.001	−0.007			
	(0.011)	(0.010)	(0.007)			
Avg IPO Rate in 1st 10 Cos' Yr-St-Ind-Stg				0.026**	0.012	0.004
				(0.013)	(0.012)	(0.008)
Cnt of Other Cos in Yr-St-Ind-Stg (log)			−0.032***			−0.033***
			(0.004)			(0.004)
Avg Synd Size for Other Cos in Yr-St-Ind-Stg (log)			0.101***			0.101***
			(0.008)			(0.008)
Avg Inv Size for Other Cos in Yr-St-Ind-Stg (log)			0.045***			0.046***
			(0.004)			(0.004)
Avg Centrality of Other VCs in Yr-St-Ind-Stg			0.030			−0.004
			(0.177)			(0.188)
Cnt of IPOs in St-Ind in 5 Prev Years (log)			0.024***			0.023***
			(0.005)			(0.005)
Cnt of Acqs in St-Ind in 5 Prev Years (log)			0.011**			0.012**
			(0.005)			(0.005)
Cnt of IPOs in Ind in 5 Prev Years (log)			0.025***			0.029***
			(0.006)			(0.006)
Cnt of Acqs in Ind in 5 Prev Years (log)			−0.058***			−0.062***
			(0.006)			(0.006)
Panel B: All Exits						
Avg Exit Rate in 1st 5 Cos' Yr-St-Ind-Stg	0.027**	0.017	0.000			
	(0.011)	(0.011)	(0.009)			
Avg Exit Rate in 1st 10 Cos' Yr-St-Ind-Stg				0.039**	0.025*	0.004
				(0.015)	(0.015)	(0.011)
Cnt of Other Cos in Yr-St-Ind-Stg (log)			−0.028***			−0.030***
			(0.005)			(0.005)
Avg Synd Size for Other Cos in Yr-St-Ind-Stg (log)			0.146***			0.148***
			(0.008)			(0.009)
Avg Inv Size for Other Cos in Yr-St-Ind-Stg (log)			0.048***			0.047***
			(0.005)			(0.005)
Avg Centrality of Other VCs in Yr-St-Ind-Stg			0.933***			0.987***
			(0.221)			(0.235)
Cnt of IPOs in St-Ind in 5 Prev Years (log)			0.007			0.006
			(0.006)			(0.006)
Cnt of Acqs in St-Ind in 5 Prev Years (log)			0.031***			0.034***
			(0.006)			(0.006)
Cnt of IPOs in Ind in 5 Prev Years (log)			−0.008			−0.005
			(0.008)			(0.008)
Cnt of Acqs in Ind in 5 Prev Years (log)			0.016**			0.011
			(0.008)			(0.008)
Fixed Effects	Y	Y	Y	Y	Y	Y
VC Firms	1107	1092	1090	818	802	802
Observations	33380	29742	29488	29666	24741	24524

Table VII: Change in Success Over Time

Notes: 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. The independent variable is the log of the cumulative count of startup companies the VC firm had invested in at the time of the current investment, including the current investment. Models 1 and 4 are OLS. Models 2 and 5 add VC firm fixed effects. Models 3 and 6 are mixed effects models where the independent variable and the constant have random coefficients. The standard deviations of the random coefficients and the estimated correlations are reported below.

Standard errors clustered by VC firm and startup company except in models 3 and 6 by VC firm. Fixed effects in regressions: Y = Year; YSIS = Year-State-Industry-Stage; Y, SIS = Year and State-Industry-Stage. Statistical significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

	(1) OLS	(2) VC FE	(3) Mixed	(4) OLS	(5) VC FE	(6) Mixed
Panel A: IPOS						
VC Firm Comp Cnt (log)	0.007***	−0.020***	−0.001	0.007***	−0.014***	0.000
	(0.002)	(0.004)	(0.002)	(0.002)	(0.004)	(0.002)
Constant			1.108***			0.724***
			(0.055)			(0.147)
sd(Firm Comp Cnt (log))			0.028***			0.0235***
			(0.003)			(0.003)
sd(Constant)			0.139***			0.105***
			(0.009)			(0.010)
corr(Firm Comp Cnt (log),Constant)			−0.937***			−0.942***
			(0.015)			(0.018)
sd(Residual)			0.368***			0.346***
			(0.004)			(0.003)
Panel B: All Exits						
VC Firm Comp Cnt (log)	0.016***	−0.013***	0.005*	0.012***	−0.014***	0.002
	(0.002)	(0.005)	(0.003)	(0.003)	(0.005)	(0.002)
Constant			1.140***			0.635***
			(0.049)			(0.150)
sd(Firm Comp Cnt (log))			0.032***			0.029***
			(0.003)			(0.003)
sd(Constant)			0.159***			0.125***
			(0.010)			(0.011)
corr(Firm Comp Cnt (log),Constant)			−0.878***			−0.880***
			(0.028)			(0.034)
sd(Residual)			0.484***			0.460***
			(0.001)			(0.001)
VC FE/REs in Regression	N	Y	Y	N	Y	Y
Fixed Effects	Y	Y	Y	YSIS	YSIS	Y, SIS
VC Firms	1133	1133	1133	1132	1129	1133
Observations	44001	44001	44003	39716	39713	44003

Table VIII: Change in Investment Round Based on Initial Success

Notes: The sample consists of the first investment made by a venture capital (VC) firm in a startup company starting with the 6th (Models 1 and 3) or the 11th (Models 2 and 4) company in which the VC firm invested. The dependent variable in Models 1-2 is a dummy variable indicating whether the round was the first VC round in the startup company and in Models 3-4 the log of the sequence number of the investment round in the startup company.

The independent variables measure the proportion of IPOs or exits (including IPOs and acquisitions) in the first 5 (Models 1 and 3) or the first ten (Models 2 and 4) companies in which the VC firm invested as well as the proportion of first rounds in those investments or the log of the average round sequence number in those investments.

OLS regressions with standard errors clustered by VC firm and startup company. Fixed effects in regressions: Y = Year. Statistical significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

	(1) Round 1	(2) Round 1	(3) Round No (log)	(4) Round No (log)
Panel A: IPOS				
Prop of IPOs in 1st 5 Cos	−0.056*		0.054	
	(0.032)		(0.041)	
Prop of IPOs in 1st 10 Cos		−0.084**		0.075
		(0.038)		(0.047)
Prop of Round 1 Invs in 1st 5 Cos	0.258***			
	(0.027)			
Prop of Round 1 Invs in 1st 10 Cos		0.342***		
		(0.032)		
Avg Round No in 1st 5 Cos (log)			0.244***	
			(0.024)	
Avg Round No in 1st 10 Cos (log)				0.319***
				(0.030)
Panel B: All Exits				
Prop of Exits in 1st 5 Cos	−0.057*		0.052	
	(0.029)		(0.035)	
Prop of Exits in 1st 10 Cos		−0.067*		0.050
		(0.036)		(0.045)
Prop of Round 1 Invs in 1st 5 Cos	0.255***			
	(0.026)			
Prop of Round 1 Invs in 1st 10 Cos		0.339***		
		(0.032)		
Avg Round No in 1st 5 Cos (log)			0.241***	
			(0.024)	
Avg Round No in 1st 10 Cos (log)				0.318***
				(0.030)
Sample Mean DV	0.515	0.515	2.109	2.104
Fixed Effects	Y	Y	Y	Y
VC Firms	1133	824	1133	824
Observations	38338	33422	38338	33422

Table IX: Change in Syndication Based on Initial Success

Notes: The sample consists of the first investment made by a venture capital (VC) firm in a startup company starting with the 6th (Models 1 and 3) or the 11th (Models 2 and 4) company in which the VC firm invested. The dependent variable in Models 1-2 is a dummy variable indicating whether the round was syndicated and in Models 3-4 the log of the number of syndicate partners in the round, including the focal VC firm as well as non-VC investors.

The independent variables measure the proportion of IPOs or exits (including IPOs and acquisitions) in the first 5 (Models 1 and 3) or the first 10 (Models 2 and 4) companies in which the VC firm invested as well as the proportion of syndicated rounds in those investments or the log of the average number of syndicate partners in those investments.

OLS regressions with standard errors clustered by VC firm and startup company. Fixed effects in regressions: Y = Year. Statistical significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

	(1) Syndicated	(2) Syndicated	(3) Synd Size (log)	(4) Synd Size (log)
Panel A: IPOS				
Prop of IPOs in 1st 5 Cos	0.095***		0.206***	
	(0.017)		(0.046)	
Prop of IPOs in 1st 10 Cos		0.104***		0.256***
		(0.019)		(0.059)
Prop Syndicated in 1st 5 Cos	0.153***			
	(0.028)			
Prop Syndicated in 1st 10 Cos		0.200***		
		(0.037)		
Avg Syndicate Size in 1st 5 Cos (log)			0.198***	
			(0.023)	
Avg Syndicate Size in 1st 10 Cos (log)				0.220***
				(0.029)
Panel B: All Exits				
Prop of Exits in 1st 5 Cos	0.079***		0.212***	
	(0.017)		(0.046)	
Prop of Exits in 1st 10 Cos		0.092***		0.296***
		(0.021)		(0.057)
Prop Syndicated in 1st 5 Cos	0.145***			
	(0.029)			
Prop Syndicated in 1st 10 Cos		0.189***		
		(0.038)		
Avg Syndicate Size in 1st 5 Cos (log)			0.197***	
			(0.023)	
Avg Syndicate Size in 1st 10 Cos (log)				0.216***
				(0.028)
Sample Mean DV	0.873	0.877	4.698	4.692
Fixed Effects	Y	Y	Y	Y
VC Firms	1133	824	1133	824
Observations	38338	33422	38338	33422

Table X: Change in Investment Size and Network Centrality

Notes: The sample consists of the first investment made by a venture capital (VC) firm in a startup company starting with the 6th (Models 1 and 3) or the 11th (Models 2 and 4) company in which the VC firm invested. The dependent variable in Models 1-2 is the log of average size of the investment the focal round (in 2015 dollars) by a syndicate member and in Models 3-4 the eigenvector centrality of the focal VC firm in the syndication network of all VC firms at the time of the investment.

The independent variables measure the proportion of IPOs or exits (including IPOs and acquisitions) in the first 5 (Models 1 and 3) or the first 10 (Models 2 and 4) companies in which the VC firm invested as well as the average size of the average investment (in 2015 dollars) in the first five or ten companies in which the VC firm invested and the eigenvector centrality at the time of the fifth or the tenth investment.

OLS regressions with standard errors clustered by VC firm and startup company. Fixed effects in regressions: Y = Year. Statistical significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

	(1) Avg Inv (log)	(2) Avg Inv (log)	(3) Centrality	(4) Centrality
Panel A: IPOs				
Prop of IPOs in 1st 5 Cos	0.479*** (0.071)		0.061*** (0.011)	
Prop of IPOs in 1st 10 Cos		0.717*** (0.080)		0.078*** (0.013)
Avg Size of Avg Inv in 1st 5 Cos (log)	0.242*** (0.032)			
Avg Size of Avg Inv in 1st 10 Cos (log)		0.293*** (0.035)		
Eigenvector Centrality at 5th Company			0.206*** (0.071)	
Eigenvector Centrality at 10th Company				0.216*** (0.060)
Panel B: All Exits				
Prop of Exits in 1st 5 Cos	0.275*** (0.065)		0.038*** (0.011)	
Prop of Exits in 1st 10 Cos		0.397*** (0.089)		0.047*** (0.010)
Avg Size of Avg Inv in 1st 5 Cos (log)	0.220*** (0.033)			
Avg Size of Avg Inv in 1st 10 Cos (log)		0.244*** (0.038)		
Eigenvector Centrality at 5th Company			0.245*** (0.078)	
Eigenvector Centrality at 10th Company				0.268*** (0.067)
Sample Mean DV	2986	3059	0.063	0.070
Fixed Effects	Y	Y	Y	Y
VC Firms	1127	822	1133	824
Observations	37559	32773	38338	33422

Table XI: Persistence of Initial Success Controlling for Changes in Access

Notes: The sample consists of the first investment made by a venture capital (VC) firm in a startup company, starting with the sixth company the VC firm invested in (Models 1-2 and 5-6) or the eleventh company the VC firm invested in (Models 3-4 and 7-8). Panel A considers whether the startup company had an IPO and Panel B considers whether the startup company had any exit, IPO or acquisition. The main independent variables measure the initial success of the VC firm by calculating the proportion of IPOs or exits in the first five or ten startup companies in which the VC firm invested. The other independent variables measure the log of the round number of the focal investment, the log of the count of participants in the syndicate of the focal round, the log of average size of the investment the focal round (in 2015 dollars) by a syndicate member, and the eigenvector centrality of the focal VC firm in the syndication network of all VC firms at the time of the investment.

OLS regression with standard errors clustered by VC firm. Fixed effects in regressions: Y = Year; YSIS = Year-State-Industry-Stage. Statistical significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: IPOs								
Prop of IPOs in 1st 5 Cos	0.120***	0.064***			0.065***	0.034***		
	(0.015)	(0.015)			(0.011)	(0.011)		
Prop of IPOs in 1st 10 Cos			0.161***	0.088***			0.083***	0.038***
			(0.017)	(0.019)			(0.014)	(0.014)
Round Number (log)		0.028***		0.026***		0.016**		0.016*
		(0.006)		(0.006)		(0.008)		(0.008)
Avg Size of Inv (log)		0.036***		0.035***		0.035***		0.035***
		(0.003)		(0.003)		(0.004)		(0.004)
Syndicate Size (log)		0.079***		0.078***		0.058***		0.057***
		(0.006)		(0.006)		(0.006)		(0.006)
Eigenvector Centrality		0.186**		0.171**		0.197***		0.202***
		(0.079)		(0.085)		(0.067)		(0.076)
Panel B: All Exits								
Prop of Exits in 1st 5 Cos	0.132***	0.049***			0.059***	0.017		
	(0.019)	(0.016)			(0.015)	(0.014)		
Prop of Exits in 1st 10 Cos			0.191***	0.078***			0.090***	0.029
			(0.024)	(0.020)			(0.021)	(0.018)
Round Number (log)		0.051***		0.052***		0.035***		0.037***
		(0.007)		(0.008)		(0.010)		(0.011)
Avg Size of Inv (log)		0.052***		0.050***		0.051***		0.050***
		(0.004)		(0.004)		(0.005)		(0.005)
Syndicate Size (log)		0.097***		0.092***		0.091***		0.090***
		(0.007)		(0.007)		(0.007)		(0.008)
Eigenvector Centrality		0.513***		0.517***		0.373***		0.389***
		(0.094)		(0.104)		(0.090)		(0.099)
Fixed Effects	Y	Y	Y	Y	YSIS	YSIS	YSIS	YSIS
VC Firms	1133	1127	824	822	1108	1106	811	810
Observations	38338	37559	33422	32773	34314	33667	29600	29061