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

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Venture capital firms' ability to repeatedly make top performing investments suggests the importance of organizational or human capital. To what extent are the attributes of performance a part of the firm's organizational capital or embodied in the human capital of the people inside the firm? We examine the performance at the partner-investment level to estimate the persistence in individual partners' ability to IPO, achieve outsized exits or fail, and the relative importance of the firm and the partner. This work furthers our understanding of whether a firm is more than the sum of its parts.

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Venture capital investments are an important engine of innovation and economic growth, but extremely risky from an individual investor's point of view. Sahlman (2010) reports that 85% of returns come from just 10% of investments. And from 1987 until 2010 only 13% of investments have achieved an initial public offering.[1] Furthermore, there are large differences in fund performance between top quartile and bottom quartile venture capital funds. In spite of the rarity of top investments, Kaplan and Schoar (2005) uncover persistence in fund performance. They show that in contrast to other asset classes such as mutual funds, venture capital 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 venture capital firms. For example, Sorensen (2007) argues that deal flow is an important feature of fund performance in the cross section, while Hochberg, Ljungqvist and Lu (2007) and Ljungqvist, Hochberg and Lu (2010) report that VC experience and networks can explain much of the cross section of fund performance. Hellmann and Puri (2002) report that VC's with industry experience are better, and Gompers, Kovner and Lerner (2009) find that VC parter specialization can explain cross-sectional differences in performance. There could also be firm policies or complementarities among partners or other attributes that allow consistent top performance.

However, it is an unanswered question as to what extent the important attributes of performance are a part of the firm's organizational capital or embodied in the human capital of the people inside the firm. An extreme possibility is that attributes are embedded in the firm and the people are substitutable, or alternatively a venture firm is simply a collection

[1] 13% of the investments included in the Venture Source data base can be found to have eventually completed an initial public offering.

of people.

An analogy to universities, another human capital intensive environment we all know well, will provide insight. The question we aim to answer is similar to asking to what extent an academic performs better at a top institution or are top institutions just collections of top academics. The greater resources, reduced teaching, better students, better colleagues, etc of top institutions could simply make any researcher more productive. This scenario implies a large effect from organizational capital. Alternatively, better research could come from human capital differences, which means that good researchers would perform well anywhere.

In venture capital firms, features such as brand, resources, reputation, firm deal flow, firm network, investment processes, better colleagues, etc would all help a partner perform better. Alternatively, an individual might have reputation, network, deal flow and a great ability to find, identify or make great investments. Furthermore, just as university quality may be more important to researchers who did particular types of research, the firm may be more important to investors involved in IPOs rather than acquisitions. We examine both of these questions.

Shedding light on the sources of performance in venture capital firms will help us make progress on a fundamental question in economics as to whether a firm is more than the sum of its parts. Williamson and Winter (1993) credit Klein (1988) with distinguishing physical from human asset specificity. They note that Klein (1988), in a response to Coase (1988), lecture 3, was the first to argue that an "organization is embedded in the human capital of the employees at" the firm, but 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." (p. 220) This suggests that the venture firm holds some of the knowledge of how to make a great investments.

Hart (1989) 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." (p. 1772) Complementarities would imply that partners should match on quality and thus firms should contain partners of similar ability as complementarities imply assortative matching (see Becker (1981), Kremer (1993), Burdett and Coles (1997) and Shimer and Smith (2000) for work on complementarities and matching).

Venture capital investing is a particularly interesting arena in which to examine these ideas both because of the importance of venture capital to the economy and to investors but also because we can assign individual investments to particular partners and follow them across time and as they move between firms. Thus, we have the ability to econometrically attribute performance to partners and firms and determine the relative importance of each.

We begin by examining persistence at the individual partner-investment level. We use the full VentureSource database of venture capital investments from 1987 to 2006 (to allow time to observe outcomes) augmented with hand collected data. We find remarkable support for Kaplan and Schoar (2005)'s fund persistence results but at the partner-investment level. 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 investors who made at least 3 investments those with one standard deviation greater percentage of IPOs in the first two investments are 14% more likely to IPO their third investment. Given the rarity of IPOs, the strength of persistence at the partner-investment level is quite strong.[2]

[2] In a complementary paper, Gompers et al. (2010) use similar data to address whether the entrepreneurs receiving VC have

We also investigate persistence in the ability to achieve a top exit through acquisition as well as persistence in the ability to fail (20% of investments neither fail, IPO nor achieve a top exit and thus, either achieve a low exit, an unreported exit or have not yet exited).[3] We find strong persistence in the ability to achieve a top exit as well as persistence in failure. Thus, on average the same people who have IPO'd will continue to IPO, those who achieve top exits through M&A will continue to do so and those who fail will continue to fail. Combining all types of exit we also find persistence in exit valuation. Overall it seems that partners have exit 'styles' insofar as they make investments that tend to exit in the same way.

Next, we include the past performance of the firm by the other partners. We find that a firm's past ability to IPO also correlates with a partner's probability of achieving an IPO on his next investment. But, of course, we cannot tell if this is because similar quality partners join together to form a firm (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 firm cohort fixed effects we still 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, achieve top M&A exits or fail. This finding demonstrates the strength of the persistence but also demonstrates that partners within the same firm are not the same. Thus, venture capital firms do not seem to simply be collections of similar quality partners.

Results from looking directly at the average persistence of venture capital partners highlights the potential importance of the partner but cannot tell us the relative importance of the firm or partner. In order to separate the firm and partner we exploit partner movement

performance persistence. They find an explanation for the source of persistence, while we attempt to separate the importance of the firm and person in outcomes.

[3]IPOs are correlated with performance in venture capital because the best exits tend to be IPOs. Furthermore, on average the largest acquisitions are more likely to have reported values because they must be reported if material to a public acquirer.

between firms. By following partners across firm moves we can examine the performance of both partners that move and those who stay to extract the impact of the firm. To the extent that partners change performance as they move firms, 'ability' will be allocated to the firm as due to complementarities, policies, brand, etc. And to the extent the moving partners do not alter their own or their co-partners' performance, 'ability' will be allocated to the partner.

Bertrand and Schoar (2003) employ a similar idea when they examine CEOs who move firms and separate out 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 determining executive compensation. We employ the method developed by Abowd, Kramarz and Margolis (1999) (hence forth AKM) and promoted by Graham, Li and Qiu (2012) to separate out partner and firm effects on the performance of venture capital investments.[4]

We find that the partner fixed effects are jointly significant across IPO, failure and exit valuation outcomes. In contrast, the estimates cannot reject the null that the VC firm fixed effects are all zero. The ability of these two fixed effects to explain cross-sectional variation in exit valuation is just as stark. The partner fixed effect estimates explain four times the variation in the size of an exit than VC firm fixed effects. Thus, performance seems to be almost entirely attributable to the partner and firm characteristics seem to matter little in venture capital investing. The estimates of partner fixed effects also demonstrate significant heterogeneity in partner type, with the top and bottom quartile partner separated by a predicted \$144m difference in exit value (whose mean is \$86m and median \$0m). The strong partner fixed effects supports further study of individual characteristics (see Zarut-

[4]Ertugrul and Krishnan (2011) use the AKM method to ask whether investment bankers matter for merger and acquisition outcomes.

skie (2010) and Bottazzi, Da Rin and Hellmann (2008)) such as gender, education, networks or experience for understanding outcomes in venture capital.

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. However, the excluded sample covers 40% of firms who are less active and smaller. The included sample is more representative of the important part of the venture capital community. The use of movers also introduces the concern that endogenous moving is effecting our results. We discuss the potential types of endogenous moving and their impact further in the body of the paper. However, what we find is that each concern should artificially attribute too large an effect to the firm. Thus, since our main finding is that the partner is extremely important and the average firm has a very limited impact, these concerns reinforce our main conclusion.

The implication from our findings, that firm attributes are relatively unimportant to partner performance or persistence, provides insight into another unexplained aspect of venture capital. The optimal venture capital firm size seems to be a few hundred million in assets under management. Only a few venture capital firms are larger and many top firms cap the amount of money they will accept even though demand from investors is much higher. Typical explanations suggest that partner time is the limiting resource but this does not explain why firms don't simply increase the number of partners. Why are there not a few huge venture capital firms with hundreds of partners instead of many firms with a few partners? Furthermore, why don't we see mergers or acquisitions between venture capital firms? Zingales and Rajan (1998) argue that without a critical firm asset there is nothing to hold a firm together or make it larger than just what is needed to overcome Coasian frictions. Our findings suggest that the organizational capital inside a venture capital firm is limited. This would imply limited size firms. If brand, process, deal flow, etc. were critical firm level characteristics then venture capital partnerships would naturally increase their size like other large human capital organizations such as investment banks or law firms.

Our analysis also helps solve a problem for investors. Whenever a partner or group of partners leaves a venture firm to start another firm, investors must decide both whether to continue to invest in their old firm as well as whether to invest in the new firm.[5] This decision requires investors to disentangle individual partner impacts on performance from the possibility that the performance was due to the firm organizational capital or partners left behind. Our results show that partners will be relatively unaffected by movement and in turn, individual partner past performance is a good predictor of future performance.

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

I. Data description

We use the database of venture capital financings, investors and entrepreneurial firms maintained by VentureSource. Using quarterly surveys, press releases and required financial documents, VentureSource provides a comprehensive picture of the venture capital market. The full database covers 1987 to 2011 and includes 27,079 financings in 16,897 entrepreneurial firms financed by 3,777 investing firms. We complement this database with information confidentially provided by several venture capital firms and publicly-available infor-

[5]See Lerner, Schoar and Wongsunwai (2007) for work on LP decisions and their ability to select funds.

mation about funds and investments.[6] Further, the data on board membership required an extensive cleaning to match VC firm to entrepreneurial firm and in turn, movers.[7] We focus on a panel of individual VC partner board seats, their dates, investment characteristics and outcomes.

The panel of venture capital partner board members covers 1987 to 2011 where a board member is any investor listed on an entrepreneurial board and associated with a venture capital or other investing firm. This definition excludes outside board members or any of the management team of the entrepreneurial firm. A board seat is assigned a date based on either the date reported in the database or if missing, assumed to be the first date the firm the board member works for made an investment. 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 whole sample. The latter restriction eliminates small VCs, those that rarely take board seats and many corporate venture capitalists. The major sample includes 19,018 financings, 11,877 entrepreneurial firms, 1,547 investing firms and 5,225 unique VC partners.[8] The average board member has 6 board seats (median 4).

Venture capital partners who switch venture capital firms are an important part of our analysis. After correcting the 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 venture capital partner with multiple board seats assigned to different VC firms. The exact dates of these moves are unknown, so we assume it occurs some point between the two board

[6]We thank Correlation Ventures for allowing us to use the extensive data they have collected on historical investments, partners and outcomes. Correlation Ventures is a venture capital fund that uses quantitative methods for investment selection.

[7]VentureSource matches partner to investment using the partner's most recent VC firm. We conducted web searches and interval validation with VC firm investment activity to determine historical placements.

[8]We call these individuals "VCs" although some work for private equity firms or are angel investors.

seats around the move.[9] Table I gives a picture of the changes in titles for the over 600 first moves and shows that many receive promotions through the move. Section III provides additional information about movers including the firms they move to and from and a comparison of non-movers.

There are several dependent variables of interest that we use throughout the analysis. We initially follow the literature and characterize success by whether the entrepreneurial firm had an initial public offering. Some 13% of entrepreneurial firms in the sample and 10% of board seats had such an exit (i.e. some entrepreneurial firms have multiple observations because there are multiple board seats). Figure 2 shows that the IPO dependent variable is a weaker measure of success since 2002 as 85% of exits were acquisitions.

We also consider success through acquisitions. We create a dummy variable for "successful acquisition" which is 1 if the entrepreneurial firm sold via a merger or acquisition at a 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 returned was more than twice the amount invested 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" the fraction of success is 24% for entrepreneurial firms and 19% for board seats. Along with these two successful outcomes, a dummy variable "Failure" is set to 1 if the firm shutdown or was still private by the end

[9]Any inconsistencies such as over-lapping boards also aided in identifying movers.
[10]Note that this variable is zero for initial public offerings. The results are insensitive to defining "successful" as $1.5-3X$ of total capital raised.

of the sample (2011). In total there are 6 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 exit value – zero for failures combined with IPO and reported acquisition values. Since some firms have yet to exit or have a missing exit valuations, we deal with these firms in two ways. For our 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.

II. Results

A large literature demonstrates that both the VC partner and VC firm are important explanatory variables in the cross-section of outcomes. VC fund performance persistence as detailed in Kaplan and Schoar (2005) shows that top (bottom) performing venture capital funds consistently outperform (underperform) their peers. We extend this finding by examining the partner-investment level outcomes to assess the extent to which the fund-level persistence manifests itself at the partner level and exit type, while controlling for deal, partner, and VC firm level attributes not possible before.

A. VC Partner Performance Persistence

When a venture capital firm makes an investment in an entrepreneurial firm, the partner who led the investment at the venture capital firm often takes a seat on the board. For each of these events, we calculate the venture capital partner's investment history. "% IPO $t-1$" measures the fraction of the partner's investments made prior to t that exited via an ini-

[11] Firms 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. This suggest we should treat them as zeros.

tial public offering. 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 or not venture capital partners who have made more investments that IPO'd in the past are more likely to IPO their current investment.

Figure 1 shows that studying persistence using pooled outcomes – investment at t and $t+1$ – introduces selection issues. There is a strong, positive relationship between IPO success rate and board seat experience. To avoid a spurious relationship between past success and future outcomes, 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 5 or 7) investments and a greater fraction of IPOs in their first two (or 4 or 6) investments are more likely to IPO their third (or fifth or seventh) investment. Our results will therefore be the persistence conditional on having a level of partner experience in number of investments.

Only considering partners with a fixed experience level may lead to an underestimate of persistence. Most likely those partners that fail to make it to t investments are typically below average and correctly prevented from continuing to invest. Without such attrition, the t^{th} investment would likely have under performed and in turn increase estimated persistence for better partners. So by comparing persistence among partners who were good enough to make t investments we are only estimating the correlation between past and future performance among a higher quality set of partners. Discovering persistence in this subgroup still requires an additional subset of partners to outperform their (selected) peers.

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, investment year, dollars invested and development stage. The estimates imply a strong relationship between a partner's earlier investment outcomes and current success. A one standard deviation increase in the the fraction of IPOs for investments made prior to t implies a 14%, 15% and 28% increase in the predicted IPO probability for investments 3, 5 and 7 respectively.

The increase in persistence as the number of required investments increases reveals additional dynamics. The coefficient is from a comparison with other investors who made the same number of investments. For example, the coefficient estimate for the 7 investment group compares investors who took board seats on 7 investments against other investors who also took 7 board seats. Thus, we are finding that some investors are able to persistently outperform other investors even among this very experienced group.

Note also that we use the eventual outcome of the earlier investments even if the exit has not yet occurred by the t'th investment. This is because we are not asking if the quality of the VC was in the public information set but only whether VCs who invest in eventual IPOs are more likely to produce an IPO their next investment. Table VI introduces 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. In unreported results, we also repeat the analysis in Table III with "public IPO" or the fraction of board seats with known success as of the current board seat. The results are qualitatively similar.

Alternative outcome measures

While the IPO is an accepted measure of partner and VC firm type, 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. Finally, "Avg. Exit value $t-1$" uses the average 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 IPO at investment three implies a 14% increase in future success probability. The predicted impacts for successful acquisition is 11% and 3% for failures. For the fifth investment these magnitudes are 12%, 13% and 7%. The analogous predictions for exit value at investment three and five are 14% and 10%. The results show that additional measures of quality further our understanding of partner performance persistence. Persistence in returns is not simply at the portfolio level, but also investment by investment at the partner-level for IPOs, high acquisition exits and failure. Thus, partners seem to have an exit 'style.' Although we cannot examine fund level returns as Kaplan and Schoar (2005) do, we can control for partner, firm, industry and time-varying characteristics in a way that was not possible in other work.

PERSISTENCE AND THE VC FIRM

A partner's performance as measured by IPOs, acquisitions or exit values exhibits strong, economically meaningful persistence. These estimations control for the experience of the venture capital firm, but lack additional variables that could explain the results. For example, VC partners could simply match to high quality firms and inherit the firm's deal flow and resources (e.g. Sorensen (2007)). We partially address this issue by including the past performance of the other partners in the firm.

Define "%VC IPO $(-i)$" as the fraction of board seats for the partner's VC firm that had an IPO excluding those investments made by the partner. If a partner is merely successful in the past and future because of the firm, then the inclusion of this control should eliminate or at least dramatically lower the coefficient on the partner's past success. Table V repeats the estimation of Table III with this additional control. Estimates in columns 2, 4, 6 and 8 show a general pattern of lower persistence related to partner past success, but the economic magnitudes are relatively unchanged. Although the inclusion of the other partner VC performance does not dramatically alter the explanatory power of the partner's past investment success, both measures are statistically meaningful in nearly all specifications. The evidence suggests that both the partner and the firm play a role in investment outcomes, but additional analysis is required to separate the two.

VC FIRM FIXED EFFECTS

Tables IV and V illustrate that there is information embedded in the performance of a partner's past investments about the quality of their future investments. When we include the past performance of the other partners in the firm we see that both the firm and the partner matter for outcome prediction. We next introduce a venture capital fund fixed effect to compare partners in the same firm investing at the same time.

Venture capital firms are long-lived, while their activity revolves around funds with limited lifespans. Lacking a comprehensive mapping of fund to board seat, we create an alternative VC fund fixed effect. 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 creates a new VC firm. The cohorts closely mimics VC funds, increasing the sample of VC firms from 1,307 to 1,806. An important identification condition of this fixed effect estimator is differences in outcomes between partner performance within firm. If partner performance is identical, the VC fixed effect absorbs anything associated with partner performance.

Table VII presents VC fixed effect results for each of the exit outcomes from Table IV. The limited dependent variable restricts the use of a probit, so estimation uses the conditional logit. Estimates show that the success of earlier investments as measured by either 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. Intuitively, those partners within a VC fund investing cohort who have better past performance are more likely to have better future performance. Simply, the typical VC fund has significant and persistent partner performance heterogeneity. The results demonstrate both that the partner matters and that assortative matching among partners is significantly less than perfect - partners have observably different abilities.

Next we move to a full three-way fixed effect specification first detailed by Abowd, Kramarz and Margolis (1999) to identify the relative importance of the partner and the firm.

III. Three-way fixed effects model

The results in Tables III - V indicate that both the venture capital firm and partner are important variables in the cross-section of outcomes. The results in Table VII with the inclusion of VC firm fixed effects has two interpretations. One, time invariant VC firm characteristics explain part of the partner performance persistence. Or alternatively, partners with significant time-invariant fixed effects match together with similar (but not perfectly similar) partners. Separating the firm and partner in investment outcomes requires moving away from study of persistence to a general cross-section analysis with fixed effects for both actors.

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

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

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 is the investment year fixed effect. The variables X_{it}, Z_{jt} and U_{kt} include time-varying controls for each. The unit of observation is the first board seat taken by the venture capital partner i at entrepreneurial 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.

Movers and the AKM method

If venture capital partners remained at one firm their entire career, one could not separate of the partner fixed effect α_i and firm fixed effect ϕ_j. The average performance of the firm's investments – IPOs, failures or exit values – would map directly to the average of the partner's outcomes. Movers from existing firms to new firms or between existing firms presents the required variation. For the venture capital sample, some 20% of partners worked at two or more VC firms.[12] 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 Abowd, Kramarz and Margolis (1999) (hereafter, AKM) refine-

[12] These numbers are between 15-30% depending on the estimation sample.

ment of this methodology and promoted by Graham, Li and Qiu (2012) to estimate the fixed effects for both movers and stayers. The estimation technique allows analysis of partners that both leave, arrive and stay with a firm.

The fixed effects estimator proposed by Abowd, Kramarz and Margolis (1999) that separates the firm and person effect has two major features. First, the set of individuals moving between firms creates sets of "connected" firms. Any two firms that have a mover that worked at or moved to are connected and in turn, all the non-movers at those firms are connected. AKM show that connections invite computationally feasible estimation of the firm and person fixed effects for each connected group, relative to a within-group benchmark. Second, the movers not only generate the set of firms and persons that can be analyzed but also provide the variation for identification of the fixed effects (see next section for details). For this analysis, the benefit of the AKM method is the ability to estimate the partner fixed effects for both movers and non-movers. Such a set is more representative if movers are very different on both observables and unobservables. A limited set of movers also mechanically lowers the joint significance of firm fixed effects, therefore the analysis should have a large set of movers for generality. The analysis of managerial compensation in Graham, Li and Qiu (2012) has significantly more detail on the methodology, its strengths and its limitations.

Mechanics of AKM

It is useful to understand the basic features of how the AKM method separately identifies the partner and firm effect using the movers.[13] Define the variable F_{ijt} as a dummy variable equal to one if partner i works at firm j at time t, and zero otherwise. We can rewrite

[13] We follow the same process as Graham, Li and Qiu (2012).

equation (1) as:

$$V_{ikt} = \beta_1 X_{it} + \beta_2 Z_{jt} + \beta_3 U_{kt} + \alpha_i + \sum_{j=1}^{J} F_{ijt}\phi_j + \gamma_t + \epsilon_{ikt}. \tag{2}$$

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

$$\overline{V}_i = \beta_1 \overline{X}_i + \beta_2 \overline{Z}_i + \beta_3 \overline{U}_i + \sum_{j=1}^{J} \overline{F}_{ij}\phi_j + \alpha_i + \overline{\gamma_t} + \overline{\epsilon}_i. \tag{3}$$

Next, demean (2) with (3) to get:

$$\begin{aligned} V_{ikt} - \overline{V}_i = &\beta_1(X_{it} - \overline{X}_i) + \beta_2(Z_{ijt} - \overline{Z}_i) + \beta_3(U_{kt} - \overline{U}_i) \\ &+ \sum_{j=1}^{J}(F_{ijt} - \overline{F}_{ij})\phi_j + (\gamma_t - \overline{\gamma_t}) + (\epsilon_{ikt} - \overline{\epsilon}_i). \end{aligned} \tag{4}$$

First note that the partner fixed effects have been removed with demeaning. Second, the term $(F_{ijt} - \overline{F}_{ij})\phi_j$ makes clear that the VC firm fixed effect is only estimated using partners that move (i.e. $F_{ijt} \neq \overline{F}_{ij}$). 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 the firms where the mover was a partner.

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

$$\hat{\alpha}_i = \overline{V}_i - \hat{\beta}_1 \overline{X}_i - \hat{\beta}_2 \overline{Z}_i - \hat{\beta}_3 \overline{U}_i - \sum_{j=1}^{J} \overline{F}_{ij}\hat{\phi}_j. \tag{5}$$

Equation (5) uses the beta estimates and firm fixed effect estimates from equation (4) and multiplies them by partner $i's$ average characteristics. It is interesting to note that the last term ensures that the partner fixed effects are reduced by the firm fixed effect estimates of all the firms where the partner worked multiplied by the fraction of his time he spent at each firm.

Econometric properties of AKM

The fixed effect estimates from the AKM method have several important econometric properties. First, both the firm and partner fixed effects are unbiased and efficient, however, they are inconsistent. Simply, the addition of a new cross-section (here, a firm or person) increases the number of parameters to estimate without sufficient information to estimate the new fixed effect. All other parameters are consistent and unbiased under standard assumptions. Most estimators of the fixed effects such as the one used by Bertrand and Schoar (2003) also lack consistency.[14] Next, the identification of the fixed effects does not require random movement of partners. Rather, the inference about their economic meaning requires careful attention to possible non-representativeness of movers or their endogenous response to VC firm performance. We address these issues in section V. Finally, the linear assumption of the model limits the types of functional forms that are often used in limited dependent variable settings. For the outcome variables "IPO," "Acquisition" and "Failure" we use the linear probability model.[15] Non-linear models that do not suffer from the incidental parameters problem, such as the conditional logit, do not invite the rich analysis of separating the person and firm fixed effects. This restriction forces us to focus the discussion of the AKM results to the continuous variable outcome "Exit valuation," while still

[14] As Graham, Li and Qiu (2012) notes, consistency of the fixed effects holds if and only if $T \to \infty$, which most panel datasets cannot satisfy with time period restrictions.

[15] The major cost of the linear probability model are 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 $-X_i \beta \leq \alpha_i \leq 1 - x_i \beta$.

reporting those of the linear probability specification for illustration.

Fixed effect results

Estimation of equation (1) starts with the data on the board seat and its investment outcome for VC partners with least four investments. This restriction ensures an ample set of outcomes to estimate both a partner and firm fixed effect. Next, the connectedness grouping eliminates all partners and firms that lack a mover to or from during the sample period. In the end, the sample in the AKM estimates for exit valuation has 2,142 partners, 649 VC firms and 645 movers.

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 excludes industry fixed effects because most partners and firms rarely switch industries.[16] Importantly, all regressions include a control for the round number of the investment which partially addresses concerns that successful VCs move into later stages investments. We use the four major outcome variables from above, however, limitations of combining linear probability and fixed effects restrict inference from IPO, acquisition and failure outcomes. Thus, our focus will mainly be on the estimates from the log exit valuation regressions. The 60% correlation between valuation and the IPO dummy show the variable contains much of the information in the standard outcome measure.

Table VIII presents the results of estimating equation (1) using the AKM method. We focus on the p-values from a test that the set fixed effects are jointly zero and those estimates relative contribution to the model R^2. The p-value from the F-test that all the partner fixed

[16] The fixed effect cannot be separated from any industry dummy variable.

effects are zero 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. These stark differences manifest themselves in the relative contribution of the fixed effects to the R^2. The $\frac{cov(Y, partnerFE)}{var(Y)}$ in Table VIII reports the covariance of the dependent variable with the partner and firm fixed effects, each scaled by the dependent variable variance. These measures in turn present the fraction of the total R^2 attributable to each. The partner fixed effects explain 3 - 6 times more of the cross-sectional variation in the outcomes than the VC firm fixed effects. For exit valuation, some 38% of the total R^2 is attributable to the estimated partner fixed effects (the omitted category are the other control variables).[17]

Not only do the estimated fixed effects point to the relative importance of firm and partner, but they also provide a picture on the heterogeneity of partners. The plot of the demeaned partner fixed effects from the largest "connected" group in Figure 4 provides economic magnitudes to the estimates.[18] 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 effect estimates. For example, using the levels analogue of the estimates, a move from the bottom quartile to top quartile partner fixed effect implies a $144m increase in predicted exit valuation. With 55% of exit valuations resulting in zero and a mean of $86m (median $0m), this difference in fixed effect suggests large and economically meaningful differences in partners.

[17]We 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.

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

IV. Partners and firm formation

With the estimates of the partner fixed effects in hand, we can partially address if and how certain types of partners form venture capital firms. Any analysis requires a counter-factual sample, which we set as the outcome of randomly matching partners to firms for the existing VC firm size distribution. Simply, we fix the number of partners ever active at the 649firms in the AKM sample and randomly reassign them to firms 100 times. If the partner fixed effect estimates from AKM measure VC partner type, then any assortative matching by partners into firms will exhibit itself through different distributions of partners in these two samples. Consider the distribution of "top" partners, which we define as VC partners with top quartile fixed effects. The columns "Random Match" in Table IX show the predicted fraction of VC firms with zero, one, two, etc. "top" partners under random matching. The columns "Sample" shows the true distribution.

Two features stand out comparing the distribution of top partners across firms. First, the true sample has over twice the number of firms with no top partners as predicted by random matching (54% vs. 23%). Second, there are significantly more VC firms in the sample with many top partners than found in the random sample. These two facts suggest there is some matching of top partners to firms *and* low-type partners to firms. Similarly, the within-firm standard deviation of the partner fixed effects in these two samples show that the random sample has approximately twice the variation as found in the data. VC firms are comprised of more similar partners than firms would have if formed through random matching. The evidence suggests that there is some sorting of partners in the tails to firms, which as we discuss below would tend to produce a larger VC firm fixed effect.

V. Robustness

The results above are robust to a wide array of specifications. According to Figures 2 and 3 there is a large set of investments that lack an outcome. We treat these firms as either non-IPOs, zero exit values or failed acquisitions depending on the specification of the regression. This treatment is reasonable because we only considered entrepreneurial firms founded prior to 2006 so most of the better firms will have exited. Nonetheless, it is possible this assumption is driving some of the results. So 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 the major results are not driven by our assumptions on outcomes for non-exited investments.

One potential concern of the AKM method is the use of movers. Their movement provides the variation to estimate the VC firm fixed effects and in turn, those of non-movers. Perhaps these movers' decisions are endogenous to their own performance or that of their past firm. AKM does not require exogenous movement, but it is important to interpret results with endogeneity in mind. First we examine the similarities between movers and stayers and their firms, and run some robustness checks. Then, in the next subsection, we consider the potential effects on the interpretation of our results.

Table X details features of the firms that are the source of movers and their destinations. Not surprisingly, firms that movers leave are larger and older. These firms also invest in earlier stage companies and relatively few information technology firms. These differences do not pose a problem for the representativeness of the VC fixed effect because both the moved to and from firm have a fixed effect estimate.

Table X highlights other features of firms that movers move from and to: for example, performance is higher at firms people leave and lower at firms they go to. This suggests that partners are being fired from good firms or leaving and starting poor firms. However, in unreported results, we find that exclusion of the year fixed effects in the AKM specification dramatically 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, i.e., partners seem to leave around (before and after) a peak in VC performance. Thus, the perceived difference to due to market timing and the inclusion of year fixed effects is important.

Next, Table XI 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 IPO performance and board seat experience ("Total board seats"). Movers are, on average, more experienced and more successful than VC partners that do not move firms. Comparing the results from this table to that of Table X, it appears that movers are not likely fired from their previous positions although the firms they move to are generally worse. Similarly, Table I tracks the change in the VC partner's titles as they make their first move. "Managing *" captures a set of high-ranking titles such as "Managing Director" with the left-hand titles being those in the first position. The patterns of title changes makes clear that the average mover is increase their rank between their first and second position.

Table XII, presents a similar comparison at the firm-level. The AKM firm sample comprises 55% (649) of VC firms with at least two partners who sat on at least 4 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. Inclusion of both the lagged partner performance and firm performance from Table IV has no measurable impact on the conclusion that the partner fixed effects are non-zero and explain a large fraction of the R^2. The inclusion of these variables does improve the p-value on the F-test that the firm fixed effects are all zero.

The AKM results control year fixed effects, however, 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 in 1997-1999, the results in Table VIII are quantitatively similar. The p-value on the F-test for VC firm fixed effects is smaller (9%), however, the partner fixed effects are still jointly significant and explain much of the variation in exit valuation.

The estimation of Table VIII produces fixed effect estimates relative to a benchmark within each group in the "connected" sample. Therefore, the comparison of estimated FE between these groups is problematic. We address these concerns following Graham, Li and Qiu (2012) by re-estimating the full model with the largest "connected group". That group comprised 86% of the sample and in turn invites a more accurate comparison of the fixed effects distribution. Both the qualitative results in Table VIII and the distribution in Figure 4 are unchanged.

The firm and partner fixed effects estimates in Table VIII suggest that the average partner explains more of the variation in the cross-section of exit values than the firm. However, there is a large heterogeneity in VCs which may have been lost in the pooling of all firms and partners. To address this, we create a sub-sample of the "most active VC firms" defined by those in the top quartile of deal volume done from 1987 to 2011 and repeat the AKM regressions with this sub-sample. Note that the connectedness requirement for the AKM estimator implies that the samples in the resulting estimates will be smaller than the full set of VCs. Generally, the VC firm effect is relatively more significant in this sub-sample. For the exit-value regression, a p-value of .5 for the F-test on firm FE goes to .06 in this sub-sample. Importantly, there are 1/3 as many firms, so clearly the average firm in the most active VC sample matters relatively more than the average firm in explaining outcomes. Although the joint significance is higher for VC firm fixed effect, the fraction of R^2 they explain is basically unchanged from the full sample. Overall, the results are robust to considering only the most active firms.

A. Endogeneity concerns

Table XI shows that movers and stayers are similar across many dimensions, while Table XII demonstrates firms in the AKM sample are active VC firms. If firms and partners in the AKM sample are still unobservably different, it could limit our inference. We now discuss resulting predictions from such non-randomness about VC firm and partner fixed effect estimates.

Recall that identification of the VC firm fixed effects comes from changes in mover performance around the move as shown in equation (4). Consider first 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 AKM method will find a large firm fixed effect. 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 it affects their performance, the AKM will attribute this to a larger average firm fixed effect. These two scenarios show that concerns about non-random movement does not necessarily lead to any bias in the estimated firm fixed effects. In these examples AKM would correctly predict non-zero VC firm fixed effect.

Our inability to find a significant VC firm fixed effect means that, on average, either firms have no firm fixed effect *or* movers simply move to firms that have nearly identical (but non-zero) firm fixed effects as their previous firm. It is not possible to rule out this possibility, however, both data and intuition suggest it is not a likely explanation. First, Table X shows that these firms are different in many ways. Furthermore, given that the largest connected sample in the AKM specification is 86% of the sample, movement to identical firms means that 86% of VC firms have the same fixed effects. Thus, virtually all VC firms must have the same fixed effect – likely zero but possibly any other number. Importantly however, such a fact also leads to the conclusion that the average VC firm is not important in cross-section of outcomes as they are all the same. We conclude that neither non-randomness of movers nor endogenous timing of firm changes can explain the results in Table VIII.

Movers can also exit their firms because of the characteristics of their partners. The specification in equation (1) ignores any 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 AKM method attributes to the VC firm fixed effect. This is because if a partner moves to a firm with better partners (or better for him) his increase in performance across the move will be attributed to the firm. The converse argument holds when bad partners exit firms because they do not provide the externalities. However, as Table VIII makes clear, most specifications find an insignificant average VC firm fixed effect. Thus, while the AKM methodology cannot separate partner externalities from the pure firm effects, our findings suggest that both externalities and other firm characteristics must not be important relative to individual partner characteristics.

Similar arguments also demonstrate that any mean-reversion in VC partner performance will bias the estimated VC firm fixed effect to be non-zero. If partners who are lucky and leave to start or go to a different firm will subsequently mean-revert. This change in performance across the move will result in a large firm fixed effect. Alternatively, if partners who are unlucky get fired and go to a new firm, they will also mean-revert. This change would again result in a large firm fixed effect. Both effects would lead the AKM regressions to over estimate the importance of the VC firm, however we find a statistically small average VC firm fixed effects.

Overall, AKM will attribute any change in performance across a move to the firm effect. Thus, the only way to estimate to low a firm effect is to find an endogenous reason why movers performance would not change even though the effect of the firm did. Each potential endogeneity issue that we can think of should artificially attribute too large an effect to the VC firm. Thus, our firm fixed effect estimates are likely too large. Since our main finding is that the average firm has little impact on performance, these endogeneity concerns reinforce our main conclusion.

VI. Conclusion

The venture capital partner can explain a large fraction of the cross-sectional variation in investment outcomes. The partner's performance is persistent over time, even after controlling for a large set of individual and VC firm controls. Overall our work provides strong support for the persistence findings of Kaplan and Schoar (2005) as well as new insights into the allocation of performance to the firm or partner.

We find that the partner fixed effects are jointly significant across IPO, failure and exit valuation outcomes. In contrast, the estimates cannot reject the null that the VC firm fixed effects are all zero. The ability of these two fixed effects to explain cross-sectional variation in exit valuation is just as stark. The partner fixed effect estimates explain three to six times the variation in the size of an exit than VC firm fixed effects. Thus, performance seems to be largely attributable to partner time-invariant characteristics and firm time-invariant characteristics seem to matter little in venture capital investing. The estimates of partner fixed effects also demonstrate significant heterogeneity in partner type, with the top and bottom quartile partner separated by a predicted \$144m difference in exit value (whose mean is \$86m and median \$0m).

Venture capital partners, it seems, have a ‘style’ of exit and are more likely to IPO, have a high value exit, fail or do none this these with a greater likelihood if they have done it before. This is true even on a relative basis among partners inside the same firm. Furthermore, we find generally that the firm level attributes are unimportant for performance compared to partner human capital. This implies partners would join together, but only to the extent that it lowered transaction costs such as accounting, or other support services or surrounding fund raising.

Our results suggest that venture capital partnerships are not much more than the sum of their partners. Partners are often significantly different from each other, but ‘good’ firms are those with a group of better partners. Thus, firms that have maintained high performance across many funds may have simply been able to hire/retain high quality partners rather than actually provide those partners with much added value.

REFERENCES

Abowd, John M., Francis Kramarz, and David N. Margolis. 1999. "High Wage Workers and High Wage Firms." *Econometrica*, 67: 251–333.

Abowd, John M., Robert H. Creecy, and Francis Kramarz. 2002. "Computing Person and Firm Effects Using Linked Longitudinal Employer-Employee Data." Longitudinal Employer-Household Dynamics, Center for Economic Studies, U.S. Census Bureau Technical Papers 2002-06.

Becker, Gary S. 1981. *Treatise on the Family.* Cambridge:Harvard University Press.

Bertrand, Marianne, and Antoinette Schoar. 2003. "Managing With Style: The Effect Of Managers On Firm Policies." *The Quarterly Journal of Economics*, 118(4): 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(3): 488–512.

Burdett, Kenneth, and Melvyn G. Coles. 1997. "Marriage and Class." *Quarterly Journal of Economics*, 112: 141–168.

Coase, Ronald H. 1988. "The Nature of the Firm: Origin, Meaning, Influence." *Journal of Law, Economics, and Organization*, 4.

Cornelissen, Thomas. 2008. "The Stata command felsdvreg to fit a linear model with two high-dimensional fixed effects." *Stata Journal*, 8(2): 170–189.

Ertugrul, Mine, and Karthik Krishnan. 2011. "Advisor Skill and Acquisition Performance: Do Investment Bankers Make a Difference?"

Gompers, Paul, Anna Kovner, and Josh Lerner. 2009. “Specialization and Success: Evidence from Venture Capital.” *Journal of Economics & Management Strategy*, 18(3): 817–844.

Gompers, Paul, Anna Kovner, Josh Lerner, and David Scharfstein. 2010. “Performance persistence in entrepreneurship.” *Journal of Financial Economics*, 96(1): 18–32.

Graham, John R., Si Li, and Jiaping Qiu. 2012. “Managerial Attributes and Executive Compensation.” *Review of Financial Studies*, 25(1): 144–186.

Hart, Oliver. 1989. “An Economist’s Perspective on the Theory of the Firm.” *Columbia Law Review*, 89(7): 1757–1774.

Hellmann, Thomas, and Manju Puri. 2002. “Venture Capital and the Professionalization of Start-Up Firms: Empirical Evidence.” *Journal of Finance*, 57(1): 169–197.

Hochberg, Yael, Alexander Ljungqvist, and Yang Lu. 2007. “Whom You Know Matters: Venture Capital Networks and Investment Performance.” *Journal of Finance*, 62(1).

Kaplan, Steven N., and Antoinette Schoar. 2005. “Private Equity Performance: Returns, Persistence, and Capital Flows.” *Journal of Finance*, 60(4).

Klein, Benjamin. 1988. “Vertical Integration as Organizational Ownership: The Fisher Body-General Motors Relationship Revisited.” *Journal of Law, Economics and Organization*, 4(1): 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(2): 731–764.

Ljungqvist, Alexander, Yael Hochberg, and Yang Lu. 2010. "Networking as a Barrier to Entry and the Competitive Supply of Venture Capital." *Journal of Finance*, 65: 829–859.

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.

Sorensen, Morton. 2007. "How smart is smart money? An empirical two-sided matching model of venture capital." *Journal of Finance*, 62: 2725–62.

Williamson, Oliver E., and Sidney G. Winter, ed. 1993. *The Nature of the Frim, Origins, Evolutions, and Development.* London:Oxford University Press.

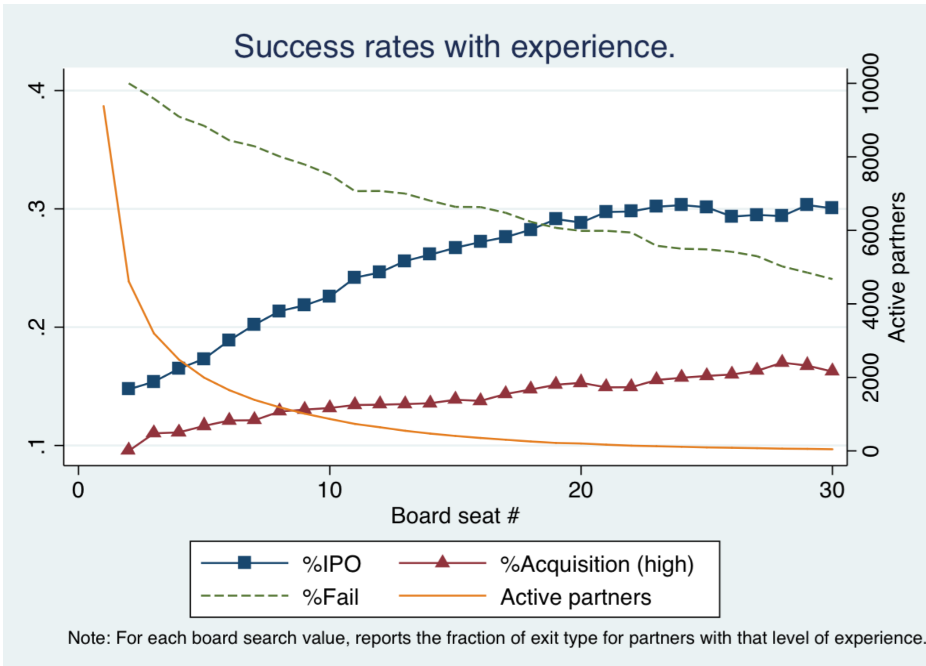
Zarutskie, Rebecca. 2010. "The role of top management team human capital in venture capital markets: Evidence from first-time funds." *Journal of Business Venturing*, 25(1): 155–172.

Zingales, Luigi, and Ragu Rajan. 1998. "Power in a Theory of the Firm." *Quarterly Journal of Economics*, 113: 387–432.

VII. Tables and Figures

FIGURE 1. PERFORMANCE AND EXPERIENCE OF VC PARTNERS

Notes: Figure displays the fraction of a VC partner's investments that have gone public as of their *N*'th investment. For example, for the average partner with at least four investments, the line shows the fraction of IPOs in these partners' history. "Active partners" shows the number of partners with at least *N* board seats.



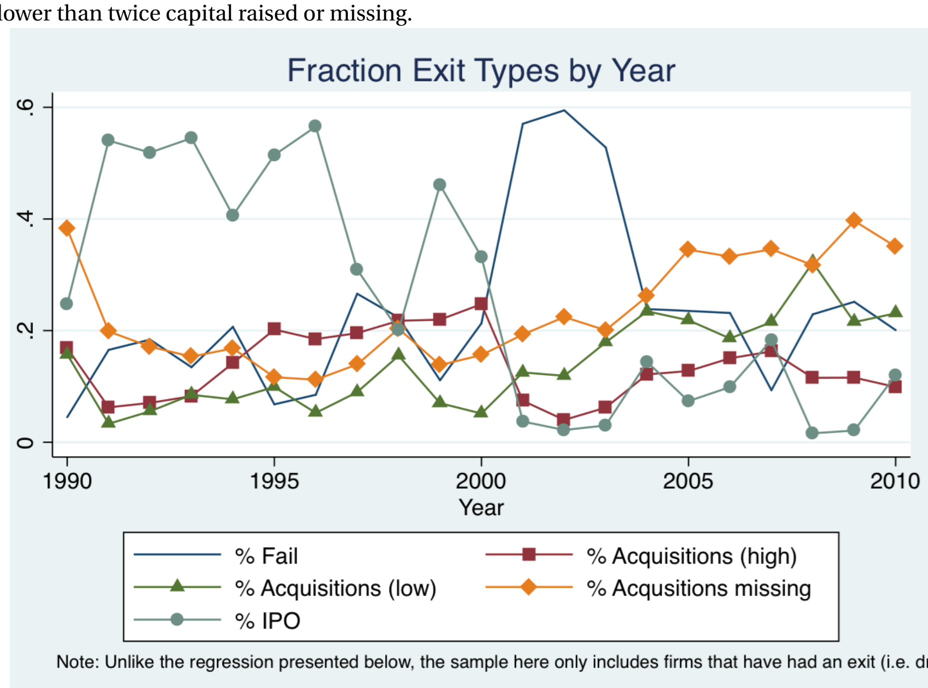


FIGURE 2. EXITS OVER TIME

Notes: Figure displays the fraction of exits that occur from 1990-2011. Includes all firms that were founded prior to 2006 and are no longer private as of the end of the sample. "% Acquisitions (high)" are the fraction of exits that were acquisitions with prices that exceeded twice the total capital raised. "% Acquisitions (low)" are the fraction of exits that were acquisitions with values lower than twice capital raised or missing.

FIGURE 3. EXITS OVER TIME BY **FINANCING** YEAR

Notes: Figure displays the fraction of exits for each board investment year and entrepreneurial observation. A given year reports the fraction of exit types for investments made in that year as of the end of the sample (2011). Includes all firms that were founded prior to 2006. "% Acquisitions (high)" are the fraction of exits that were acquisitions with prices that exceeded twice the total capital raised. "% Acquisitions (low)" are the fraction of exits that were acquisitions with values lower than twice capital raised. "% Acquisitions miss" are the fraction of exits with acquisitions that are also missing exit valuations.

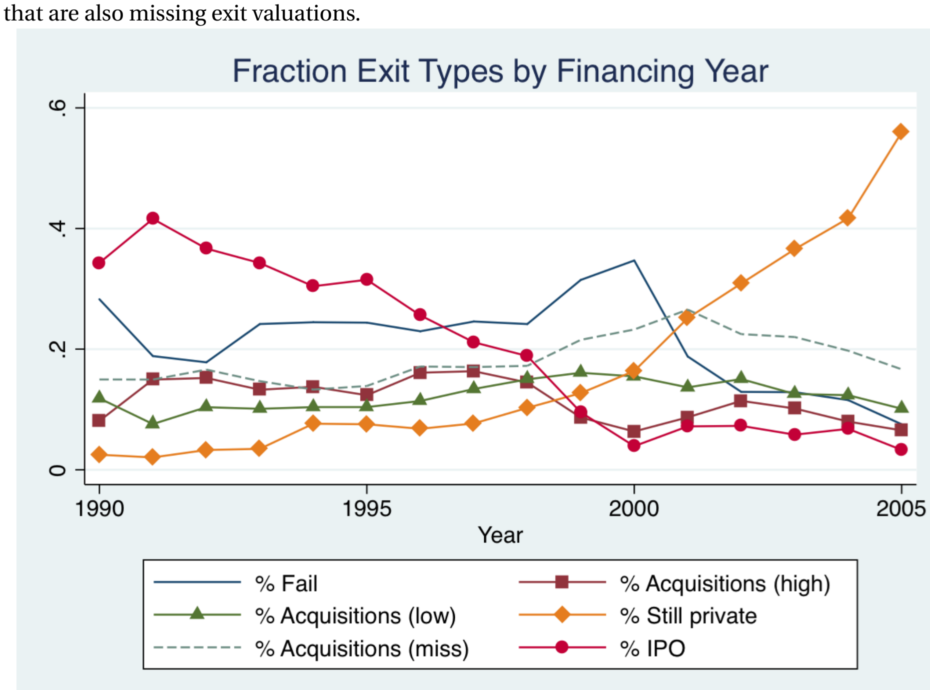


FIGURE 4. FIXED EFFECT DISTRIBUTION: EXIT VALUE

Notes: Figure displays the distribution estimated fixed effects from the AKM regression using log valuation for IPO or successful acquisition as the dependent variable (0 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) that comprise 86% of VC partners in the full specification. This restriction ensures that the fixed effects estimates are comparable.

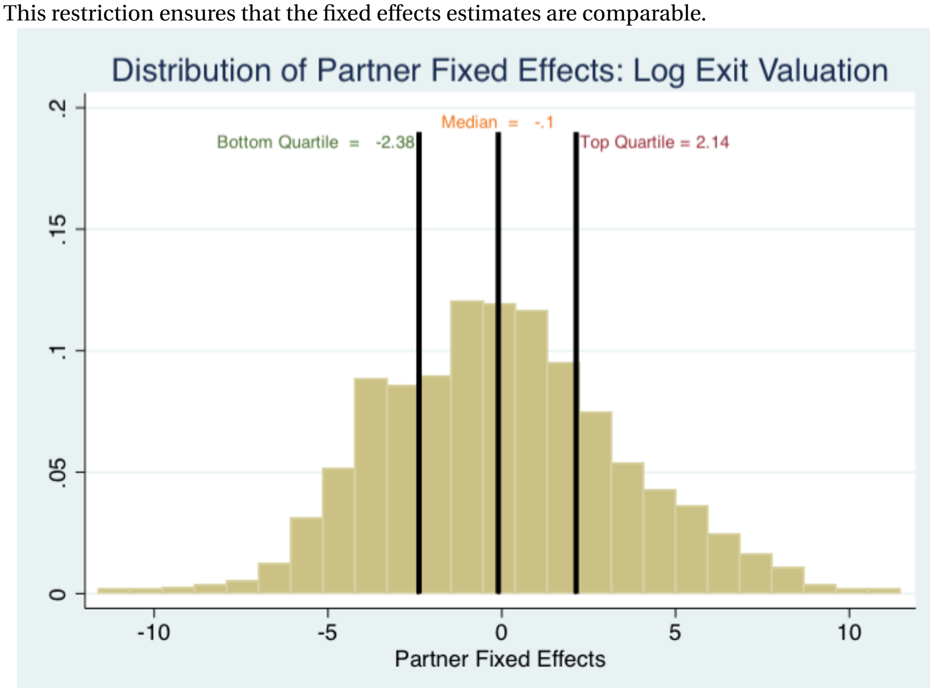


TABLE I—TITLE CHANGES FOR FIRST VC PARTNER MOVE

Notes: Tabulates the titles transitions from the VC partner first move. The left-most title list are the set of titles for the partner's first job, while the top-most titles are the new titles at the second job. "Managing *" is a bucket for a top ranking title such as "Managing Partner" or "Managing Director." Titles are ranked as best as possible by perceived rank. "Other" captures a host of one-off titles and includes "Associate" or "Analyst."

	Title at new firm					
	Managing *	Gen. Partner, Partner	Venture Partner/Principal	Vice Pres.Other	%	
Managing *	37	26	7	1	15	14%
General Partner, Partner	118	102	20	4	47	45%
Venture Partner, Principal	14	21	10	1	8	8%
Vice President	9	16	1	0	3	5%
Other	57	85	10	0	30	28%
%	37%	39%	7%	1%	5%	

TABLE II—SUMMARY STATISTICS

Notes: Table reports the characteristics of the sample of partners in most analyses. 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. "IPO" is a dummy for an IPO exit, "% IPO t-1" is the fraction of IPOs in the partner's history as of that investment and "Acquisition" is a dummy for an acquisition exit ("Fail" is for failures). "Log exit value" is the log of exit value for a given investment, "% VC IPO (-i)" is the fraction of IPOs for all partners not including the one of interest at the VC firm. "Years experience" is the number of years experience as of the board seat, "# VC firm investments" is the total number of board seat investments made by the partners VC firm. "Round #" is the round number of the board seat investment and "$ raised" is the investment amount. "Years since previous board" tracks the number of years between the current and last board seat, while "CA" and "MA" identify the state of the entrepreneurial firm. "IT" is the fraction of investments in information technology and "Biotech" is the fraction of biotech investments.

	Investment Experience					
	Two	Three	Five	Seven	Other	Total
IPO	0.120	0.129	0.129	0.125	0.128	0.127
	(0.325)	(0.335)	(0.335)	(0.331)	(0.334)	(0.333)
% IPO t-1	0.145	0.160	0.180	0.197	0.219	0.193
	(0.352)	(0.284)	(0.238)	(0.216)	(0.211)	(0.257)
Acquisition	0.0987	0.0878	0.106	0.0995	0.0980	0.0975
	(0.298)	(0.283)	(0.309)	(0.299)	(0.297)	(0.297)
Fail	0.448	0.446	0.447	0.446	0.448	0.447
	(0.497)	(0.497)	(0.497)	(0.497)	(0.497)	(0.497)
Log exit value	1.422	1.407	1.493	1.494	1.528	1.488
	(2.272)	(2.278)	(2.267)	(2.336)	(2.403)	(2.348)
% VC IPO (-i)	0.181	0.189	0.215	0.221	0.222	0.210
	(0.226)	(0.223)	(0.230)	(0.241)	(0.279)	(0.257)
Years experience	1.749	2.813	4.377	5.727	7.660	5.532
	(2.114)	(2.576)	(2.980)	(3.326)	(4.848)	(4.679)
# VC firm investments	68.62	77.84	98.58	117.0	167.1	128.2
	(122.1)	(121.9)	(139.0)	(142.0)	(188.2)	(168.8)
Round #	2.057	2.104	2.097	2.003	2.021	2.044
	(1.463)	(1.549)	(1.545)	(1.484)	(1.464)	(1.484)
$ raised	12.45	11.97	11.52	10.80	12.52	12.24
	(23.65)	(20.06)	(16.12)	(15.14)	(21.79)	(21.14)
Years since previous board	1.742	1.219	0.960	0.828	0.793	1.039
	(2.113)	(1.495)	(1.167)	(1.026)	(0.980)	(1.392)
CA	0.373	0.399	0.417	0.444	0.482	0.443
	(0.484)	(0.490)	(0.493)	(0.497)	(0.500)	(0.497)
MA	0.120	0.121	0.124	0.121	0.128	0.125
	(0.325)	(0.326)	(0.330)	(0.326)	(0.335)	(0.331)
IT	0.512	0.520	0.522	0.557	0.565	0.545
	(0.500)	(0.500)	(0.500)	(0.497)	(0.496)	(0.498)
Biotech	0.227	0.226	0.243	0.236	0.236	0.234
	(0.419)	(0.418)	(0.429)	(0.424)	(0.425)	(0.423)
Observations	4541	3428	2184	1507	13508	25618

TABLE III—PARTNER PERFORMANCE PERSISTENCE

Notes: Dependent variable is 1 for columns if the investment that the VC had a board seat at time t on exited via IPO by the end of the sample. All specifications are probit. Each column only includes one observation per partner, who each were only observed at one VC firm so that all control variables are defined. "% IPO $t-1$" is the VC partner's IPO success rate as of the investment at t. "Log yrs. partner experience" is the years since the partner took the first board seat as of $t+1$. "VC total deals (log)" if the log of the total board seats taken by the VC firm of the partner as of t. "Log round #" is the log of the financing round sequence number. "$ raised" is the capital invested in the financing when the board seat was taken. "Years since previous board" is the time between the $t+1$ and t investment. "Year FE" are fixed effects for the year of the investment at the date of the dependent variable t. "Industry FE" are dummies for "Information Technology," "Healthcare" and "Other" defined by the entrepreneurial firm invested in at time t. Standard errors clustered at the investment year. Significance: * $p<0.10$, ** $p<0.05$, *** $p<0.01$.

	IPO_2	IPO_3	IPO_5	IPO_7
	(1)	(2)	(3)	(4)
% IPO t-1	0.252***	0.386***	0.643***	1.137***
	(0.0797)	(0.118)	(0.228)	(0.228)
Log years partner exp.		-0.00673	-0.111*	-0.0170
		(0.0457)	(0.0670)	(0.0849)
VC total deals (log)	0.0256	0.00557	0.0909**	0.0495
	(0.0227)	(0.0249)	(0.0427)	(0.0723)
Log round #	0.461***	0.289***	0.321**	0.233**
	(0.0632)	(0.0608)	(0.152)	(0.101)
$ raised	0.00284	0.00657***	0.0128***	0.0127***
	(0.00175)	(0.00253)	(0.00366)	(0.00380)
Years since previous board	0.00149	0.0148	-0.0141	-0.0602
	(0.0146)	(0.0296)	(0.0457)	(0.0465)
Constant	-2.837***	-2.459***	-2.553***	-2.657***
	(0.160)	(0.155)	(0.284)	(0.352)
Observations	3744	2592	1460	1055
Pseudo R^2	0.180	0.196	0.228	0.214
Year FE?	Y	Y	Y	Y
Industry FE?	Y	Y	Y	Y
Estimation	Probit	Probit	Probit	Probit

TABLE IV—PARTNER PERFORMANCE PERSISTENCE BY EXIT TYPES

Notes: Probit regressions (OLS for columns 3 and 6) of three different dependent variables with the same specification as Table III. Each column only includes one observation per partner who were observed at only one VC firm. "ACQ_t" is 1 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" is 1 if it resulted in an 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 (0 if failure or missing). "% Acq. $t-1$" is the fraction of the partner's investments prior to t that has a successful acquisition. "Fail rate $t-1$" is the same, but the fraction that failed. "Avg. Exit value $t-1$" is the average exit values (log of average) prior to this investment. "Partner exper." is the log of the years of partner experience as a board member. See Table III for the remaining control variable definitions. Standard errors clustered at the investment year. 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	0.279**			0.393**		
	(0.129)			(0.193)		
% Fail t-1		0.205***			0.249*	
		(0.0548)			(0.146)	
Avg. Exit value t-1			0.0875***			0.0713**
			(0.0132)			(0.0303)
Log years partner exp.	0.00138	-0.0108	-0.0656	-0.0490	0.0739**	-0.132
	(0.0291)	(0.0295)	(0.0543)	(0.0572)	(0.0346)	(0.0861)
VC total deals (log)	0.0577**	-0.0517***	0.0438*	0.00585	-0.0717***	0.104**
	(0.0225)	(0.0134)	(0.0228)	(0.0323)	(0.0256)	(0.0426)
Log round #	-0.128***	-0.220***	0.324***	0.0388	-0.293***	0.423***
	(0.0491)	(0.0580)	(0.0715)	(0.0625)	(0.0612)	(0.110)
$ raised	-0.000263	-0.00332*	0.0119*	-0.00357*	-0.00386	0.0178**
	(0.00189)	(0.00180)	(0.00661)	(0.00188)	(0.00264)	(0.00695)
Years since previous board	-0.00311	0.0156	0.0406	-0.0143	0.00782	-0.00701
	(0.0334)	(0.0147)	(0.0405)	(0.0522)	(0.0337)	(0.0459)
Constant	-2.068***	1.736***	1.705***	-1.821***	1.202***	-0.898***
	(0.135)	(0.0910)	(0.126)	(0.238)	(0.196)	(0.306)
Observations	3296	3296	3296	2142	2142	2142
R^2			0.102			0.139
Pseudo R^2	0.044	0.057		0.042	0.082	
Year FE?	Y	Y	Y	Y	Y	Y
Industry FE?	Y	Y	Y	Y	Y	Y
Model	Probit	Probit	OLS	Probit	Probit	OLS

TABLE V—PARTNER PERFORMANCE PERSISTENCE WITH VC FIRM CONTROLS

Notes: Dependent variable is 1 for columns if the investment that the VC had a board seat at time t on exited via IPO by the end of the sample. All specifications are probit. Each column only includes one observation per partner, who each were only observed at one VC firm so that all control variables are defined. "% IPO $t-1$" is the VC partner's IPO success rate as of the investment at t. "% VC IPO (-i)" is the IPO success rate for the VC firm excluding those investments and outcomes associated with the VC partner. All other controls as defined in Table III. Standard errors clustered at the investment year. Significance: * $p<0.10$, ** $p<0.05$, *** $p<0.01$.

	IPO_2 (1)	IPO_2 (2)	IPO_3 (3)	IPO_3 (4)	IPO_5 (5)	IPO_5 (6)	IPO_7 (7)	IPO_7 (8)
% IPO t-1	0.252***	0.182*	0.386***	0.322**	0.643***	0.540**	1.137***	1.106***
	(0.0797)	(0.100)	(0.118)	(0.132)	(0.228)	(0.242)	(0.228)	(0.233)
% VC IPO (-i)		0.565***		0.180		0.534**		0.729**
		(0.183)		(0.185)		(0.212)		(0.307)
Log years partner exp.			-0.00673	-0.0141	-0.111*	-0.0675	-0.0170	-0.0495
			(0.0457)	(0.0472)	(0.0670)	(0.0701)	(0.0849)	(0.0994)
VC total deals (log)	0.0256	0.00560	0.00557	0.00222	0.0909**	0.0765	0.0495	-0.00525
	(0.0227)	(0.0264)	(0.0249)	(0.0288)	(0.0427)	(0.0511)	(0.0723)	(0.0814)
Log round #	0.461***	0.445***	0.289***	0.316***	0.321**	0.284*	0.233**	0.242**
	(0.0632)	(0.0620)	(0.0608)	(0.0544)	(0.152)	(0.154)	(0.101)	(0.107)
$ raised	0.00284	0.00258	0.00657***	0.00612**	0.0128***	0.0121***	0.0127***	0.0147***
	(0.00175)	(0.00186)	(0.00253)	(0.00270)	(0.00366)	(0.00356)	(0.00380)	(0.00507)
Years since previous board	0.00149	0.00854	0.0148	0.0167	-0.0141	-0.0384	-0.0602	-0.0680
	(0.0146)	(0.0163)	(0.0296)	(0.0328)	(0.0457)	(0.0424)	(0.0465)	(0.0543)
Constant	-2.837***	-2.781***	-2.459***	-2.478***	-2.553***	-2.809***	-2.657***	-2.502***
	(0.160)	(0.162)	(0.155)	(0.144)	(0.284)	(0.332)	(0.352)	(0.341)
Observations	3744	3645	2592	2512	1460	1413	1055	1028
Pseudo R^2	0.180	0.181	0.196	0.197	0.228	0.232	0.214	0.235
Year FE?	Y	Y	Y	Y	Y	Y	Y	Y
Industry FE?	Y	Y	Y	Y	Y	Y	Y	Y
Estimation	Probit	Probit	Probit	Probit	Probit	Probit	Probit	Probit

TABLE VI—PARTNER PERFORMANCE PERSISTENCE WITH VC FIRM CONTROLS: ADDITIONAL LAGS

Notes: Dependent variable is 1 for columns if the investment that the VC had a board seat at time t on exited via IPO by the end of the sample. All specifications are probit. Each column only includes one observation per partner, who each were only observed at one VC firm so that all control variables are defined. "% IPO $t-1$" is the VC partner's IPO success rate as of the investment at t. "% IPO $t-2$" is the fraction of the partners $t = 1, 2, \ldots, t-2$ investments. "% IPO $t-3$" is the fraction of the partners $t = 1, 2, \ldots, t-3$ investments. All other controls as defined in Table III. Standard errors clustered at the investment year. Significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

	IPO_3 (1)	IPO_3 (2)	IPO_5 (3)	IPO_5 (4)	IPO_5 (5)	IPO_7 (6)	IPO_7 (7)	IPO_7 (8)
% IPO t-1	0.386***		0.643***			1.137***		
	(0.118)		(0.228)			(0.228)		
% IPO t-2		0.240***		0.446**			1.063***	
		(0.0930)		(0.194)			(0.199)	
% IPO t-3					0.265*			0.978***
					(0.157)			(0.178)
Log years partner exp.	-0.00673	-0.00837	-0.111*	-0.112	-0.0991	-0.0170	-0.0254	-0.0372
	(0.0457)	(0.0462)	(0.0670)	(0.0696)	(0.0681)	(0.0849)	(0.0851)	(0.0889)
VC total deals (log)	0.00557	0.00735	0.0909**	0.0953**	0.0965**	0.0495	0.0475	0.0534
	(0.0249)	(0.0250)	(0.0427)	(0.0426)	(0.0422)	(0.0723)	(0.0722)	(0.0704)
Log round #	0.289***	0.292***	0.321**	0.320**	0.322**	0.233**	0.236**	0.229**
	(0.0608)	(0.0616)	(0.152)	(0.152)	(0.152)	(0.101)	(0.102)	(0.104)
$ raised	0.00657***	0.00658***	0.0128***	0.0130***	0.0132***	0.0127***	0.0131***	0.0134***
	(0.00253)	(0.00254)	(0.00366)	(0.00370)	(0.00374)	(0.00380)	(0.00401)	(0.00403)
Years since previous board	0.0148	0.0181	-0.0141	-0.0112	-0.00687	-0.0602	-0.0625	-0.0547
	(0.0296)	(0.0297)	(0.0457)	(0.0461)	(0.0464)	(0.0465)	(0.0453)	(0.0434)
Constant	-2.459***	-2.457***	-2.553***	-2.536***	-2.570***	-2.657***	-2.651***	-2.671***
	(0.155)	(0.154)	(0.284)	(0.284)	(0.283)	(0.352)	(0.345)	(0.347)
Observations	2592	2592	1460	1460	1460	1055	1055	1055
Pseudo R^2	0.196	0.194	0.228	0.226	0.224	0.214	0.214	0.214
Year FE?	Y	Y	Y	Y	Y	Y	Y	Y
Industry FE?	Y	Y	Y	Y	Y	Y	Y	Y
Estimation	Probit	Probit	Probit	Probit	Probit	Probit	Probit	Probit

TABLE VII—PARTNER PERFORMANCE PERSISTENCE VC FIRM FIXED EFFECTS

Notes: Fixed effects regression where the unit is the VC firm in five-year investment windows (i.e. VC cohort). Estimation uses the conditional logit specification for the limited dependent variable IPO_t which is equal to one if the entrepreneurial firm the VC partner sat on the board at t went public. ACQ_t is equal to 1 if the investment was a successful acquisition. $Fail_t$ is equal to 1 if the 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 the final exit valuation (0 if failure). The model in columns 7 and 8 are simple fixed effects estimators. The VC firm cohort must have at least 3 active partners to be included. "% IPO $t-1$" is the VC partner's IPO success rate as of the investment at t. "% Acq. $t-1$" is the fraction of the partner's investments prior to t that has a successful acquisition. "Fail rate $t-1$" is the same, but the fraction that failed. "Year FE" and "Industry FE" are investment year and industry of the entrepreneurial firm invested in at time t. "Additonal controls" include the log of the round number, dollars invested and years since previous board seat as defined in Table III. Standard errors clustered at the investment year. 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	0.600**	0.915*						
	(0.269)	(0.539)						
% Acq. t-1			0.599*	1.416**				
			(0.323)	(0.628)				
% Fail t-1					0.0453	0.340		
					(0.153)	(0.317)		
Avg. Exit value t-1							0.0637***	0.0519
							(0.0239)	(0.0456)
Log years partner exp.	0.0674	-0.0378	0.112	-0.164	0.0141	0.141*	0.0865*	-0.0742
	(0.0710)	(0.144)	(0.0707)	(0.130)	(0.0432)	(0.0848)	(0.0493)	(0.0970)
VC total deals (log)	-0.724***	-1.148***	-0.0967	-0.214	0.205**	0.316**	-0.412***	-0.784***
	(0.132)	(0.284)	(0.139)	(0.209)	(0.0799)	(0.148)	(0.0882)	(0.157)
Observations	1477	620	1353	578	2795	1228	4374	2089
R^2							0.034	0.050
Pseudo R^2	0.092	0.092	0.013	0.052	0.020	0.026		
Total VC Cohorts	290	147	265	138	638	315	1716	948
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
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 VIII—PARTNER AND VC FIRM FIXED EFFECTS

Notes: Three-way fixed effects regressions using the method detailed in Abowd, Creecy and Kramarz (2002) and Abowd, Kramarz and Margolis (1999) to estimate both the VC firm and VC partner fixed effects. Estimation implemented using the Stata code "felsdvreg" as described in Cornelissen (2008). The unit of observation is the VC partner, board seat and entrepreneurial firm outcome. Column 1 uses log of any acquisition valuation or the IPO valuation as the dependent variable (0 if failed or missing), column 2 use the dummy variable "IPO" and column 3 uses a successful acquisition ($\geq$ 2 times capital invested) dummy variable. Column 4 uses the dummy variable defined to be 1 if the investment failed. Firms without an IPO or successful acquisition have a 0 as the dependent variable in columns 1 - 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 FE (similarly for the last row and VC FE). The percentages in parentheses report the fraction of the R^2 that are attributable to the firm and partner FEs (see Graham, Li and Qiu (2012) for details). "Log round #" is the log of the financing sequence number, "Log $ invested" is the log of the total dollars invested in the financing round when the board seat is taken and "Total VC Experience (log)" is the log of the total board seats made by the VC firm as of the current investment. "Log partner exp." is the log of the total boards seats taken by the VC partner as of the investment. "Log fund sequence" is the log of the fund sequence, set to the five-year windows since VC founding. "Year FE" are year fixed effects for the investment year of the board seat.. "Industry FE" are dummies for the investment industry. "Mean dep. var" reports the mean of the dependent variable. Total VC firms is the total VC firms in the sample, however, only 563 have estimated FE because each connected group has a benchmark. Significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

	Exit Valuation	IPO	Acquisition	Failure
	(1)	(2)	(3)	(4)
F-test on FE (p-value)				
VC Partner FE	0.003	0.071	0.808	0.00
VC Firm FE	0.4616	0.6451	0.4069	0.6788
Relative importance of estimates inR^2. %'s are fraction R^2 explained by covariate.				
$\frac{cov(Y,PartnerFE)}{var(Y)}$	0.137 (38%)	0.101 (36%)	0.109 (75%)	0.127 (53%)
$\frac{cov(Y,VCFE)}{var(Y)}$	0.04 (8%)	0.024 (8%)	0.03 (23%)	0.03 (6.5%)
Log round #	0.290***	0.0488***	-0.00630	-0.0718***
	(0.0571)	(0.00917)	(0.00699)	(0.00922)
Log dollars invested	0.293***	0.0332***	-0.00148	-0.0421***
	(0.0501)	(0.00613)	(0.00545)	(0.00742)
Total VC experience	-0.112***	-0.00642	-0.0128*	0.0177*
	(0.0416)	(0.00619)	(0.00673)	(0.0102)
Log partner experience	-0.0699	-0.0100	-0.00912	0.00132
	(0.0481)	(0.00804)	(0.00607)	(0.0164)
Log fund sequence	0.163*	0.0201	0.0234**	-0.0415**
	(0.0963)	(0.0145)	(0.0115)	(0.0184)
Observations	20693	20693	20693	20693
R^2	.26	.278	.151	.233
Mean dep. var	$1.68	.161	.11	.27
# Movers	645	645	645	645
# Partners	2142	2142	2142	2142
# VC Firms	649	649	649	649
Year FE?	Y	Y	Y	Y
Industry FE?	N	N	N	N

TABLE IX—MATCHING OF TOP PARTNERS TO VC FIRMS

Notes: Table compares the sorting of top VC partners to firms in the sample and one created through random matching. A top VC partner is defined by having a top quartile partner fixed effect estimate from the AKM regression. The partner and VC firm must be in the largest connected group (i.e. group of firms connected by movement of partners). Further, we only consider VC firms with at least 3 active partners. "# of top quartile partners" is the number of total top quartile VC partners ever active at a VC firm. Column (1) N reports these numbers and (2) the fraction of all VC firms. Columns (3) and (4) report the result of 100 random matchings of partners to firms for the known VC firm size distribution. The VC firm size distribution is fixed to that observed in the data and th algorithm randomly re-orders partners to firms. Column (4) calculates the fraction of firms is each sub-group that had n partners. A large positive (negative) difference between the percentages reported in column (3) and (4) suggest that firms in the sample have an over-representation (under-) of top quartile partners relative to that predicted from random matching.

	Sample		Random match	
	(1)	(2)	(3)	(4)
# top quartile partners	N	% firms	N	% firms
0	133	54.3%	58.1	23.7%
1	34	13.9%	80	32.7%
2	17	6.97%	53.7	21.9%
3	25	10.3%	26.2	10.7%
4	13	5.3%	13.7	5.6%
5	5	2%	6.6	2.7%
6+	18	7.4%	6.8	2.8%
Total VC firms	245		245	

TABLE X—CHARACTERISTICS OF FIRMS MOVED TO AND FROM

Notes: Characteristics of firms that movers left and moved to. A mover is a VC partner that switched VC firms during the sample period. Observations are entrepreneurial firm and VC investor with board seat, where the former received its first capital prior to 2006. Numbers reported are the mean across each sub-sample. "Moved To" are the sample of firms that only ever had a mover move to that firm. "Moved From" are the firms that only ever had a mover leave the firm. Column 3 reports the differences in means and their significance between the two samples. "Exit valuation" is the total dollars the entrepreneurial firm sold for at exit (0 if failure or still private by end of sample). "% IPO" is the fraction of the VC's investments with board seats that had an IPO. "$ invested" is the average investment amount when the VC took the board seat. "Round #" is the average round number when the VC took the board seat. and "Year first inv." is the first year the VC is observed taking the board seat. "Information Technology" is the fraction of board seats on companies in the IT industry. "Total investments" is the total number of boards seats taken by the VC firm. Significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

	Moved To	Moved From	Difference/s.e.
Exit value (m)	41.19	59.23	-18.04**
			(6.800)
% IPO	0.0584	0.177	-0.119***
			(0.0138)
$ invested	15.72	11.54	4.173*
			(1.873)
Round #	2.519	1.793	0.726***
			(0.110)
Investment year	2002.5	1996.4	6.015***
			(0.372)
Year first inv.	1999.8	1992.0	7.808***
			(0.509)
Information Tech.	0.527	0.434	0.0928**
			(0.0320)
Total investments	8.906	7.450	1.456*
			(0.564)
Observations	319	171	

TABLE XI—CHARACTERISTICS OF PARTNERS WHO MOVE AND STAY

Notes: Table reports the characteristics of partners who move and stay in the full fixed effect regressions. Numbers reported are the mean across each sub-sample. "Mover" are the partners that moved at least once. "Stayer" are the partners that are in the "connected" sample (i.e. worked at a firm with a mover). Column 3 reports the difference in means and their significance. "Fraction IPO" is the fraction of the partner's investments that had an IPO. "Exit value $m" is the dollars the investment sold for at exit (0 if failure). "Total board seats" is the total board seats for the partner and "Round #" is the average round number when the partner took the board seat. "$ invested" is the average investment amount when the partner took the board seat and "Year career start" is the first year the partner is observed taking the board seat. "Fraction IT investments" is the fraction of board seats on companies in the IT industry. Significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

	Mover	Stayer	Difference/s.e.
Fraction IPO	0.139	0.116	0.0230**
			(0.00700)
Exit value $m	68.61	60.35	8.260
			(4.379)
Total board seats	10.83	8.799	2.026***
			(0.284)
Total VC board seats	31.00	34.06	-3.052
			(1.889)
Round #	2.054	1.995	0.0596
			(0.0347)
$ invested	11.26	11.89	-0.621
			(0.509)
Year career start	1999.3	1999.7	-0.430**
			(0.166)
IT investments	0.511	0.528	-0.0169
			(0.0156)
Observations	645	1498	

TABLE XII—CHARACTERISTICS OF VC FIRMS IN AND OUT OF AKM SAMPLE

Notes: Characteristics of VC firms in and out of the full fixed effect regressions in Table VIII. Numbers reported are the mean across each sub-sample. "Non-AKM Sample" are the VC firms that had a partner with at least four board seats, but lacked a mover to/from the firm. "AKM Sample" are those firms in Table VIII. The third column reports the differences and statistical significance. "Fraction IPO" is the fraction of the VC's investments that had an IPO. "Exit value \$m" is the dollars the investment sold for at exit (0 if failure). "\$ invested" is the average investment amount when the VC took the board seat. "Round #" is the average round number when the VC took the board seat. "Investment year" is the investment year of the board seat and "Year first inv." is the first year the VC is observed ever taking the board seat. "Fraction IT investments" is the fraction of board seats with companies in the IT industry. Significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

	AKM Sample	Non-AKM Sample	Difference/s.e.
Fraction IPO	0.128	0.0982	0.0299**
			(0.00985)
Exit value	59.92	40.45	19.47***
			(5.036)
$ invested	12.48	11.52	0.960
			(0.771)
Round #	2.129	2.048	0.0817
			(0.0550)
Investment year	1999.5	2000.1	-0.511*
			(0.248)
Year first inv.	1995.2	1997.0	-1.847***
			(0.371)
Information Tech.	0.497	0.508	-0.0118
			(0.0202)
Total investments	12.04	6.852	5.190***
			(0.428)
Observations	646	480	