

Is a VC Partnership Greater Than the Sum of its Partners?

MICHAEL EWENS and MATTHEW RHODES-KROPF*

ABSTRACT

This paper investigates whether individual venture capitalists have repeatable investment skill and the extent to which their skill is impacted by the VC firm where they work. We examine a unique data set that tracks the performance of individual venture capitalists' investments over time and as they move between firms. We find evidence of skill and exit style differences even among venture partners investing at the same VC firm at the same time. Furthermore, our estimates suggest the partner's human capital is two to five times more important than the VC firm's organizational capital in explaining performance.

JEL classification: G24, G30.

*Ewens is with Carnegie Mellon University, Tepper School of Business and Rhodes-Kropf is with Harvard Business School. We thank Viral Acharya, Joshua Coval, Peter DeMarzo, Joan Farre-Mensa, Thomas Hellmann, Bill Kerr, Josh Lerner, Ramana Nanda, David Robinson, Merih Sevilir, and Morten Sorensen for fruitful discussion and comments as well as participants at the American Finance Association meetings, Fed/NYU Conferences on Private Equity, Washington University 9th Annual Corporate Finance Conference, Stanford / JOIM Private Equity conference, Jackson Hole Finance Group conference, Harvard University, Stanford University GSB, Case Western University, as well as Correlation Ventures and *VentureSource* for access to the data. Both authors are advisors to and investors in Correlation Ventures. All errors are our own.

Venture capital (VC) investments are an important engine of innovation and economic growth, but extremely risky from an individual investor's point of view. For instance, Sahlman (2010) reports that 85% of returns come from just 10% of investments, and over the period 1987 to 2012 only 12.8% of investments achieved an initial public offering.¹ Furthermore, there are large differences in fund performance between top-quartile and bottom-quartile VC funds. In spite of the rarity of top-performing investments, however, Kaplan and Schoar (2005) report persistence in fund performance. They show that in contrast to other asset classes such as mutual funds, VC firms that have a fund that outperforms the industry are likely to outperform with their next fund.

The ability to consistently produce top-performing investments implies that there is something unique and time-invariant about VC firms. For example, deal flow (Sorensen (2007)) and networks (Hochberg, Ljungqvist, and Lu (2007)) can explain much of the cross section of VC fund performance. Hellmann and Puri (2002) report that higher quality VCs have industry experience and Gompers, Kovner, and Lerner (2009) find that VC partner specialization can explain cross-sectional differences in performance. There could also be firm policies or complementarities among partners or other attributes that facilitate consistent top performance.

However, the extent the attributes important to performance are part of the VC firm's organizational capital versus embodied in the human capital of the people inside the VC firm is an open question. An extreme possibility is that such attributes are embedded in the firm and the people are substitutable. At the other extreme, a venture firm is simply a collection of people. To illustrate, consider another human-capital-intensive environment we all know well, namely, universities. The question we explore is similar to asking whether an academic performs better at a top institution or whether top institutions are just collections of top academics. The greater resources, reduced teaching, better students, better colleagues, etc. of top institutions could make any researcher more productive, which would imply a large effect from organizational capital. Alternatively, better research could come from human capital differences, implying that researchers would perform equally well at any school. In the context of VC firms, features such as brand, resources, reputation, firm deal flow, firm network, investment processes, better colleagues, etc. could all help a partner perform better. Alternatively, an individual might have the reputation, network, deal flow, and ability to find, identify, or make investments. Furthermore, just as university quality may be more important to researchers who do particular types of research, the firm may be more important to

partners involved in IPOs rather than acquisitions.

Shedding light on the sources of performance in VC firms improves our understanding of whether a firm is more than the sum of its parts. Williamson and Winter (1993) credit (Klein, 1988, p. 220) with distinguishing physical from human asset specificity. They note that Klein (1988), in a response to Coase (1988), was the first to argue that while an “organization is embedded in the human capital of the employees” at the firm, it is “greater than the sum of its parts. The employees come and go but the organization maintains the memory of past trials and the knowledge of how to best do something.” Under this hypothesis, the venture firm holds some of the knowledge of how to make great investments. Hart(1989, p. 1772) further argues that “the observation that the whole of organizational capital is typically greater than the sum of its parts is equivalent to the observation that the total output of a group of workers typically exceeds the sum of the workers’ individual outputs, to the extent that there are complementarities.” Complementarities with a VC firm would imply that partners should match on quality and thus firms should contain partners of similar ability (see Becker (1981), Kremer (1993), Burdett and Coles (1997), and Shimer and Smith (2000) for work on complementarities and matching).

VC provides an opportunity to study this question because we can assign individual investments to partners and follow the latter over time as they move between firms, which allows us to analyze the relative importance of partners and firms in performance. On the other hand, focusing on VC limits the generalizability of our results.

We begin by examining persistence at the individual partner-investment level. To do so, we use the *VentureSource* database of VC investments in entrepreneurial firms founded between 1987-2005 (to allow time to observe outcomes) augmented with hand-collected data. We find evidence of venture partner skill. For example, controlling for observable firm, partner, and investment characteristics such as time, industry, dollars invested, VC experience, investment round number, firm founding date, etc., we find that among partners who made at least three investments, a one standard deviation increase in past IPO rate implies a 18% higher probability of an IPO in their third investment.² Given the rarity of IPOs, the strength of persistence at the partner-investment level is quite high, particularly in light of recent work by Phalippou (2010), who argues that ex-ante persistence comes only from low performance and that the Kaplan and Schoar (2005) results are exaggerated. Our evidence of strong persistence in IPOs, even with numerous deal- and

partner-level controls not before possible, provides support for Kaplan and Schoar’s (2005) original fund-level persistence results as well as recent work on fund persistence by Hochberg, Ljungqvist, and Vissing-Jrgensen (2014) and Harris, Jenkinson, Kaplan, and Stucke (2014).

We also investigate persistence in other types of exits. On average, the same partners who have IPO’d will continue to IPO, those who achieve top exits through a merger or acquisition will continue to do so, and those who fail will continue to fail. Overall, it seems that partners have exit “styles” insofar as they make investments that tend to exit in the same way.³

Next, we include the past performance of the firm’s other partners to study the role of the firm in partner performance persistence. We find that a firm’s past IPO success rate also correlates with a partner’s probability of achieving an IPO on his next investment. Of course, we cannot tell if this is because similar-quality partners join together to form a firm (as implied by assortative matching), in which case past firm performance is just more information about partner quality, or if better firms make it more likely that a partner will IPO.

When we include a measure of VC fund fixed effects using five-year investment windows, we continue to find significant persistence. That is, even comparing partners in the same firm investing at the same time, we find persistence in their relative ability to IPO or achieve top merger and acquisition exits. This finding demonstrates the strength of the persistence. Assortative matching should have driven like-quality partners to join together, but on average VC firms do not seem to be collections of similar-quality partners.

The performance persistence of the average VC partner highlights the potential importance of the partner as well as the firm but does not reveal their relative importance. To separate the firm and the partner, we exploit partner movement between firms. To the extent that partners change performance as they move firms, “ability” will be allocated to the firm based on complementarities, policies, brand, etc. If moving partners do not alter their own or their co-partners’ performance, then “ability” will be allocated to the partner. Bertrand and Schoar (2003) employ a similar idea when they examine CEOs who move firms to identify manager effects on firm policies, while Graham, Li, and Qiu (2012) use executives who move to determine the relative importance of firm and person in executive compensation. We employ the method developed by Abowd, Kramarz, and Margolis (1999) (henceforth AKM) and Abowd, Creecy, and Kramarz (2002) to distinguish partner and firm effects on the performance of VC investments.⁴

Estimates of the VC partner and firm fixed effects provide evidence on the relative importance of VC partner human capital and VC firm organizational capital. Across different specifications we find that the partner fixed effects are more likely to be jointly significant than the VC firm fixed effects, and that the partner fixed effects estimates explain two to five times the variation in exit values relative to VC firm fixed effects. Thus, our estimates suggest that both the partner and the VC firm can affect performance, but the partner's human capital is more important. The partner fixed effect estimates also demonstrate significant heterogeneity in partner type. Translated into level of exit valuation, the distribution of partner fixed effects implies that top-quartile partners produce at least \$82m on average in exit valuation, while bottom-quartile partners produce less than \$4m. To put this in context, the mean exit value is \$151m and the median is zero. The strong partner fixed effects calls for further study of individual partner characteristics (see Zarutskie (2010), Bottazzi, Da Rin, and Hellmann (2008), and Acharya, Gottschalg, Hahn, and Kehoe (2013)), such as gender, education, networks, and experience, to better understand VC outcomes.

The use of movers in this part of the analysis clearly restricts our sample to partners at firms where someone transferred to or away from the firm. The excluded sample covers 40% of VC firms that are less active and smaller. The included sample represents the active and central part of the VC community as it covers 74% of venture-backed investments.

The use of movers also introduces the concern that endogenous moving affects our results. In our final sample, over 30% of partners change firms and thus provide ample data on movement. However, our findings only tell us the average effect of movement on partners who move. The extent to which partners who do not move would be similarly affected is unknown. As in all papers that use movement as an identification strategy, some endogeneity concerns cannot be eliminated. What we can do is consider the probable impacts from endogenous movement as well as examine different subsamples and controls to address empirical concerns.

Recall that the estimation technique uses changes in movers' investment performance around the move to identify firm fixed effects. We separately study partners who move to historically worse-performing firms compared to those who move to historically better-performing firms. Movers to better firms are more likely choosing to move and doing so in anticipation of changes to their performance. We also consider partners who move to very different firms versus partners who move to similar firms. In all cases, the conclusions about the relative value of the firm are similar.

Despite these and other attempts to deal with endogeneity, however, we acknowledge that we cannot completely eliminate the issue and thus our results must be interpreted with some caution.

The balance of the paper is organized as follows. First, in Section I we explore the data and variables of interest. Next, in Section II we study persistence at the partner level across a range of outcomes. Section III presents estimation of a full fixed effects model, and Sections IV and V present subsample and robustness results for all estimates. Section VI concludes.

I. Data Description

The main data set begins with the VC financings, investors, partners, and entrepreneurial firms from the *VentureSource* database maintained by Dow Jones. Using quarterly surveys, press releases, and regulatory filings, *VentureSource* provides a comprehensive picture of the VC market. The full database covers 1987 to 2012 and includes 27,079 financings in 16,897 entrepreneurial firms financed by 3,777 investing firms. We augment the data on three fronts with information provided confidentially by several VC firms, limited partners, web searches and public data sources.⁵ First, we extend exit or investment valuations – more often missing in similar databases – for a larger set of acquisitions and public offerings through searches of S-1 filings, a merge of *VentureSource* with SDC’s merger and acquisition data, and analysis of some limited partner and VC firm portfolios.⁶ We believe the resulting exit valuations are more representative of exits than those in the standard data sources. Second, we conduct web searches of VC firm websites, Capital IQ biography data, and other pieces of data within *VentureSource* to identify where VC partners in *VentureSource* worked when they made their investments. These consistency checks also ensure that we separately identify partners with the same name. The resulting database covers the employment history of VC partners from 1987 to 2012. We further validate a large, random pool of board seats using *VentureXpert* and “Form D” regulatory filings. The latter are the required filings of sales of private securities that report amounts invested and directors (i.e., VC board members). This analysis found no systematic errors and confirmed that we have a comprehensive data set of venture partner investments.

The panel of VC partner board members covers 1987 to 2012, where a board member is any investor listed on an entrepreneurial board and associated with a VC or other investing firm. This definition excludes outside board members or any of the management team of the entrepreneurial

firm. We only include board members in the data that have at least two entrepreneurial board seats for firms founded prior to 2006 and whose investing firm has made at least four investments over the full sample period. The latter restriction eliminates small VCs, those that rarely take board seats, and many corporate venture capitalists. The major sample includes 19,031 financings, 11,885 entrepreneurial firms, 1,573 investing firms, and 5,324 unique VC partners.⁷ The average board member has six board seats (median four).

VC partners who switch VC firms are an important part of our analysis. After correcting data on board membership that matches partners to board seats, we can track movement of individuals between VC firms. We label a mover as a VC partner with multiple board seats assigned to different VC firms. Analyzing the change in titles for mover's first move shows that the vast majority are promoted or remain at the same level. In particular, 45% of movers start as general partners (GP), with 76% moving up to managing director or remaining a GP, while only 27% of the movers who start as managing directors appear to be demoted after their first move.⁸ Section III provides additional information about movers and the firms they move to and from, as well as a comparison with nonmovers.

We employ several dependent variables of interest throughout the analysis.⁹ We initially follow the literature and characterize success by whether the entrepreneurial firm had an IPO. Some 12% of entrepreneurial firms in the sample and 10% of board seats have such an exit (some entrepreneurial firms have multiple observations because there are multiple board seats). The *IPO* variable is a weaker measure of success since 2002, as 90% of nonfailure exits are acquisitions.

We also consider success through acquisitions. We create the dummy variable *Successful acquisition* that equals one if the entrepreneurial firm sold via a merger or acquisition at a reported value at least twice the total capital invested. We cannot determine actual returns for acquisitions because we do not know the amount returned to the VC at exit, but if the total sale value was more than twice the amount invested, then it is likely to be a more successful exit on average than exits with a smaller exit value to investment ratio.¹⁰ We also cannot use all acquisition outcomes because some do not report a value and many appear to be disguised failures. However, the largest acquisitions (greatest successes) tend to have reported values because the acquisition is material to the public acquirer and thus required to be disclosed.

Combining IPOs and successful acquisitions into a single outcome, the fraction of success is

23% for entrepreneurial firms and 21% for board seats. Along with these two success variables, a dummy variable *Failure* is set to one if the firm shutdown, is still private by the end of the sample (through 2012), or was acquired for less than twice total capital invested. The sample only includes entrepreneurial firms founded prior to 2006, so this allows still private firms six years to exit. In total there are six possibilities for an investment in our sample: IPO, successful acquisition, low acquisition, no-reported-value acquisition, failure, or still private. As a final measure, we summarize all outcomes into one variable using the log of one plus the exit value, which we set to zero for failures. Since some firms have yet to exit or have a missing exit valuation, we deal with these firms in two ways. In the main analysis we treat them as zeros, but we also drop them from the sample and find similar results.¹¹ Table II details these dependent variables and a host of controls that we use through the analysis.

[Place Table II about here]

II. Results: VC Partner Performance Persistence

When a VC firm makes an investment in an entrepreneurial firm, the partner who led the investment at the VC firm often takes a seat on the board. For each of these events, we calculate the VC partner's investment history. In particular, $\% IPO_{t-1}$ measures the fraction of the partner's investments made prior to t that exited via an IPO. Performance persistence implies that past performance has predictive power for future outcomes. Our analysis of persistence tracks the relationship between a partner's investment success and the outcome of the current board seat investment (IPO_t). Thus, we ask whether VC partners who have made more investments that IPO'd in the past are more likely to IPO their current investment.

Attrition in the data may lead to a spurious relationship between past success and future outcomes. The null hypothesis of no persistence implies that each new investment is a random draw. Presumably, worse-performing partners are more likely to leave the sample. If this is true, then under the null hypothesis of pure luck, the majority of active partners in the data would be those that got lucky. Naively examining the data would thus result in a finding of positive persistence. However, if we looked only at partners who did at least t investments, then these

partners' past success would have no correlation with the outcome of their next investment.

To avoid labeling luck as persistence, the following regressions only consider cross sections within the set of partners with t investments. That is, we ask whether partners with at least three (or five or seven) investments and a greater fraction of IPOs in their first two (or four or six) investments are more likely to IPO their third (or fifth or seventh) investment. Our results therefore concern persistence conditional on having a level of partner experience in number of investments.¹²

Before reporting regression results we note that the probability that a partner's second investment IPOs is unconditionally 12.5%. However, conditional on the first investment IPOing the probability of the second IPOing is 35%, while conditional on the first investment not IPOing the probability of the second IPOing is 8%. This same persistence is found formally in the regressions below.

[Place Table III about here]

Table III reports the results of a probit regression on cross sections of partner experience for the second, third, fifth, and seventh investment. Controls include the age of the VC firm, the time the VC has been taking board seats, and entrepreneurial firm characteristics such as industry ("Information Technology," "Healthcare," "Consumer/Retail," and "Other"), investment year, dollars invested, and development stage (round number fixed effects), with standard errors clustered at the investment year.¹³ The estimates imply a strong relationship between a partner's earlier investment outcomes and current success.¹⁴ A one standard deviation increase in the the fraction of IPOs for investments made prior to t implies a 18%, 15%, and 18% increase in the predicted IPO probability for the third, fifth, and seventh investments respectively (where one standard deviation is 29%, 24%, and 21% respectively). The signs on the coefficients on the major control variables are as expected, although the estimate for the log of partner experience in years merits discussion. Each subsample conditions on experience, so this control gives the relative speed at which a partner gets to t investments. The negative coefficient in some specifications implies that partners that take longer to get to that t th investment are relatively less likely to have a subsequent IPO.

Note that the coefficient on persistence is from a comparison with other partners who made the same number of investments. It would seem that skill might differentiate partners as they start their career, but attrition could reduce the sample to only increasingly more skilled partners, which

would result in narrower, or possibly no, skill differences in the most experienced group. At the same time, for partners with a greater number of investments we have more data about the partner, and thus presumably more accurate estimates of partner quality. Overall, although each subsample is possibly quite different, we find significant skill differences at each experience level.

Note that the analysis above uses the eventual outcome of earlier investments even if the exit has not yet occurred by the t 'th investment. Thus, we are not asking if the quality of the VC was in the public information set but only whether VC partners who invest in eventual IPOs are more likely to produce an IPO with their next investment. In the Internet Appendix, we repeat the analysis in Table III using the public IPO rate, that is, the fraction of board seats with known success as of the current board seat. The results are similar.¹⁵ Knowledge about initial success at the time of the next investment does not measurably affect the quality of the next investment. This result runs against the idea that persistence comes from initial luck that provides a “halo” making it easier to access future good investments.

A. *Alternative Outcome Measures*

While IPO is an accepted measure of partner and VC firm success, there is a large range of other outcome variables for entrepreneurial investments. Consider the three additional outcome variables discussed above: successful acquisition, failure, and exit valuation. For each, we create an analogue to $\% IPO\ t - 1$ that summarizes a partner's fraction of success or failure: $\% Acq.\ t - 1$ is the fraction of the partner's investments made prior to t that had a successful acquisition, $\% Fail\ t - 1$ measures the same but uses investment failure, and $Avg.\ Exit\ value\ t - 1$ uses the average of one plus the exit value of all investments made prior to t (logged).

Columns 1 and 3 of Table IV again show a strong correlation between the success (or failure) of earlier investments and future outcomes. Recall that a one standard deviation increase in the fraction of IPOs at the third investment implies a 18% increase in future success probability. The predicted impacts for a one standard deviation increase in historical successful acquisitions or failures at the third investment is 10% and 8%, respectively. For the fifth investment these magnitudes are 15% (IPO), 10% (acquisition), and 6% (failure). The analogous predictions for a one standard deviation increase in historical exit value at investments three and five are 13% and 14%.

[Place Table IV about here]

The results show that additional controls and measures of quality further our understanding of partner performance persistence. Persistence in returns exists not simply at the portfolio level, but also investment by investment at the partner level for IPOs, successful acquisition exits, and failure, even controlling for partner, firm, industry, and time-varying characteristics in a way that was not possible in other work. Overall, partners seem to have an exit “style.”¹⁶

B. Persistence and the VC Firm

Does the persistence above stem from the partner or the firm where the partner works? That is, do VC partners simply match to high quality firms and inherit the firm’s deal flow and resources (e.g., (Sorensen (2007)))? To address this question, we include the past performance of the other partners in the firm. Define $\%VC\ IPO (-i)$ as the fraction of board seats in the partner’s VC firm that had an IPO excluding those investments made by the partner. If a partner is merely successful because of the firm, then the inclusion of this control should eliminate or at least dramatically reduce the coefficient on the partner’s past success. The last four columns of Table III introduce this control. The inclusion of other-partner VC performance does not alter the explanatory power of the partner’s past investment success. In fact, both measures are statistically meaningful in nearly all specifications. This evidence suggests that both the partner and the firm play a role in investment outcomes, but additional analysis is required to separate the two. If similarly skilled partners join together then data on other partners’ performance may just provide more information about the partner in question. Alternatively, a significant part of the performance of all the partners stems from the firm. We next introduce a VC fund fixed effects to compare partners in the same firm investing at the same time.

C. VC Fund Fixed Effects

VC firms are potentially long-lived and each firm raises a new fund to invest typically every few years. Partners, as well as the size of funds, can change. To compare partners at the same firm investing at the same time we would like to include fund fixed effects. Lacking a comprehensive mapping of fund to board seat, however, we create VC fund fixed effects. For each VC firm in the

sample, we create “cohorts” of active VC partners by five-year windows. Starting from the first investment made by the VC firm, each five years is associated with a new firm cohort.

[Place Table V about here]

Table V presents VC cohort fixed effects results for each of the exit outcomes from Table IV using a conditional logit framework. This estimation compares partners investing at the same firm in the same time period. The estimates show that the success of earlier investments as measured by IPO or successful acquisition predicts higher probabilities of such events in the future for IPOs and successful acquisitions. The results for failure persistence are weaker and statistically insignificant, while the exit value results in columns 7 and 8 remain strong. The results demonstrate that the partner matters and that assortative matching among partners is significantly less than perfect – partners at the same firms have observably different abilities.

Taken together, our findings suggest that persistence does not arise simply because funds tend to make the same type of investments at similar times. Rather, persistence seems to be due to real partner skill.

III. Three-Way Fixed Effects Model

The results in Table III indicate that both the VC firm and the partner are important variables in the cross section of outcomes. The results in Tables III or V that include historical firm performance or VC fund fixed effects have two interpretations. First, VC firm characteristics explain part of the partner performance persistence. Alternatively, partners with significant skill match together with similar (but not perfectly similar) partners. Separating the effects of the firm and the partner on investment outcomes requires moving away from a study of persistence to a general cross-sectional analysis with fixed effects for both actors.

Consider the following linear model of exit valuation V_{ijkt} :

$$V_{ijkt} = \beta_1 X_{it} + \beta_2 Z_{jt} + \beta_3 U_{kt} + \alpha_i + \phi_j + \gamma_t + \epsilon_{ijkt}. \quad (1)$$

In equation (1), i denotes the VC partner, j the VC firm, k the entrepreneurial firm, and t the date of the investment; γ_t captures the investment year fixed effects. The variables X_{it} , Z_{jt} ,

and U_{kt} include time-varying controls for partner, VC firm, and entrepreneurial firm. The unit of observation is partner i sitting on entrepreneurial firm k 's board of directors while the partner works at VC firm j (which invests in firm k). The date t is defined by the first investment made by VC firm j in firm k . Our focus is the retrieval of the partner and firm fixed effects α_i and ϕ_j , which requires movements of partners between firms.

Bertrand and Schoar (2003) use movers within a sample of CEOs to identify whether individual fixed effects can explain cross-sectional variation in corporate policy variables. We use the AKM refinement of this methodology developed further in Abowd, Creecy, and Kramarz (2002). AKM are part of a large literature in labor economics that attempts to isolate sources that are statistically related to employment compensation. Graham, Li, and Qiu (2012) use this refinement to examine the impact of the firm and the individual on executive compensation. The AKM method provides estimates of firm and partner fixed effects for both movers and stayers. The inclusion of fixed effects for all partners and firms results in a potentially large set of parameter estimates, typically reduced by transforming the data using the within estimator. This transformation demeans by one of the fixed effects dimensions. AKM show that this approach does not simultaneously address heterogeneity and allow parameter recovery, but including firm fixed effects after first sweeping out partner heterogeneity produces the standard result from a dummy variable regression. As in the Bertrand and Schoar (2003) study, one also has to define the sample in which fixed effects can be estimated, theirs being the mobility sample of CEOs. The analogous group in the AKM method is the “connected” group.

As detailed by Abowd, Creecy, and Kramarz (2002), the “connectedness” sample comprises the set of firms and partners that can be identified with the AKM method. Graph theory is used to determine groups of individuals that are connected. Abowd, Creecy, and Kramarz (2002) further detail the normalization procedure used to ensure that the fixed effects estimates are comparable in the full sample.

The connectedness sample requires some that partners be employed by multiple firms. Any two firms are connected if a partner moves from one to the other and any string of firms is connected if they are connected to a firm that is connected to another firm. For example, if a partner from firm A moved to firm B and another partner moved from firm B to firm C, then firms A, B, and C are connected. If another partner moved from firm D to A, B, or C, then A, B, C, and D are

all connected. Abowd, Creedy, and Kramarz (2002) show that connections invite computationally feasible estimation of the firm and person fixed effects for each connected group, relative to a within-group benchmark. The benefit of this method is the ability to estimate the partner fixed effects for both movers and nonmovers.¹⁷

It is useful to understand the basic features of how the AKM method separately identifies partner and firm effects using the movers.¹⁸ Define F_{ilt} as a dummy variable equal to one if partner i works at firm l at time t , and zero otherwise. We can rewrite equation (1) as

$$V_{ijkt} = \beta_1 X_{it} + \beta_2 Z_{jt} + \beta_3 U_{kt} + \alpha_i + \sum_{l=1}^J F_{ilt} \phi_l + \gamma_t + \epsilon_{ijkt}. \quad (2)$$

The AKM method first sweeps out the partner fixed effects by averaging over partner i 's investments to get

$$\bar{V}_i = \beta_1 \bar{X}_i + \beta_2 \bar{Z}_i + \beta_3 \bar{U}_i + \sum_{l=1}^J \bar{F}_{il} \phi_l + \alpha_i + \bar{\gamma}_t + \bar{\epsilon}_i. \quad (3)$$

Here, \bar{V}_i is partner i 's average exit valuation across the full sample period. Next, demean (2) with (3) to get:

$$\begin{aligned} V_{ijkt} - \bar{V}_i = & \beta_1 (X_{it} - \bar{X}_i) + \beta_2 (Z_{jt} - \bar{Z}_i) + \beta_3 (U_{kt} - \bar{U}_i) \\ & + \sum_{l=1}^J (F_{ilt} - \bar{F}_{il}) \phi_l + (\gamma_t - \bar{\gamma}_t) + (\epsilon_{ijkt} - \bar{\epsilon}_i). \end{aligned} \quad (4)$$

Above, the partner fixed effects have been removed with demeaning. Moreover, the term $(F_{ilt} - \bar{F}_{il}) \phi_l$ makes clear that the VC firm fixed effects are only identified using partners that move (i.e., $F_{ilt} \neq \bar{F}_{il}$). Analogous to the description in Graham, Li, and Qiu (2012), the differences in performance for partners changing VC firms allow us to estimate the firm fixed effects for firms in which the mover was a partner.

Finally, we recover the partner fixed effects using the estimates from the standard least square dummy variable regression in (4) and the following equation:

$$\hat{\alpha}_i = \bar{V}_i - \hat{\beta}_1 \bar{X}_i - \hat{\beta}_2 \bar{Z}_i - \hat{\beta}_3 \bar{U}_i - \sum_{l=1}^J \bar{F}_{il} \hat{\phi}_l. \quad (5)$$

Equation (5) uses the beta estimates and firm fixed effects estimates from equation (4) and multiplies them by partner i 's average characteristics. Note that the last term ensures that the partner fixed effects are reduced by the firm fixed effects estimates of all VC firms in which the partner worked multiplied by the fraction of his time he spent at each VC firm.

Several properties of the AKM estimator are worth highlighting. An important source of variation is the mobility of partners, which if limited can bias the estimates of the fixed effects. While this issue exists in all studies that use mobility, it is not severe in our sample with 30% movers. Next, an important benefit of including both movers and stayers in the connectedness sample is the increased precision of a larger sample. Including only movers as in Bertrand and Schoar (2003) would shrink the number of partners nearly 70%. Next, the fixed effects estimates themselves have properties similar to other estimators. As shown by Wooldridge (2010), the estimates of the time-varying variable coefficients are unbiased and consistent, while the fixed effects estimates are only unbiased. Last, the connectedness sample requires dropping one partner by normalizing the group mean to zero for each of the connected groups, and comparison of fixed effects across these groups requires a normalization as discussed in Abowd, Creedy, and Kramarz (2002). None of the results discussed below change when we focus on the one main connected group or simply avoid using the latter normalization procedure.

A. Fixed Effects Results

Estimation of equation (1) starts with the data on the board seat and its investment outcome for VC partners with at least four investments. This restriction ensures an ample set of outcomes for estimating both partner and firm fixed effects. Next, the connectedness grouping eliminates all partners and firms that lack a mover (to or from) during the sample period. Based on this procedure, the sample in the AKM estimates for exit valuation has 2,114 partners, 623 VC firms, and 603 movers. This collection of VC firms accounts for 70% of all financing events, 74% of all entrepreneurial firms, and 84% of all dollars invested.

Estimation of the full fixed effects model includes time-varying controls for VC firm experience, entrepreneurial firm stage, dollars invested, and VC partner experience. Additionally, the model has year fixed effects, but initially excludes industry fixed effects because most partners and firms rarely switch industries.¹⁹ Importantly, all regressions include a control for the round number of

the investment, which addresses concerns about risk differences at different stages. We use the four major outcome variables from above, but focus on the estimates from the log exit valuation regressions.²⁰ The 60% correlation between valuation and the IPO dummy shows that the exit valuation variable contains much of the information in the standard outcome measure.

[Place Table VI about here]

Table VI presents the results of estimating equation (1) using the AKM method. We focus on the estimates' relative contribution to the model R^2 and on the p -values from a test that the set of fixed effects are jointly zero (or the same).²¹ The ratio $\frac{cov(Y, partnerFE)}{var(Y)}$ reports the covariance of the dependent variable with the partner and firm fixed effects, each scaled by the dependent variable's variance. Rather than focus on the level of R^2 , these measures present the fraction of the total R^2 attributable to each type of fixed effects. For exit valuation, some 46% of the total R^2 is attributable to the partner fixed effects (the omitted category is all other control variables), while 8% of the total R^2 is attributable to the firm fixed effects.²² Thus, the partner has almost five times more explanatory power than the firm. These stark differences in explanatory power are reflected in the hypothesis tests on the fixed effects. The F -test that all partner fixed effects are the same is rejected in all but the successful acquisitions specifications. The p -value for the analogous test on VC firm fixed effects consistently fails to reject the null. The estimates imply that the average partner has explanatory power in the outcome regressions.

Not only do the estimated fixed effects point to the relative importance of the firm and the partner, but they also provide insights into partner heterogeneity. In Figure 1, the plot of the demeaned partner fixed effects from the largest connected group provides economic magnitudes for the estimates.²³ The reported fixed effects are in units of log exit valuation and demeaned. The largest connected group – 86% of the full AKM sample – exhibits significant variation in the fixed effects estimates. Adding the group mean and taking the exponential of the fixed effects, the implied exit value advantage of the top-quartile versus bottom-quartile partner fixed effects is at least \$82m. To put this in perspective, 55% of exits result in no return and the mean exit value is \$151m.

[Place Figure 1 about here]

IV. Subsamples

Additional estimation of the full fixed effects model allows us to better understand the role of the firm versus person, as well as address some possible empirical concerns. Table VII presents five separate regressions for log exit valuation. Column 1 considers the set of VC firms that are in the top 10% of experience as measured by total board seats (the 81 most active firms). The movers and stayers of these firms are then included if they satisfy the connectedness criterion. Focusing on this sample helps us examine whether there are VC firms that have built up organizational capital over time. The results from the F -test are much more favorable towards the firm. This suggests that in the sample of top VC firms, the partner and the VC firm are both important in explaining the cross section of outcomes, with the partner explaining over three times as much as the firm.

Column 2 considers the first six investments of all VC partners from the full sample. Here, we examine whether the firm is relatively more important for partners with less experience. For example, in an academic setting, younger faculty members may be more impacted by their university. We find some support for this idea in that the partner again explains roughly three times more exit value variation than the firm.

The main model (1) excludes industry fixed effects as they are only identified for partners that invest in multiple industries.²⁴ We include industry fixed effects in column 3 of Table VII and find very similar results. However, a large fraction of partners invest in only one industry (primarily biotech), and thus, in column 4 we consider only partners who make biotech investments. We again find very similar results. These tests suggest that the relative firm and partner effects stem from within-industry variation. We also reestimate column 3 including industry fixed effects with firms categorized into 17 or alternatively 115 different industries (results reported in the Internet Appendix). The partner continues to explain more than three times more than the firm. We also directly compare partners versus industries dropping firm fixed effects and directly employing the AKM methodology on partners and industries. Now partners who invest in only one industry are the stayers and partners who invest across industries are the movers that provide the needed variation. The variance decomposition reported in the Internet Appendix shows that the partner explains six times more than the industry when using the four, 17, or 115 industry categorizations. Thus, partner performance persistence does not seem to arise from industry effects. Partners

still demonstrate performance persistence when they change industries (even with coarsely defined industry classifications). This is a remarkable finding as it suggests that investing skill comes from something other than industry knowledge.

[Place Table VII about here]

The last column of Table VII attempts to address concerns about the relative sample size of partners to firms. The main specification has approximately 2,100 partners to 623 firms, possibly giving less power to identify firm fixed effects. Here, we use a random sampling procedure to generate 1,000 different samples where the total number of partners equals the total number of firms. Fixing the set of movers to 300, we construct the connectedness sample and then select stayers to equal the total number of firms and partners. The estimation is run on each sample. The table reports median F -test p -values and means of the R^2 contributions. The R^2 contributions still favor the partner, by two-to-one, while the F -test continues to fail to reject the null that all firm fixed effects are the same or zero.

V. Robustness

The results above are robust to a wide array of specifications. In our main analysis, a large set of investments lack an outcome. We treat these firms as non-IPOs, zero exit values, or failed acquisitions depending on the specification. This treatment is reasonable because we only consider entrepreneurial firms founded prior to 2006, so many of the better firms will have exited. Nonetheless, it is possible that this assumption is driving some of the results. To address this concern, we repeat each estimation without investments that lack an exit event as of the end of the sample. The results – persistence, F -tests, and R^2 contributions – are similar for exit value, successful acquisitions, and IPO/acquisitions. The results for IPOs are weaker for the partner fixed effects in the AKM model, which is likely driven by the near absence of IPOs post-2001. We conclude that our main results are not driven by our assumptions on outcomes for non-exited investments.

Next, a potential concern with the AKM method is its use of movers. Partner movement provides the variation necessary to estimate VC firm fixed effects and in turn the fixed effects of nonmovers. However, movers' decisions are potentially endogenous to their own performance or

that of their past firm. To address this concern, we first examine the similarities between movers and stayers and their firms, and run some robustness checks. We then consider the potential implications for interpretation of our results.

Panel A of Table VIII summarizes characteristics of the firms that are the source of the movers and their destinations. Not surprisingly, we find that firms movers leave are larger and older. These firms also invest in earlier-stage companies than firms without movers, but in similar industries.

[Place Table VIII about here]

In addition, performance is higher at the firms people leave and lower at the firms they go to. This result suggests that the average mover is being fired from good firms or otherwise selecting relatively worse firms to join. However, in the Internet Appendix we find that exclusion of year fixed effects in the AKM specification increases the size and importance of VC fixed effects. This difference implies that much of the partner movement is correlated with changes in investment performance over time, that is, partners seem to leave around (before and after) a peak in VC performance. Thus, the perceived difference is due to market timing and the inclusion of year fixed effects is important.

Panel B of Table VIII compares the characteristics of movers and stayers, reporting the means and resulting two-sample t -tests for a set of observables. Movers and stayers are similar across most dimensions, excluding investment stage (round number) and total number of investments. Similarly, the analysis of title changes discussed in Section I (and in the Internet Appendix) shows that the majority of movers take positions at their second firm with a higher or similar title.

Finally, Panel C of Table VIII presents a similar comparison at the firm level. The AKM firm sample comprises 55% (623) of VC firms with at least two partners who sat on at least four board seats. The excluded firms are those that never had a mover move to or from the firm. Such firms are likely very young or those that failed after their first fund. The exit value and IPO rate differences show that the included firms are larger and generally more successful.

The AKM method is also robust to the time-varying performance measures used in Tables III and IV, which Graham, Li, and Qiu (2012) note help control for any assortative matching between firms and movers. A better match may result in improved firm performance, which could bias the firm fixed effects estimates. Inclusion of both lagged partner performance and firm performance

from Table IV has no measurable impact on the conclusion that the partner fixed effects are nonzero and explain a large fraction of the R^2 . However, inclusion of these variables does reduce the p -value on the F -test that the firm fixed effects are all zero.

While the AKM results control for year fixed effects, one might argue that much of the large exit values generated in the asset class were driven by those in the late 1990s. If we exclude all financings over the 1997 to 1999 period, the results in Table VI are quantitatively similar. The p -value on the F -test for VC firm fixed effects is smaller (9%), but, the partner fixed effects are still jointly significant and explain much of the variation in exit valuation.

The estimation of Table VI produces fixed effects estimates relative to a benchmark within each group in the connected sample, and thus, we cannot compare estimated fixed effects between these groups without the normalization procedure of Cornelissen (2008). We address this concern by reestimating the full model with the largest connected group (86% of the full sample). The results in Table VI are basically unchanged.

Turning now to potential implications for interpretation of our results, Panel B of Table VIII shows that movers and stayers are similar across many dimensions, while Panel C of Table VIII demonstrates that firms in the AKM sample are larger, more active VC firms. If firms and partners in the AKM sample are also unobservably different, this could limit our inference. Below, we discuss the impact of selection or omitted variables for VC firm and partner fixed effects estimates.

Recall that identification of the VC firm fixed effects comes from changes in mover performance around the move as shown in equation (4). Suppose that movers are simply partners fired by their past firms. If such partners move to worse firms post-firing and this affects their performance, then the estimation will find large firm fixed effects. Now suppose that movers are on average high quality partners seeking better prospects at relatively better firms. Again, if these partners move to better firms and this affects their performance, the estimation will attribute the performance change to larger average firm fixed effects. These two scenarios seem the most economically plausible and suggest that nonrandom movement does not necessarily lead to any bias in the estimated firm fixed effects.

However, it is likely that movers who choose to move (i.e., those not asked to leave) do so in anticipation of improvements to performance. If partners most likely to be helped by a move are those that make a costly move, then the firm fixed effects may be overestimated relative to the

true effects of the average partner. Alternatively, movers could be those partners who are relatively unaffected by their location. In this case, the firm effects estimates may be biased downwards. We cannot rule out either concern so one must be cautious in interpreting our results. However, we can examine different subsamples to gauge the generalizability of the main result.

[Place Table IX about here]

In Table IX columns 1 and 2 we divide partners into two groups, namely, those that moved to a firm with a historically worse IPO rate than their current firm and those that moved to a firm with a relatively better historical IPO rate (where the historical rate is calculated as of the date of the move). These two groups are likely moving for different reasons. On average, those that move to a worse firm are presumably those that are asked to leave, while those that move to a better firm may be those choosing to seek a better opportunity. In column 1 we see that the partner is about six times as important as the firm in the group that moved to a worse firm. In column 2 we see that the partner is only 2.5 times as important as the firm. If the group of partners that moved to higher-performing firms chose to do so, then it is likely that they anticipated positive benefits to their own performance. This sample, therefore, may have too large an estimate of the true firm effects on the average partner. Alternatively, the firm effects may simply be larger among higher quality firms. The relatively lower explanatory power of the partner in this sample suggests that endogeneity affects our results but does not substantially bias our overall conclusions.

Perhaps firms in the connected sample are connected because partners only move between very similar firms. Note that 86% of the sample is in our largest connected group. This argument would thus mean that the majority of firms have a relatively similar impact on the partner – which is what our findings suggest. Further, the average absolute difference in performance for all moves between existing firms is 18.5% (standard deviation 14%). This means that on average partners are moving to firms with very different IPO rates given that the average IPO rate is 12.8%. To address concerns about the characteristics of firms involved in moves, Table IX columns 3 and 4 divide partners into two groups. Column 4 uses only movers that moved to firms with very similar historical IPO rates (below-median absolute difference), while column 3 considers those movers that moved to a firm with a historical IPO rate very different from their own firm’s historical rate (better or worse). We find very similar results among partners that move to different firms but

the estimate of firm effects is even smaller among partners that move to more similar firms (as expected). Thus, some of the finding that the firm is relatively unimportant comes from partners moving between similar firms.²⁵

Movers may also exit their firms for reasons related to the characteristics of their partners. The specification in equation (1) ignores externalities between VC partners. For example, all partners may benefit from working with top partners (i.e., both improve) and movers will want to exploit this by working with them. Any positive externalities would increase the partner’s performance post-move, which the estimator would attribute to VC firm fixed effects because performance would differ between positions at VC firms. In the Internet Appendix, we analyze the similarity of the fixed effects among partners at the same firm and find significant matching in partner quality. However, as Table VI makes clear, most specifications find limited VC firm fixed effects. Thus, while the estimation cannot separate partner externalities from pure firm effects, our findings suggest that on average both externalities and other firm characteristics are less important than individual partner characteristics.

Similar arguments suggest that mean-reversion in VC partner performance may bias the estimated VC firm fixed effects. If partners who are lucky leave to go to a better firm, they will subsequently mean-revert. Similarly, if partners who are unlucky get fired and go to a new firm, they will also mean-revert. The estimation attributes any change in performance across a move to firm fixed effects. Thus, one would expect that all else equal the performance change due to mean-reversion would be assigned to the firm. If so, this would lead to an overestimate of the importance of the VC firm. This plausible scenario does not alter our conclusions as we find statistically small average VC firm fixed effects. Mean-reversion, however, could combine with other effects to dampen the estimated firm effects. If, for example, partners get lucky and move to a better firm and are helped by the new firm but simultaneously mean-revert, then the mean-reversions will bias down effects of the firm.

Our findings suggest that on average firms have relatively limited impact on partner performance, but this is a relative statement. That is, all firms could be quite important but have a similar impact, in which case the fixed effects estimation would find a small relative importance and an insignificant joint p -value. This conclusion would only relate to connected firms as firms in different connect samples cannot be compared. However, the largest connected sample in the AKM

specification comprises 86% of our sample. Thus, economically, what we find is that on average VC firms seem to be relatively similar to each other. This implies that the location of an average partner is not particularly relevant to investing outcomes.

In general, endogeneity issues could artificially attribute too large or too small an effect to the VC firm. Since our main finding is that the average firm has relatively little impact on performance, endogeneity concerns that result in too large an effect would only reinforce this finding. Thus, we are only concerned that the endogeneity in movement has biased our results to produce firm effects that are too low. Although we find a similar effect in many subsamples, if the 30% of partners who move are those whose performance is unaffected by their location, then we have underestimated the effect of a move on those partners who stay.

VI. Conclusion

In this paper, we find that the VC partner can explain a large fraction of the cross-sectional variation in investment outcomes. Further, the partner's performance is persistent over time, even after controlling for a large set of individual and VC firm controls. VC partners also appear to have a style of exit. Overall, our work provides strong support for the idea the venture partners have investing skill, as well as new insights into the allocation of performance to the firm or partner.

The new evidence that VC firm attributes are relatively less important than partner attributes shed light on another unexplained aspect of VC. The optimal VC firm size seems to be a few hundred million in assets under management. Few VC firms are larger and many top firms cap the amount of money they will accept below total demand. Typical explanations suggest that partner time is the limiting resource but this does not explain why firms do not simply increase the number of partners. Why are there not a few huge VC firms with hundreds of partners instead of many firms with a few partners? Other human capital intensive organizations such as investment banks or law firms become quite large. Furthermore, why don't we see mergers or acquisitions between VC firms? Zingales and Rajan (1998) argue that without a critical firm asset there is nothing to hold a firm together or make it larger other than what is just needed to overcome Coasian frictions. Our findings are consistent with the idea that the organizational capital inside a VC firm is limited, which limits firm size. Given this result, it appears that brand, process, deal flow, etc. are not

critical firm-level characteristics, but rather are partner attributes.

Our work may also benefit limited partners (LPs) who are concerned about investing in a new fund of a venture partner or group of venture partners who have left a VC firm to start another VC firm.²⁶ Many LPs express reservations because the venture partners may have left the “secret sauce” behind. This decision requires LPs to disentangle individual partner impacts on performance from the possibility that the performance was due to the firm organizational capital the partners left behind. Our results suggest that venture partners are relatively unaffected by movement and that individual venture partner past performance is a good predictor of future performance.

Overall, the results suggest that VC partners are often significantly different from each other, but high quality firms are those with a group of better partners. What then is a VC firm? We suspect that the benefits of joining together may relate to fundraising. This would be an interesting avenue for future research.

REFERENCES

- Abowd, John M., Robert H. Creecy, and Francis Kramarz, 2002, Computing person and firm effects using linked longitudinal employer-employee data, Technical Report 2002-06, U.S. Census Bureau.
- Abowd, John M., Francis Kramarz, and David N. Margolis, 1999, High wage workers and high wage firms, *Econometrica* 67, 251–333.
- Acharya, Viral V, Oliver F Gottschalg, Moritz Hahn, and Conor Kehoe, 2013, Corporate governance and value creation: Evidence from private equity, *Review of Financial Studies* 26, 368–402.
- Becker, Gary S., 1981, *Treatise on the Family* (Harvard University Press, Cambridge).
- Bertrand, Marianne, and Antoinette Schoar, 2003, Managing with style: The effect of managers on firm policies, *Quarterly Journal of Economics* 118, 1169–1208.
- 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.
- Burdett, Kenneth, and Melvyn G. Coles, 1997, Marriage and class, *Quarterly Journal of Economics* 112, 141–168.
- Chemmanur, Thomas J., Mine Ertugrul, and Karthik Krishnan, 2014, Is it the investment bank or the investment banker: A study of the role of investment banker human capital in acquisitions, Working paper, Boston College.
- Coase, Ronald H., 1988, The nature of the firm: Origin, meaning, influence, *Journal of Law, Economics, and Organization* 4, 3–17.
- Cornelissen, Thomas, 2008, The Stata command `felsdvvreg` to fit a linear model with two high-dimensional fixed effects, *Stata Journal* 8, 170–189.
- Gompers, Paul, Anna Kovner, and Josh Lerner, 2009, Specialization and success: Evidence from venture capital, *Journal of Economics & Management Strategy* 18, 817–844.

- Gompers, Paul, Anna Kovner, Josh Lerner, and David Scharfstein, 2010, Performance persistence in entrepreneurship, *Journal of Financial Economics* 96, 18–32.
- Graham, John R., Si Li, and Jiaping Qiu, 2012, Managerial attributes and executive compensation, *Review of Financial Studies* 25, 144–186.
- 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, NBER.
- Hart, Oliver, 1989, An economist’s perspective on the theory of the firm, *Columbia Law Review* 89, 1757–1774.
- Hellmann, Thomas, 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.
- Hochberg, Yael V., Alexander Ljungqvist, and Annette Vissing-Jørgensen, 2014, Informational holdup and performance persistence in venture capital, *Review of Financial Studies* 27, 102–152.
- Kaplan, Steven N., and Antoinette Schoar, 2005, Private equity performance: Returns, persistence, and capital flows, *The Journal of Finance* 60, 1791–1823.
- Klein, Benjamin, 1988, Vertical integration as organizational ownership: The Fisher Body-General Motors relationship revisited, *Journal of Law, Economics and Organization* 4, 199–213.
- Kremer, Michael, 1993, The O-ring theory of economic development, *Quarterly Journal of Economics* 103, 551–575.
- Lerner, Josh, Antoinette Schoar, and Wan Wongsunwai, 2007, Smart institutions, foolish choices: The limited partner performance puzzle, *Journal of Finance* 62, 731–764.
- Phalippou, Ludovic, 2010, Venture capital funds: Flow-performance relationship and performance persistence, *Journal of Banking & Finance* 34, 568–577.

- Sahlman, William, 2010, Risk and reward in venture capital, *Harvard Business School Note 811-036*, 1–37.
- Shimer, Robert, and Lones Smith, 2000, Assortative matching and search, *Econometrica* 68, 343–369.
- Smith, Richard, Roberto Pedace, and Vijay Sathe, 2010, Venture capital fund performance: The effects of exits, abandonment, persistence, experience, and reputation, Working paper, University of California, Riverside.
- Sorensen, Morton, 2007, How smart is smart money? An empirical two-sided matching model of venture capital, *Journal of Finance* 62, 2725–2762.
- Williamson, Oliver E., and Sidney G. Winter, eds., 1993, *The Nature of the Firm, Origins, Evolutions, and Development* (Oxford University Press, London).
- Wooldridge, Jeffrey M., 2010, *Econometric Analysis of Cross Section and Panel Data* (The MIT Press).
- Zarutskie, Rebecca, 2010, The role of top management team human capital in venture capital markets: Evidence from first-time funds, *Journal of Business Venturing* 25, 155–172.
- Zingales, Luigi, and Ragu Rajan, 1998, Power in a theory of the firm, *Quarterly Journal of Economics* 113, 387–432.

Notes

¹Of the investments included in the VentureSource databases, 12.8% eventually complete an IPO.

²In a complementary paper, Gompers, Kovner, Lerner, and Scharfstein (2010) examine whether the entrepreneurs receiving VC demonstrate performance persistence. They find an explanation for the source of persistence, while we attempt to separate the importance of the firm and the person in outcomes.

³Venture partners determine which deals they want to do and then seek approval from their other partners. Partners are not assigned deals, nor do they have to give deals they like to other partners. Deals are typically passed between partners if the partner who finds a particular deal does not feel he has the time or expertise to investigate or manage the deal. Thus, this style persistence seems to be a quality of the VC partner.

⁴Chemmanur, Ertugrul, and Krishnan (2014) use the AKM method to examine whether investment bankers matter for merger and acquisition outcomes.

⁵We thank Correlation Ventures for allowing us to use the extensive data they have collected on historical investments, partners, and outcomes. Correlation Ventures is a VC fund that uses quantitative methods for investment selection. As such, they are attempting to build a comprehensive set of historical venture deals and outcomes.

⁶An additional 1,200 exit valuations (a 20% increase) results from this search.

⁷We define anyone who invests in venture financing and sits on the board as a “VC” although some VC investors may work for a firm that also does later-stage investing in more established firms (often referred to as a PE firm), and some may be individual, or so-called “angel,” investors.

⁸The full analysis of title changes can be found in the Internet Appendix, available in the online version of the article on the Journal of Finance website.

⁹All outcomes are measured as of the end of 2012.

¹⁰Note that this variable is zero for IPOs. The results are insensitive to defining “successful” as 1.5 – 3X of total capital raised.

¹¹Firms that have not exited are often thought to be the living dead and firms that don’t report exit values tend to have smaller exits. The cutoff of founding dates pre-2006 implies the entrepreneurial firms have six years to exit. This suggests we should treat them as zeros.

¹²As we condition on partners with increasingly more investments, the sample becomes less representative. The persistence estimates we find are conditional on making t investments. They are not the average amount of skill but rather the relative skill among partners with t investments. The Internet Appendix provides the results from a regression that pools all the experience levels.

¹³We also use a 17 industry classification as well as a 115 industry classification with similar results.

¹⁴Phalippou (2010) argues that fund-level persistence is nonexistent or mainly driven by the left tail. Our results support the original Kaplan and Schoar (2005) persistence result as partner-level persistence should lead to fund persistence unless fees are adjusted to match skill (something rarely done in VC firms).

¹⁵Also in the Internet Appendix, we introduce a longer history to the persistence regressions, such as the partner's IPO rate as of two investments previous (IPO_{t-2}). Longer lags remain statistically significant, while the size falls as we go further back in the partner's investment history.

¹⁶This result echos findings in a working paper by Smith, Pedace, and Sathe (2010) who report that funds that have a high percentage of IPOs or merger and acquisition exits tend to have a higher percentage in their next fund.

¹⁷The analysis of managerial compensation in Graham, Li, and Qiu (2012) has more detail on the methodology, its strengths, and its limitations.

¹⁸This discussion follows Graham, Li, and Qiu (2012).

¹⁹Industry fixed effects can only be identified from partners who invest in different industries over time (much like firm fixed effects). Table VII includes industry fixed effects and finds similar results. Section IV discusses possible biases due to industry effects.

²⁰For the outcome variables *IPO*, *Successful acquisition*, and *Failure*, we use the linear probability model. The major cost of the linear probability model is bounded fixed effects estimates. Let $X_i\hat{\beta}$ be the predicted values from a general model with this form. Here, the estimates of the one-way fixed effects are bounded $-X_i\beta \leq \alpha_i \leq 1 - x_i\beta$. Nonlinear models that do not suffer from the incidental parameters problem, such as the conditional logit, do not invite a rich analysis separating person and firm fixed effects. This restriction forces us to focus our discussion of the AKM results to the continuous variable outcome *Exit valuation*, while still reporting those of the linear probability specification for illustration.

²¹The reported F -test results only consider the largest connected group.

²²We also repeated the analysis using the more memory-intensive method of including dummy variables for partner, firm, and year. The results, as expected, are the same.

²³Any report of the estimated fixed effects from AKM must condition on such a grouping because the estimates are relative to a within-group reference fixed effect.

²⁴The main industries include “Information Technology,” “Healthcare,” “Consumer/Retail,” and “Other.” A finer level of industries introduces 17 categories, each a subset of these four.

²⁵Even though the partners are moving to firms that are observably very different, it is possible that partners move to firms that are operationally quite similar, in which case the limited effect of the firm could stem from this similarity.

²⁶See Gompers, Kovner, Lerner, and Scharfstein (2010) for work on LP decisions and their ability to select funds.

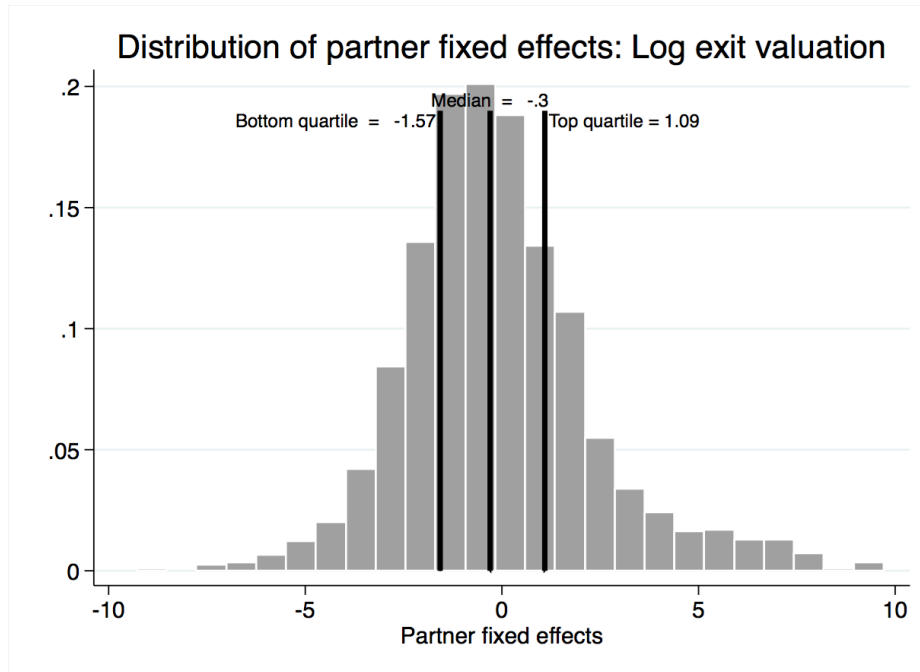


Figure 1. Distribution of Partner Fixed Effects This figure displays the distribution of estimated fixed effects from the AKM regression using the log valuation for IPO or successful acquisition as the dependent variable (zero if no exit, failure, or unreported). The estimates are normalized so the mean value of the partner fixed effects is zero. The sample of estimated fixed effects only includes those in the largest connected sample (i.e., sets of firms connected by movers), which comprise 86% of VC partners in the full specification. This restriction ensures that the fixed effects estimates are comparable.

Table I Variable Definitions

Notes: Tables describes the main variables used throughout the paper.

Variable	Description
IPO	A dummy variable for an IPO exit.
% IPO $t - 1$	Fraction of IPOs in the partner's history as of that investment.
% Acq. $t - 1$	Fraction of the partner's investments prior to t that has a successful acquisition.
% Fail rate $t - 1$	Fraction of the partner's investments prior to t that has a successful acquisition.
Avg. Exit value $t - 1$	The log of one plus average exit values for investments done prior to the partner's current investment.
Successful Acq.	A dummy for an acquisition exit that has a reported exit value greater than two times capital invested.
Fail	A dummy variable for entrepreneurial firm failure.
Log exit value	The log of one plus the exit value (in millions) for a given investment.
% VC IPO ($-i$)	The fraction of IPOs for all partners not including the one of interest at the VC firm as of a board seat at time t .
Years experience	A partner's number of years experience as of the board seat.
# VC firm investments	The total number of board seat investments made by the partners VC firm.
Round #	The round number of the board seat investment (all truncated to a maximum of seven).
Dollars invested (log)	The total investment (in millions) in the financing event.
Years since previous board	The number of years between the current and last board seat for a VC partner.
CA	A dummy variable equal to one if the entrepreneurial firm is based in California.
MA	A dummy variable equal to one if the entrepreneurial firm is based in Massachusetts.
IT	The fraction of a VC partner's investments in information technology.
Biotech	The fraction a VC partner's investments in biotech investments.
Partner experience yrs. (log)	The log of the years since the partner took the first board seat as of t .
VC total deals (log)	The log of the total board seats taken by the VC firm of the partner as of t .
Year FE	Fixed effects for the year of the investment at the date of the dependent variable t .
Industry FE	Fixed effects for the entrepreneurial firm industry: "Information Technology," "Healthcare," "Consumer/Retail" and "Other."
"VC experience yrs. (log)"	The log of the total board seats made by the VC firm as of the current investment.
"Fund sequence (log)"	The log of the fund sequence, set to the five-year windows since VC firm founding.

Table II Summary Statistics

This table reports characteristics of the sample of partners in most analyses below. The unit of observation is the VC partner matched to an entrepreneurial investment through a board seat. Column “Two” summarizes the partners at their second investment, “Three” at their third investment and so on. “Other” pools all the excluded investment numbers and “Total” is the full sample. See Table I for variable definitions.

	Investment Experience					
	Two	Three	Five	Seven	Other	Total
IPO	0.129 (0.335)	0.126 (0.332)	0.139 (0.346)	0.126 (0.332)	0.126 (0.332)	0.128 (0.334)
% IPO $t - 1$	0.166 (0.372)	0.178 (0.294)	0.184 (0.238)	0.199 (0.217)	0.221 (0.210)	0.202 (0.259)
Successful acq.	0.100 (0.300)	0.0942 (0.292)	0.103 (0.304)	0.104 (0.305)	0.0987 (0.298)	0.0991 (0.299)
% Fail $t - 1$	0.379 (0.484)	0.368 (0.359)	0.353 (0.270)	0.346 (0.227)	0.327 (0.217)	0.345 (0.303)
Log exit value	1.613 (2.282)	1.594 (2.261)	1.720 (2.344)	1.701 (2.363)	1.719 (2.412)	1.684 (2.363)
% VC IPO ($-i$)	0.212 (0.236)	0.216 (0.227)	0.228 (0.211)	0.226 (0.190)	0.226 (0.177)	0.223 (0.199)
Years experience	1.689 (1.910)	2.811 (2.481)	4.345 (2.911)	5.650 (3.261)	7.483 (4.722)	5.506 (4.555)
# VC firm investments	76.37 (124.5)	85.22 (126.7)	106.7 (146.5)	125.5 (147.6)	174.8 (188.7)	137.4 (171.4)
Round #	2.004 (1.391)	2.051 (1.451)	2.075 (1.502)	1.997 (1.433)	1.991 (1.412)	2.009 (1.423)
Dollars invested	12.43 (23.39)	12.05 (20.52)	11.75 (18.63)	11.09 (15.71)	12.53 (20.84)	12.29 (20.78)
Years since previous board	1.671 (1.890)	1.178 (1.357)	0.905 (1.038)	0.757 (0.852)	0.740 (0.877)	0.968 (1.233)
CA	0.367 (0.482)	0.401 (0.490)	0.418 (0.493)	0.446 (0.497)	0.486 (0.500)	0.446 (0.497)
MA	0.125 (0.331)	0.118 (0.322)	0.119 (0.324)	0.129 (0.335)	0.128 (0.334)	0.125 (0.331)
IT	0.534 (0.499)	0.547 (0.498)	0.545 (0.498)	0.565 (0.496)	0.571 (0.495)	0.559 (0.497)
Biotech	0.245 (0.430)	0.247 (0.431)	0.250 (0.433)	0.249 (0.432)	0.240 (0.427)	0.243 (0.429)
Observations	4,860	3,636	2,083	1,536	13,551	25,666

Table III Partner Performance Persistence: With and Without VC Firm Controls

This table reports regressions where the dependent variable is one if the investment that the VC had a board seat at time t exited via IPO by the end of the sample. All specifications are probit. Each column includes only one observation per partner, who was observed only at one VC firm, so that all control variables are defined. The dependent variable IPO- t is equal to one if the entrepreneurial firm that was the VC partner's t^{th} investment eventually went public. Table I defines the variables. Standard errors are clustered at the investment year level. Significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

	IPO-2 (1)	IPO-3 (2)	IPO-5 (3)	IPO-7 (4)	IPO-2 (5)	IPO-3 (6)	IPO-5 (7)	IPO-7 (8)
% IPO $t-1$	0.219*** (0.0544)	0.224** (0.104)	0.426*** (0.143)	0.648*** (0.214)	0.110* (0.0654)	0.340*** (0.109)	0.461*** (0.160)	0.594*** (0.214)
% VC IPO ($-i$)					0.318* (0.172)	-0.153 (0.177)	0.358* (0.191)	0.654** (0.331)
Partner experience yrs. (log)		-0.0270 (0.0386)	-0.0975* (0.0506)	-0.0938 (0.0576)		-0.0386 (0.0431)	-0.0874 (0.0686)	-0.135** (0.0683)
VC total deals (log)	0.000173 (0.0210)	0.00882 (0.0218)	0.0822*** (0.0299)	0.0749** (0.0360)	0.0405 (0.0292)	0.0286 (0.0296)	0.0725** (0.0323)	0.0301 (0.0516)
Dollars invested (log)	0.208*** (0.0309)	0.281*** (0.0441)	0.277*** (0.0798)	0.285*** (0.0567)	0.224*** (0.0455)	0.270*** (0.0482)	0.270*** (0.0839)	0.309*** (0.0559)
Years since previous board	-0.00796 (0.0129)	0.0210 (0.0228)	0.0310 (0.0335)	-0.00102 (0.0590)	-0.0135 (0.0162)	0.00468 (0.0334)	0.0158 (0.0309)	0.0381 (0.0639)
Constant	-2.805*** (0.142)	-2.430*** (0.154)	-2.685*** (0.274)	-2.452*** (0.352)	-3.023*** (0.215)	-2.935*** (0.167)	-3.052*** (0.272)	-2.396*** (0.394)
Observations	4857	3653	2242	1535	3839	3003	2016	1430
Pseudo R^2	0.228	0.218	0.223	0.198	0.245	0.212	0.234	0.207
Year FE?	Y	Y	Y	Y	Y	Y	Y	Y
Industry FE?	Y	Y	Y	Y	Y	Y	Y	Y
Round # FE?	Y	Y	Y	Y	Y	Y	Y	Y
Estimation	Probit	Probit	Probit	Probit	Probit	Probit	Probit	Probit

Table IV Partner Performance Persistence by Exit Types

This table reports probit regressions (OLS for columns 3 and 6) for three different dependent variables using the same specification as Table III. Each column includes only one observation per partner, who was observed at only one VC firm. ACQ- t is one if the partner's t^{th} board seat investment resulted in a successful acquisition (i.e., sold for at least twice capital invested) and Fail- t is one if it resulted in a failure or the firm had yet to exit by the end of the sample. Exit value t is the log of the exit value at sale of the entrepreneurial firm (zero if failure or missing). See Table I for control variable definitions. Standard errors are clustered at the investment year level. Note that observation counts differ slightly from Table III because of observations dropped due to multicollinearity. Significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

	ACQ-3 (1)	Fail-3 (2)	Exit Value-3 (3)	ACQ-5 (4)	Fail-5 (5)	Exit value-5 (6)
% Acq. $t - 1$	0.275** (0.134)			0.442** (0.189)		
% Fail $t - 1$		0.0709* (0.0412)			0.297** (0.126)	
Avg. exit value $t - 1$			0.0844*** (0.0167)			0.107*** (0.0348)
Partner experience yrs. (log)	-0.0181 (0.0365)	0.0624*** (0.0190)	-0.0516 (0.0473)	-0.0570 (0.0609)	0.0547 (0.0401)	-0.183 (0.113)
VC total deals (log)	0.0321 (0.0205)	-0.0521*** (0.0164)	0.0236 (0.0221)	0.0299 (0.0361)	-0.0575*** (0.0144)	0.113** (0.0420)
Dollars invested (log)	0.0178 (0.0273)	-0.0828*** (0.0301)	0.375*** (0.0514)	-0.0812* (0.0471)	-0.0229 (0.0286)	0.254*** (0.0706)
Years since previous board	0.0248 (0.0326)	-0.0282* (0.0161)	0.0256 (0.0461)	-0.0627 (0.0456)	0.0404 (0.0356)	0.00977 (0.0465)
Constant	-2.127*** (0.109)	1.119*** (0.0833)	2.654*** (0.126)	-1.558*** (0.243)	0.675*** (0.139)	2.783*** (0.206)
Observations	3566	3566	3566	2239	2239	2239
R^2			0.143			0.144
Pseudo R^2	0.048	0.062		0.043	0.073	
Year FE?	Y	Y	Y	Y	Y	Y
Industry FE?	Y	Y	Y	Y	Y	Y
Round # FE?	Y	Y	Y	Y	Y	Y
Model	Probit	Probit	OLS	Probit	Probit	OLS

Table V Partner Performance Persistence VC Firm Fixed Effects

This table reports fixed effects regressions where the unit is the VC firm in five-year investment windows (i.e., VC cohort). The estimation uses the conditional logit specification for the limited dependent variable IPO- t , which is equal to one if the entrepreneurial firm that was the VC partner's t^{th} investment eventually went public. ACQ- t is equal to one if the t^{th} investment was a successful acquisition. Fail- t is equal to one if that investment failed. The conditional logit requires some variation in the dependent variable for each partner, which is why the samples sizes differ across specifications. Exit value is the log of one plus the exit valuation (zero if failure). The model in columns 7 and 8 use simple fixed effects estimators. The VC firm cohort must have at least three active partners to be included. Controls are defined in Table I. "Additional controls" include dollars invested and years since previous board seat as defined in Table I. Standard errors are clustered at the investment year level. Significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

	IPO-3 (1)	IPO-5 (2)	ACQ-3 (3)	ACQ-5 (4)	Fail-3 (5)	Fail-5 (6)	Exit value-3 (7)	Exit value-5 (8)
% IPO $t - 1$	0.648** (0.261)	1.113** (0.533)						
% Acq. $t - 1$			0.573* (0.321)	1.486** (0.658)				
% Fail $t - 1$					0.0207 (0.153)	0.332 (0.327)		
Avg. exit value $t - 1$							0.0640*** (0.0246)	0.125*** (0.0481)
Partner experience yrs. (log)	0.107 (0.0704)	-0.0639 (0.147)	0.0388 (0.0705)	-0.0297 (0.136)	0.0593 (0.0428)	0.136 (0.0854)	0.0539 (0.0488)	-0.0968 (0.0979)
VC total deals (log)	-0.715*** (0.128)	-1.555*** (0.333)	-0.140 (0.134)	-0.213 (0.218)	0.283*** (0.0791)	0.458*** (0.144)	-0.442*** (0.0839)	-0.705*** (0.151)
Observations	1522	650	1366	550	2897	1232	4554	2145
R^2							0.038	0.046
Pseudo R^2	0.103	0.128	0.026	0.054	0.014	0.025		
Total VC Cohorts	302	154	273	130	658	326	1777	959
VC Cohort FE?	Y	Y	Y	Y	Y	Y	Y	Y
Year FE?	N	N	N	N	N	N	N	N
Industry FE?	Y	Y	Y	Y	Y	Y	Y	Y
Round # FE?	Y	Y	Y	Y	Y	Y	Y	Y
Additional controls?	Y	Y	Y	Y	Y	Y	Y	Y
Estimation	Cond. Logit	Cond. Logit	Cond. Logit	Cond. Logit	Cond. Logit	Cond. Logit	OLS	OLS

Table VI Partner and VC Firm Fixed Effects

This table reports three-way fixed effects regressions using the method detailed in Abowd, Creecy, and Kramarz (2002) and AKM to estimate both VC firm and VC partner fixed effects. The estimation is implemented using the Stata command “felsdsvreg” as described in Cornelissen (2008). The unit of observation is the VC partner, board seat, and entrepreneurial firm outcome. Column 1 uses the log of one plus the exit valuation as the dependent variable (zero if failed or missing), column 2 uses the dummy variable IPO, and column 3 uses a successful acquisition (≥ 2 times capital invested) dummy variable. Column 4 uses the dummy variable Failure, defined as one if the investment failed. Firms without an IPO or successful acquisition have a zero as the dependent variable in columns 2 and 3. The rows for “ F -test on FE” report the p -value from the null that the estimated VC partner or VC firm fixed effects are jointly zero. $\frac{cov(Y, PartnerFE)}{var(Y)}$ reports the “beta” for the partner fixed effects (similarly for the last row and VC fixed effects). The percentages in parentheses report the fraction of the R^2 that are attributable to the firm and partner fixed effects (see Graham, Li, and Qiu (2012)) for details). Table I defines the control variables. “Mean dep. variable” reports the mean of the dependent variable. “# VC firms” is the total VC firms in the sample. Robust standard errors clustered at the VC firm level are reported in parentheses. Significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

	Exit Valuation (1)	IPO (2)	Acquisition (3)	Failure (4)
Relative importance of estimates in R^2 . %'s are fraction R^2 explained by covariate.				
$\frac{cov(Y, PartnerFE)}{var(Y)}$	0.12 (46%)	0.10 (38%)	0.10 (62%)	0.12 (57%)
$\frac{cov(Y, VCFE)}{var(Y)}$	0.02 (8%)	0.04 (12%)	0.03 (25%)	0.02 (10%)
F -test on FE (p -value)				
VC Partner FE	< 0.01	0.06	0.79	< 0.01
VC Firm FE	0.78	0.70	0.3	0.74
Round # (log)	0.352*** (0.0473)	0.0506*** (0.00679)	-0.00526 (0.00615)	-0.0760*** (0.00861)
Dollars invested (log)	0.281*** (0.0296)	0.0348*** (0.00409)	-0.00222 (0.00360)	-0.0380*** (0.00604)
Partner experience yrs. (log)	-0.115 (0.0763)	-0.00966 (0.0103)	-0.00746 (0.00981)	0.0132 (0.0137)
VC experience yrs. (log)	-0.0414 (0.0653)	-0.00678 (0.00878)	-0.0150* (0.00782)	0.00850 (0.0128)
Fund sequence (log)	0.231 (0.146)	0.00472 (0.0182)	0.0387* (0.0210)	-0.0560* (0.0308)
Observations	19617	19617	19617	19617
R^2	.26	.27	.16	.22
Mean dep. variable	\$151m	.14	.11	.40
# Movers	603	603	603	603
# Stayers	1511	1511	1511	1511
# VC Firms	625	625	625	625
Year FE?	Y	Y	Y	Y
Industry FE?	N	N	N	N

Table VII Partner and VC Firm Fixed Effects: Subsamples

This table reports three-way fixed effects regressions using the method detailed in Abowd et al. (2002) and AKM to estimate both VC firm and VC partner fixed effects. The estimation is implemented using the Stata command “felsdsvreg” as described in Cornelissen (2008). The unit of observation is the VC partner, board seat, and entrepreneurial firm outcome. All regressions use the log of exit valuation as in Table VI, column 1. “Top VCs” considers only the set of VCs in the top 10% of total investment experience who are also connected by at least on VC partner mover. “≤ 6 inv.” includes only movers and stayers for the first six of their investments over their whole career (i.e., when the partners are young). “Ind. FE” runs the full AKM specification with industry fixed effects. “Bio.” includes only partners that made healthcare investments. “Subset stayers” is the result of a set of random samples of partners and firms such that the total number of partners equals the number of firms. The AKM regression was run 1,000 times over the random samples. We report the median p -values and average proportion of R^2 . Coefficient estimates are excluded, but mimic those of column 1 of Table VI. Robust standard errors clustered at the VC firm level reported in parentheses. Significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

	Top VCs (1)	≤ 6 inv. (2)	Ind. FE (3)	Bio. (4)	Subset stayers (5)
Relative importance of estimates in R^2 . %s are fraction R^2 explained by covariate.					
$\frac{cov(Y, PartnerFE)}{var(Y)}$	0.09 (40%)	0.23 (57%)	0.12 (46%)	0.13 (50%)	0.13 (42%)
$\frac{cov(Y, VC FE)}{var(Y)}$	0.03 (13%)	0.04 (17%)	0.02 (8%)	0.02 (8%)	0.06 (20%)
F -test on FE (p -value)					Median
VC Partner FE	< 0.01	< 0.01	0.01	< 0.01	0.04
VC Firm FE	0.08	0.49	0.50	0.51	0.61
Round # (log)	0.325*** (0.0705)	0.326*** (0.0752)	0.371*** (0.0523)	0.316*** (0.0699)	
Dollars invested (log)	0.295*** (0.0430)	0.272*** (0.0442)	0.291*** (0.0341)	0.334*** (0.0395)	
Partner experience yrs. (log)	-0.157 (0.143)	-0.135 (0.107)	-0.137 (0.0865)	-0.176 (0.122)	
VC experience yrs. (log)	-0.136 (0.0905)	0.0480 (0.0972)	-0.0381 (0.0730)	-0.138 (0.0988)	
Fund sequence (log)	0.283 (0.248)	0.0480 (0.217)	0.315** (0.152)	0.221 (0.219)	
Observations	9720	9381	14730	7981	
R^2	.24	.37	.28	.25	.31
# Movers	90	432	462	278	300
# Stayers	846	1440	972	509	105
# VC Firms	81	515	530	373	427
Year FE?	Y	Y	Y	Y	Y
Industry FE?	N	N	Y	N	N

Table VIII Characteristics of Firms, Partners, and Full AKM Sample

This table reports characteristics of firms that movers left and moved to, partners that move and stay and firms in and out of the sample. A mover is a VC partner that switched VC firms during the sample period. Each panel considers a different set of observations. In Panel A, observations are entrepreneurial firm and VC investor with a board seat, where the former received its first capital prior to 2006. Numbers reported are the mean across each subsample. "Moved To" comprises firms that only had a mover move to that firm. "Moved From" comprises firms that only had a mover leave the firm. Column 3 reports the differences in means and their significance between the two samples. Panel B reports the characteristics of partners who move and stay in the full fixed effects regressions. Numbers reported are the mean across each subsample. "Mover" comprises partners that moved at least once. "Stayer" comprises partners that are in the connected sample (i.e., worked at a firm with a mover). Column 6 reports the difference in means and their significance. Panel C reports the characteristics of VC firms in and out of the full fixed effects regressions in Table VI. Numbers reported are the mean across each subsample. "Non-AKM Firms" are the VC firms that had a partner with at least four board seats, but lacked a mover to/from the firm. "AKM Firms" are those firms in Table VI. Column 9 reports the differences and statistical significance. "Exit valuation" is the total dollars the entrepreneurial firm sold for at exit (0 if failure or still private by end of sample). Table I defines the variables. "Diff/s.e." reports the difference, the standard error, and significance from the two-sided t-test. Significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

	Panel A: Firms from and to			Panel B: Stayers vs. movers			Panel C: Firms in and out of sample		
	Moved To (1)	Moved From (2)	Diff (s.e.) (3)	Mover (4)	Stayer (5)	Diff (s.e.) (6)	AKM Firms (7)	Non-AKM Firms (8)	Diff (s.e.) (9)
Exit value (m)	62.07	78.28	-16.20 (21.74)	97.12	124.1	-26.98 (24.39)	89.52	51.43	38.10*** (11.10)
% IPO	0.0574	0.181	-0.124*** (0.0143)	0.120	0.118	0.0198 (0.00728)	0.115	0.0935	0.0220* (0.00985)
\$ invested	16.22	11.83	4.389* (1.869)	11.74	12.58	-0.844 (0.481)	12.99	11.63	1.365 (0.777)
Round #	2.540	1.800	0.739*** (0.111)	2.088	1.989	0.0988** (0.0358)	2.168	2.053	0.115* (0.0550)
Investment year	2002.6	1996.5	6.041*** (0.364)				2000.2	2000.3	-0.0911 (0.202)
Year first inv.	1999.9	1992.2	7.773*** (0.494)	2000.0	2000.0	0.0155 (0.145)	1996.7	1997.7	-0.941*** (0.264)
Information tech.	0.527	0.535	-0.0082 (0.0319)	0.536	0.563	-0.0261 (0.0173)	0.526	0.517	0.00933 (0.0202)
Total investments	8.967	7.328	1.640** (0.557)	10.79	9.964	0.822* (0.330)	12.08	6.810	5.265*** (0.417)
Observations	304	174		602	1511		623	500	

Table IX Partner and VC Firm Fixed Effects: Different Movers

This table reports three-way fixed effects regressions using the method detailed in Abowd, Creedy, and Kramarz (2002) and AKM to estimate both VC firm and VC partner fixed effects. The estimation is implemented using the Stata command “felsdsvreg” as described in Cornelissen (2008). The unit of observation is the VC partner, board seat, and entrepreneurial firm outcome. All regressions use the log of exit valuation. “Similar” starts with movers who moved to a firm that was in the lower 50% of the difference between new versus previous firm performance. “Different” starts with the movers who moved to a firm that was in the top 50% of the difference between new versus previous firm performance. The connected group is constructed after restricting to this set of movers. “Moved down” includes movers whose new firm’s IPO rate was higher than their previous firm’s IPO rate as of the move. “Moved up” is the same, but when the new firm has the same or better historical performance. If a mover moves to a new firm or forms a new firm, the firm and mover are excluded from these regressions. All other variables are defined in Table I. Robust standard errors clustered at the VC firm level are reported in parentheses. Significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

	Moved down (1)	Moved up (2)	Similar (3)	Different (4)
Relative importance of estimates in R^2 . %s are fraction R^2 explained by covariate.				
$\frac{cov(Y, PartnerFE)}{var(Y)}$	0.12 (50%)	0.10 (43%)	0.14 (70%)	0.11 (47%)
$\frac{cov(Y, VC FE)}{var(Y)}$	0.02 (8%)	0.04 (17%)	< 0.001 (0%)	0.02 (9%)
<i>F</i> -test on FE (<i>p</i> -value)				
VC Partner FE	< 0.01	0.01	< 0.01	< 0.01
VC Firm FE	0.72	0.51	0.57	0.68
Round # (log)	0.335*** (0.0572)	0.359*** (0.0636)	0.366*** (0.0587)	0.277*** (0.0588)
Dollars invested (log)	0.261*** (0.0330)	0.281*** (0.0390)	0.286*** (0.0383)	0.246*** (0.0350)
Partner experience yrs. (log)	-0.0952 (0.115)	-0.0181 (0.115)	-0.0533 (0.113)	-0.0232 (0.119)
VC experience yrs. (log)	-0.0251 (0.0860)	-0.124 (0.0916)	-0.0921 (0.0892)	-0.0670 (0.0848)
Fund sequence (log)	0.104 (0.175)	0.261 (0.217)	0.159 (0.193)	0.241 (0.208)
Observations	13163	10213	11813	10498
R^2	.25	.24	.24	.25
# Movers	254	155	218	191
# Stayers	1134	878	1040	891
# VC Firms	311	240	288	261
Year FE?	Y	Y	Y	Y
Industry FE?	N	N	N	N