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UNIVERSITY OF CALIFORNIA, SAN DIEGO

Venture Capital Returns, New Firms and Social Networks

A dissertation submitted in partial satisfaction of the
requirements for the degree
Doctor of Philosophy

in

Economics

by

Michael Ewens

Committee in charge:

Professor Jun Liu, Chair
Professor David Miller
Professor Allan Timmermann
Professor Rossen Valkanov
Professor Halbert White

2010

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The dissertation of Michael Ewens is approved, and it is acceptable in quality and form for publication on microfilm and electronically:

Chair

University of California, San Diego

2010

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ABSTRACT OF THE DISSERTATION

Venture Capital Returns, New Firms and Social Networks

by

Michael Ewens

Doctor of Philosophy in Economics

University of California, San Diego, 2010

Professor Jun Liu, Chair

These chapters study the return of venture capital investments with a focus on outliers and examine the formation of new firms that invest in entrepreneurial companies. First, I formulate a model and estimator of venture capital (VC) returns motivated by the entrepreneurial firm life-cycle and the extreme return outcomes of typical venture capital investments. The model incorporates tail events and the estimator corrects for sample selection bias and endogenous investment holding periods. I find that an asymmetric three-state mixture distribution is a better characterization of returns than the standard single-state model. Mixture states mimic typical VC outcomes: "winners", "break-even" and "failures." Imposing normality on venture capital investment returns understates downside risk and kurtosis. In contrast to earlier studies, the mixture model reveals a leptokurtic, negatively-skewed returns distribution. Next, I investigate the consequences of venture capital employee spinoffs for parent firms and the characteristics of their founders. As predicted by the spinoff formation model of Cabral and Wang (2009), high type partners and low type partners at failing parent firms are the most likely to leave and start a new venture capital firm. After accounting for the endogeneity of the timing of spinoff formation, estimates reveal a large, negative impact of spinoffs on parent firm performance. The results indicate that a renewed focus on the venture capital partner, rather than the whole firm, could reveal new features of venture capital performance. Finally, the source of the competitive

advantage of employee spinoff firms and their formation's negative impact on parent firms is often attributed to a transfer of knowledge from parent firm to spinoff. The third chapter studies one potential asset transfer in the venture capital industry that can explain both patterns: social networks. Results comparing the social network evolution of venture capital spinoffs and other new firms show that the former have more central network positions and gain those positions more quickly. Non-spinoffs are more likely to join smaller, more isolated cliques in the network. Spinoffs also have higher survival rates, co-invest with more experienced investors and produce more positive exit outcomes for their investments.

1 A New Model of Venture Capital Risk and Return

Abstract

I formulate a model and estimator of venture capital (VC) returns motivated by the entrepreneurial firm life-cycle and the extreme return outcomes of typical venture capital investments. The model incorporates tail events and the estimator corrects for sample selection bias and endogenous investment holding periods. I find that an asymmetric three-state mixture distribution is a better characterization of returns than the standard single-state model. Mixture states mimic typical VC outcomes: “winners,” “break-even” and “failures.” Imposing normality on venture capital investment returns understates downside risk and kurtosis. In contrast to earlier studies, the mixture model reveals a leptokurtic, negatively-skewed returns distribution. Two new implications follow from the results. First, volatility as an estimate of risk underestimates the frequency and magnitude of large, negative VC returns. Investors in venture capital may need to incorporate additional moments or semivariance into their allocation decisions. Second, a microcap index benchmark previously shown to mimic the means and CAPM alphas of VC returns lacks the downside risk or fat tails of the VC mixture distribution. Thus, VC investments offer some risk and return features unavailable in publicly traded equities.

1.1 Introduction

Accurately characterizing the risk and return of venture capital investments informs capital allocation and reveals how tail events are reflected in returns. Venture capital-backed firms play an important role in economic growth through the creation of new technologies and firms. For example, clean energy startups received some $7 billion in venture capital in 2008 and in 2009 clean-energy is on pace to be the most popular industry for venture capital. Major investors in this asset class – limited partners or LPs – include pension funds, investment banks and endowments. These institutions may invest 10 - 20% of their portfolio in venture capital and thus require an accurate measure of the risk and return for allocation decisions.[1] LPs also use returns estimates for comparison of venture capital to publicly-traded alternatives that lack the former's illiquidity and fees. Discovering if and how non-normality characterizes the returns distribution of venture capital investments should illustrate one way the asset class differs from standard public indices.

Extreme outcomes characterize venture capital (VC) returns. Complete capital loss is common, while large positive returns can determine the survival of a VC fund. The frequency of large negative and positive returns typical of VC investments do not resemble those predicted by the log normal distribution. The current literature assumes normality for log returns, trims extremes and potentially ignores risk heterogeneity by pooling distinct outcomes such as bankruptcies and "home runs." Confident in the accuracy of observed extreme returns, I must address tail events in any risk and return estimator. Failure to account for the unique features of venture capital investments could result in misleading estimates of risk and return used by both investors in venture capital and venture capitalists.

I present a model of VC risk and return that incorporates typical extreme investment outcomes and I show that a mixture distribution best fits the data. Estimates implies a risk and return environment with negative skewness and excess kurtosis and thus suggest that the standard volatility risk measure offers poor inference about return outcomes. My work extends previous studies (Cochrane (2005), Korteweg and Sorensen (2009)) by accounting for non-normal features of the returns distribution. Two new implications emerge from this study. First, the significant and extreme downside risk revealed by the mixture is not replicated in the standard public equity microcap index. Venture capital returns present a unique investment opportunity distinct from the standard public benchmark. Second, the deviations from normality imply that

[1] For example, in June 2009, the California public employee pension fund committed 14% of its $183 billion fund to private equity and venture capital.

standard risk measures do not adequately characterize venture capital returns as they underestimate the frequency and magnitude of tail events. Thus, investors in venture capital funds may need an alternative risk measure for asset allocation. The final shape of the returns distribution indicates that conventional, single-state models underestimate downside risk.

The paper's first contribution is a model of risk and return that incorporates tail events. A continuous time returns process approximates the evolution of entrepreneurial firm value and includes the Fama and French pricing factors. This structure requires the calculation of round-to-round returns, which measure the increase in valuation between either two private financing events or a financing and exit. Although not explicitly earned by venture capitalists, round-to-round returns approximate portfolio outcomes and increase the number of available return observations. Through the parameterization of the state means, a K-state normal mixture distribution allows return characteristics such as market risk to differ across state. Moreover, as a semi-parametric estimator, a mixture model incorporates multi-modal distributions, fat tails and skewness. Following Berk, Green and Naik (1999,2004), I let entrepreneurial firm size impact the mixing probabilities. The final state probabilities map to ex-ante likelihoods of each return outcome. I estimate the model with financing data covering 1987-2007 from the VentureOne database that includes over 50,000 financing events of over 15,000 entrepreneurial firms.

Despite the database's comprehensiveness and lack of systematic measurement error, sample selection bias and endogenous regressors hinder any attempt to estimate unbiased risk characteristics. Observed venture capital returns suffer from sample selection while investment holding period – a key regressor in this paper's returns model – is endogenous in the market model. Cochrane (2005) presents a novel, intuitive sample selection model whose incorporation into a returns process dramatically alters risk and return estimates. I use a rich set of entrepreneurial firm observables and a more flexible selection function to correct for selection bias. Using lagged capital stock as an instrument, I model cross-sectional sample selection in VC returns with a Heckman-like ordered probit proposed by Hwang et. al. (2005). The theory behind CAPM gives instrument validity and estimates indicate that the instrument is not weak. Next, the venture capitalist investment process generates shorter holding periods for large returns and thus a negative correlation between a regressor and the error term. This endogeneity results in too small a beta and too large an alpha. I incorporate endogenous holding periods in a duration model where historical industry exit times provide exogenous variation.

The paper's next major contribution combines each of these empirical problems into a tractable estimator from Wooldridge (2003). A three-stage model integrates sample selection, the endogenous holding period and the mixture returns process to produce unbiased risk and return estimates. Before estimating the full mixture model, I run a single-state model for comparison to previous results in the literature. The structure of the returns model requires a GLS correction that divides all variables in the discrete estimator by the square root of the holding period.[2] Single-state estimates give an arithmetic alpha of 40%, annualized log volatility of 99% and beta of 1.9. The corrections for endogenous holding periods and sample selection have the expected impacts on parameter estimates: beta increases and alpha falls.

Next, I test whether a K-state mixture (K > 1) better fits the observed returns. Both statistical tests and economic reasoning suggest that a three-state returns model is a better fit than the normal, single-state process widely used in the literature. The three-state mixture estimates present a venture capital returns distribution composed of tail events with distinct risk characteristics. Using the mean log return, mixture states map to “winners,” “failures” and “break-even.” The implied CAPM alpha and beta depend on the individual state. Right tail returns earn a 101% alpha with an insignificant market loading, compared to a statistically insignificant alpha for left tail outcomes. Ex-ante, 25% of returns draw from the “failure” state (mean log return of -200%), while 62% of returns stem from a distribution with a mean log return of 22%. The state probabilities predict that "winners" are four times as likely for entrepreneurial firms with a capital stock of less than $1 million than for firms that have raised more than $10 million. In contrast to Cochrane (2005), estimates show that systematic risk increases with entrepreneurial firm size. Surprisingly, the probability of the failure state is constant across an entrepreneurial firm’s life. Although the population log volatility of 104% differs little from the single-state estimate, the final mixture estimates present a returns distribution with excess kurtosis and negative skew.

The non-normal features of the mixture distribution differ from current results in the literature and show that characterizing risk in venture capital requires more than volatility. As with any non-symmetric returns distribution, volatility of VC investment outcomes fails to characterize the frequency and magnitude of tail events. In particular, only 52% of returns are within one standard deviation of the mean return compared to 68% for a normal distribution. The negative skew also reveals a downside risk ignored by standard single-state estimators as shown by a semi-variance 50% larger than population variance. These non-normal features indicate that standard moment conditions used in asset allocation miss distinctive features of VC outcomes. LPs and even venture capitalists may need to incorporate different measures of risk such as semi-variance for optimal portfolio choice (e.g. Markowitz (1959)).

[2] I show in the Appendix that one must divide by the predicted holding periods from the second stage duration model to ensure that the endogeneity does not hamper unbiased parameter estimates.

I compare the mixture distribution to that of a microcap index shown by Cochrane (2005) to mimic means and alphas of venture capital investments. I investigate whether the same conclusions about non-normality and downside risk are present in this index. I find that a single-state normal model rather than a three-state mixture characterizes all deciles of the microcap index. The microcap index lacks the skewness and kurtosis features found in VC investment returns. I conclude that VC assets add unique risk and return features to a portfolio of public stocks.

I check the robustness of the model's assumptions on estimates. All estimators require an assumed value for bankrupt firms earned by the VC investors, which I set to 25% of the original investment. Results are insensitive to a wide and sensible range of this cutoff values for out of business outcomes, while general conclusions about alphas, betas and distribution shape are only sensitive to very small cutoffs. As the out of business cutoff value falls, the returns distribution approaches a four-state mixture with the same basic population estimates of the three-state model. Finally, the results are robust to additional mixture states. No information is lost if the model is re-run with a four-state mixture. The tails shift outward slightly, but all major means, volatilities and risk parameters remain unchanged.

The paper proceeds as follows. Section II and III describe the literature and motivate the mixture model. Section IV details the mixture model and returns model, while Section V summarizes the data. I present an estimator in Section VI and the results in Section VII. Finally, Section VIII compares the estimated returns distribution to public markets and Section IX discusses robustness checks.

1.2 Literature

The distinction between venture capital funds and venture capital financings translates into two different types of returns. Cochrane (2005) is the most comprehensive investigation of the returns to venture capital investments. His innovative model illustrates the severe sample selection of investment-level VC data. With his estimates, he concludes that "there is nothing special about venture capital per se" as he demonstrates its returns closely mimic a unique NASDAQ micro-cap index over the same time period. Hwang, Quigley and Woodward (2005) and Peng (2001) build indexes of venture capital investments to gauge their risk and return against public equity returns. Hwang et. al. find that investments in venture capital do not significantly outperform the market index, though they show there exist optimal portfolio allocations with some share of private equity. Using a modified and defunct version of the VentureOne data, Peng finds a strong correlation between venture capital returns and the NASDAQ and thus a

CAPM beta of over 4.

The literature on VC fund returns compares them to public assets and investigates its cross- sectional features. Kaplan and Schoar (2005) show that S&P 500 returns exceed equal-weighted VC fund returns, while size-weighted returns marginally exceed those of public markets. However, Phalippou and Zollo (2005) argue that the size weighting procedure creates an upward bias on return calculation as it over-weights most recently raised VC funds. Phalippou and Gottschlag (forthcoming) argue that risk-adjusted private equity fund returns underperform the S&P 500 by 6% a year. Jones and Rhodes-Kropf (2003) finds that VC fund returns earn a zero alpha on average, confirming their hypothesis that the investor market is perfectly competitive. Using a database weighted toward buyout funds and non-high-tech firms, Ljungqvist and Richardson (2003) conclude that fund returns exceed the S&P 500 for 1980 - 1996. Several studies investigate the cross-sectional distribution of VC fund returns.

Kaplan and Schoar (2005) also find significant performance heterogeneity and persistence for top funds. Sorensen (2007) shows that are sorting plays a leading role in explaining heterogeneity, while others (e.g. Ljungqvist, Hochberg and Lu (forthcoming)) show that an investor's social network predicts success. Finally, Gompers (1996) and Jones and Rhodes-Kropf (2003) suggest that a VC's early success at finding "winners" determines both survival and future returns.

1.3 Typical Entrepreneurial Outcomes

I present a new model of venture capital risk and return motivated by the typical development process of entrepreneurial firms. Consider a fictional biotechnology firm BioMix that just received its first venture investment. BioMix is developing a new gene therapy for sale to the public, which requires completion of three research and development stages as illustrated in Figure 1.1.

BioMix must first complete drug development. If successful, BioMix receives second VC investment and enters the next stage. If drug development fails, the firm shuts down and investors lose most of their capital. The second stage begins human trials of the drug and applying for FDA approval. Failure at this stage results in another loss for investors, but one where assets like patents can be sold to recoup some of the invested capital. If the FDA approves the drug for sale, Bio Mix begins production and marketing. The size of the drug's market determines the final return earned by investors. A market with little competition results in a huge return to investors, while a market with a new rival substitute drug generates below-average returns. This story illustrates three basic return outcomes: winners, failures and break-even. Many venture capitalists break their portfolio outcomes into such groups. For example, the venture capital firm Union Square Ventures presented prospective limited partners with expectations of one-third of their portfolio outcomes in each scenario.[3] The returns model incorporates this multi-state returns structure.

1.4 Model

1.4.1 Mixture distribution

The BioMix story and VC expectations suggests that VC return outcomes fall into three basic categories: winners, failures and break-even. A standard model for estimating an outcome equation when distinct processes generate observations is a mixture model. A cross-sectional mixture model supposes there are K unique states of the world, where each state follows a process defined by a pdf $f(\cdot)$. Estimation of a mixture seeks to identify the number of states, their probabilities and their characteristics. Typically, the states are distinguished by the first two moments of the distribution $f(\cdot)$. The outcome equation throughout this paper will be a returns process to investing in entrepreneurial firms. In the BioMix example, I hypothesize that the mean return to each of the possible success and failure outcomes differ.

Suppose the outcome of an investment in entrepreneurial firm i's j'th financing event is generated by one of K mixture states. Let S_{ij} indicate the mixture state of the return to this investment, R_{ij}. Then

$$P(S_{ij} = k) = p_k \qquad k = 1, 2, \ldots, K \tag{1.1}$$

with $\sum_{k=1}^{K} p_k = 1$. I assume throughout that returns to each state are normally distributed with mean μ_k and volatility σ_k. The returns process parameterizes the mean and thus produces the typical risk and return characteristics. The final pdf of all returns (R) is a linear combination of each state distribution:

$$f(R) = \sum_{k=1}^{K} p_k f_k(R) \tag{1.2}$$

where $f_k(R) = f(R|S_i = k)$ is a normal pdf with mean μ_k and volatility σ_k. As formulated, this mixture distribution resembles the measurement error model in Cochrane (2005).

[3] http://www.avc.com/a_vc/2008/08/venture-fund--1.html

Motivated by a significant amount of large annualized returns immediately prior to IPOs and data entry mistakes, Cochrane (2005) addresses return outliers with a uniform measurement error process on all returns that trims $\pi\%$ of the returns distribution (where π is estimated). Without the measurement error process, his log market model fits all observed returns with an enormous mean and variance influenced by a few outliers in both tails. The uniform trimming predominantly removes the positive and negative tail events. As I will discuss below, the database used in this paper suffers from little systematic measurement error, so a new approach is required to deal with extreme outcomes. A mixture accommodates extreme outcomes and potentially presents economically intuitive states that mimic those of the BioMix outcomes. A mixture model is also a flexible estimator that can incorporate non-normal returns, fat tails and skewness. Such features are an accepted fact of most VC investment returns, however, the literature has yet to incorporate them into an estimator.

State probabilities

Motivated by theory and past empirical results, I enrich the probability distribution over mixture states in (1.1). Berk, Green and Naik (1999) attempt to explain how and why the Fama and French pricing factors describe the cross-section of expected returns. They show that differences in a firm's proportion of "growth options" to assets in place can explain differences in returns between small and large firms. Small firms have a larger proportion of growth options which alters their expected returns. Berk, Green and Naik (2004) formulate a model of staged investments in R&D projects that predicts differences in risk premiums across the project's life. Finally, Cochrane (2005) estimates alpha's and betas across development stage and shows systematic risk falls as firms develop. These results suggest that the development stage of an entrepreneurial firm predicts outcome and should be incorporated into the probability a return is in a mixture state. The finance literature on state switching follows this same approach when it incorporates covariates into transition probabilities (see Hamilton and Owyang (2009) and Perez-Quiros and Timmermann (2001)).

In equation (1.2), the mixing probabilities p_k are fixed across returns. The results discussed above indicate that for given states of the mixture, entrepreneurial firm size impacts state membership. Formally, let there be a covariate $Z = (Z_1, \ldots Z_N)$ that proxies for firm size at each financing event. Then let state probabilities p_k follow a multinomial logit:

$$p_k = \frac{\exp(Z\rho_k)}{\sum_{k=1}^{K} \exp(\rho_k Z)} \tag{1.3}$$

If the coefficients $(\rho_1, \ldots \rho_K)$ are insignificant, the model reduces to fixed state probabilities. Finally, identification of the coefficients of the state probabilities requires (Jiang and Tanner (1999)) a covariate not included in the returns model. I discuss variable options in the data section below.

Caveats

I argue that the mixture model can identify unique groups within the returns distribution that map to typical outcomes in venture capital investments. McLachlan and Peel (2000) show that if this is a goal of estimation, then the number of components found for the mixture may not directly map to the number of groups in the underlying population. The disconnect stems from how a mixture of normals fits a skewed distribution. If some of the states of the mixture are in fact better approximated by a skewed distribution, then "more than one normal component may be needed to model a skewed group-conditional distribution." (pp 176) I return to this issue when testing for the number of states in the mixture.

1.4.2 Returns

I now discuss the returns process underlying each state of the mixture. I assume the development of entrepreneurial firm valuation follows a log-continuous process. The prevalence of outliers requires the use of log returns. I follow the model presented by Cochrane (2005):

$$d \ln V = (r^f + \gamma_k)dt + \beta_k(d \ln V^m - r^f dt) + \sigma_k dB^v \tag{1.4}$$

$$d \ln V^m = \mu_m dt + \sigma_m dB^{\tilde{m}} \tag{1.5}$$

where V and V^m are the values of the entrepreneurial firm and market and the subscript k represents the state of the K-state mixture. I assume that $E[dB^v dB^{\tilde{m}}] = 0$ and let $dB^v \sim N(0, dt)$ (i.e. Brownian motion). The dependence between the return variance and holding period dt will factor prominently in parameter estimation. Cochrane shows that (1.4) implies the following continuous time returns process in levels:

$$\frac{dV}{V} - r^f dt = [\gamma_k + \frac{1}{2}\beta_k(\beta_k - 1)\sigma_m^2 + \frac{1}{2}\sigma_k^2]dt + \beta_k(\frac{dV^m}{V^m} - r^f dt) + \sigma_k dB^v. \tag{1.6}$$

For the above, the mapping from the log market model parameters to the standard level-CAPM α and β is:

$$\alpha_k = \gamma_k + 1/2\beta_k(\beta_k - 1)\sigma_m^2 + 1/2\sigma_k^2 \tag{1.7}$$

and β_k is the same as in the levels market model.

Timing

Venture capital returns rarely occur over periodic intervals. Let entrepreneurial firm i have financing events at the following calendar times:

$$\tau^i = (\tau_{i0}, \tau_{i1}, \ldots, \tau_{iT^i}) \tag{1.8}$$

where $T^i + 1$ is the total number of financing events for firm i and τ_{ij} is the calendar date of each. For example, a τ^i might look like:

$$\tau^i = (4/4/98, 5/15/2000, 10/12/2000, 6/1/2004).$$

Define an exit for a VC financing as any subsequent capital infusion that involves transfer of equity. The resulting round-to-round returns includes IPOs, acquisitions, bankruptcies and private financings. The holding period for firm i's financing j is

$$\tau_{ij+1} - \tau_{ij}.$$

The holding period unit throughout the paper will be months. Note that if VC financings occurred at regular intervals, the holding period would be constant across j for each firm i. Write the T^i observed log returns as

$$r^i = (r_{\tau_{i1}}, r_{\tau_{i2}}, \ldots, r_{\tau_{iT^i}}) \tag{1.9}$$

where $j = 1, 2, \ldots, T^i$ and

$$r_{\tau_{ij}} = \ln \frac{V_{\tau_{ij+1}}}{V_{\tau_{ij}}}. \tag{1.10}$$

$V^i_{\tau_{ij}}$ is the value of the firm at time τ_{ij} and $r_{\tau_{ij}}$ is the log return to investing in the j financing for firm i and selling that stake $\tau_{ij+1} - \tau_{ij}$ months later at the $j+1$th financing. I use non-annualized returns in all estimations (with holding period as an independent variable), while the returns incorporate ownership dilution across financing events and holding period as a dependent variable. I can now write the discrete version of (1.4), which takes the following form:

$$r^{i}_{\tau_{ij}} = (\gamma_k + r^f)(\tau_{ij+1} - \tau_{ij}) + \beta_k (r^{m}_{\tau_{ij}} - r^f(\tau_{ij+1} - \tau_{ij})) + \varepsilon_{k,\tau_{ij}} \tag{1.11}$$

where $r^{m}_{\tau_{ij}} = \ln \frac{V^{m}_{\tau_{ij+1}}}{V^{m}_{\tau_{ij}}}$ and $\varepsilon_{k,\tau_{ij}} \sim N(0, \sigma^2(\tau_{ij+1} - \tau_{ij}))$. The distribution of $\varepsilon_{\tau_{ij}}$ follows from the Brownian motion assumption and represents the prevalent heterogeneity in VC investment holding periods. I use (1.11) for all estimations of risk and return, which resemble the round-to-round returns in Cochrane (2005). The simplified returns model in (1.11) ignores overlapping value revelation across entrepreneurial firms and therefore possible correlations between them. Finally, inclusion of additional pricing factors like Fama and French (FF) are simply added onto (1.4) and the discrete model. The only change is the mapping of log parameters to level parameters, where α_k becomes:

$$\alpha_k = \gamma + .5 * \zeta' diag(\Gamma) - .5\zeta'\Gamma\zeta \tag{1.12}$$

with $\zeta = (\beta, SMB, HML)$ and Γ is the covariance matrix of market returns and FF factors "small minus big" and "high minus low." The population variance is a product of state means and volatilities:

$$\sigma^2 = \sum_{k=1}^{K} p_k(\sigma_k^2 + \mu_k^2) - \mu$$

where $\mu = \sum_{k=1}^{K} p_k \mu_k$ is the population return.

The returns model is one of value paths and the returns they generate, while the data is a cross-section of thousands of path realizations. Thus, I assume that each realization is an independent draw of the returns model. Simply, each observed return informs the estimator about the true path of entrepreneurial firm valuation.

1.4.3 Sample Selection

The ideal data set of venture capital financings would include periodic value revelations by all entrepreneurial firms. The database, however, suffers from two related problems:

1. Sample selection in returns: high value, high quality firms reveal their value more often.

2. Endogenous holding periods: the timing of the financing events – and thus value revelation – occurs more quickly for high value, high quality firms.

Hwang et al. (2005) summarizes the first problem: "[F]irms receiving financing at any point in time are those whose prospects are more promising than other firms'." Simply, investors invest in entrepreneurial firms whose expected return far exceeds the investor's cost of capital; a condition met more often for growing, high value firms. As returns are generated in the database with new exit events, it includes relatively more exits for financings of high-quality firms. Moreover, entrepreneurial firms that exit via initial public offering (IPO) typically require more capital and thus more financing events than firms that fail to go public. Thus, the database includes more returns associated with IPOs than failures and estimates of means and arithmetic α are too large.

Any corrections for sample selection must model VC exit events. Although an entrepreneurial firm can "exit" via bankruptcy, IPO or acquisition, the company's financings can exit in a slightly different way. The three possible outcomes for a VC investment are:

- new financing round $\Longrightarrow$ firm can have more financing events
- IPO or acquisition $\Longrightarrow$ firm has no more financing events
- bankruptcy $\Longrightarrow$ firm has no more financing events

The fourth state is the non-exit event: the firm did not receive new capital by the end of the sample period and the last known financing event lacks an exit. IPOs, acquisitions and bankruptcies are absorbing states.

Model

I follow the sample selection correction approach of Hwang et. al. (2005) and model the exit events as an ordered probit. The model should predict outcomes that lead to observed values of the outcome equation. Ignoring missing data, new financing events generate observed returns when existing investors sell their equity stakes. One can think of financing events as times when the underlying value of the firm is revealed by new investors who buy out the existing investors.

Let each financing event have an unobserved latent variable defined by:

$$Y_{ij}^{*} = \theta Z_{ij} + \nu_{ij} \qquad \nu_{ij} \sim N(0,1) \tag{1.13}$$

Here Z_{ij} includes the independent variables from the returns model and an instrument for firm i's, j'th financing discussed below. Selection follows from $E[\varepsilon_{\tau_{ij}}|\nu_{ij}] = \rho\nu_{ij}$ where $\varepsilon_{\tau_{ij}}$ is the error term in the returns model. Financings that exited in bankruptcy have a low realization of Y_{ij}^{*} while those that exited via IPO, new financing or acquisition have a high realization. The remainder of financings have yet to exit at the end of the sample either because the firm's poor prospects generated little interest from investors or there was too little time to observe the exit. Define

$$Y_{ij} = \begin{cases} 0 & \text{if financing exits in bankruptcy } Y^*_{ij} < \alpha_1 \\ 1 & \text{if no financing occurs as of end of sample } \alpha_1 \leq Y^*_{ij} < \alpha_2 \\ 2 & \text{if financing exits with IPO, acquisition or new round } Y^*_{ij} \geq \alpha_2 \end{cases} \tag{1.14}$$

for unknown cutpoints $\alpha_1 < \alpha_2$.[4] Given the distributional assumptions for ν_{ij}, the conditional distribution of Y_{ij} given Z_{ij} is:

$$P(Y = 0|Z) = \Phi(\alpha_1 - Z\theta)$$

$$P(Y = 1|Z) = \Phi(\alpha_2 - Z\theta) - \Phi(\alpha_1 - Z\theta)$$

$$P(Y = 2|Z) = 1 - \Phi(\alpha_2 - Z\theta).$$

where $\Phi(\cdot)$ is the standard normal cdf. Finally, log returns are only observed when $Y_{ij} \in (0,2)$, which will be the conditioning statement in the log market model. In particular,

$$E[r^i_{\tau_{ij}}|Y^*_{ij} > \alpha_2] = (\gamma_k + r^f)(\tau_{ij+1} - \tau_{ij}) + \beta_k(r^m_{\tau_{ij}} - r^f(\tau_{ij+1} - \tau_{ij})) + \rho\sigma_k Mills_{ij2} \tag{1.15}$$

$$E[\ln r^i_{\tau_{ij}}|Y^*_{ij} < \alpha_1] = (\gamma_k + r^f)(\tau_{ij+1} - \tau_{ij}) + \beta_k(r^m_{\tau_{ij}} - r^f(\tau_{ij+1} - \tau_{ij})) + \rho\sigma_k Mills_{ij1} \tag{1.16}$$

where

$$Mills_{ij2} = \frac{\phi(\alpha_2 - \theta Z_{ij})}{\Phi(-(\alpha_2 - \theta Z_{ij}))}$$

$$Mills_{ij1} = -\frac{\phi(\alpha_1 - \theta Z_{ij})}{\Phi(\alpha_1 - \theta Z_{ij})}$$

with ϕ and Φ are the standard normal pdf and cdf[5].

[4] I define the latent variable at the financing level, so it effectively restarts for each firm at each financing event.
[5] See Hwang et. al. (2005) for derivation.

Selection and mixture

The combination of a mixture model and a sample selection model results in an important assumption:

$$E[\varepsilon_{il}|S_i = j, Y_{ij} > \alpha_2] \neq E[\varepsilon_{il}|S_i = j, Y_{ij} > \alpha_2]$$

for $j \neq k$. Simply, the sample selection effect depends on mixture outcome because I let the coefficients on the inverse Mills terms to depend on the mixture state. For example, conditional on a "bad" state outcome, the effect of selection may be relatively small. Incorporating this assumption requires a straightforward modification of the sample selection conditioning in (1.13):

$$E[\varepsilon_{k,\tau_{ij}}|\nu_{ij}] = \rho_k \nu_{ij}$$

Thus, (1.15) and (1.16) require further conditioning on mixture state to become:

$$E[r^i_{\tau_{ij}}|S_i = k, Y^*_{ij} > \alpha_2] = (\gamma_k + r^f)(\tau_{ij+1} - \tau_{ij}) + \beta_k(r^m_{\tau_{ij}} - r^f(\tau_{ij+1} - \tau_{ij})) + \rho_k \sigma_k Mills_2$$

$$E[r^i_{\tau_{ij}}|S_i = k, Y^*_{ij} < \alpha_1] = (\gamma_k + r^f)(\tau_{ij+1} - \tau_{ij}) + \beta_k(r^m_{\tau_{ij}} - r^f(\tau_{ij+1} - \tau_{ij})) + \rho_k \sigma_k Mills_1$$

I test this assumption in the mixture estimates by imposing fixed Mills coefficients across states and testing whether the restriction improves model fit.

1.4.4 Endogenous holding periods

The second issue hindering unbiased parameter estimation stems from endogenous timing:

2. Endogenous holding periods: the timing of the financing events – and thus value revelation – occurs more quickly for high value, high quality firms.

Hall and Woodward (2008) summarize the problem as follows:

> Investments with longer holding periods tend to have lower per-period returns, so they have negative values of the idiosyncratic component [...]. Longer holding periods raise the cumulative [market] return. Thus the two variables are negatively correlated. (page 27)

Unlike public market investments, if you hold long in VC, the returns tend to fall. The resulting bias generates too low a CAPM beta and too high a CAPM alpha. The bias stems from a process where financing events occur after the underlying value of the firm reaches some unobserved threshold. Entrepreneurial firms whose value is growing will not only have relatively more financing exits than the average firm, but the time between the events will be relatively shorter. Cochrane (2005) models this idea explicitly with a selection function that resembles a duration model of venture capital exits conditional on valuation. The data on venture capital holding periods confirms the endogeneity problem.

Table 1.1 compares holding periods across different levels of returns. The latter illustrates that the mean holding period weakly falls as observed returns increase. Although median durations do not fall directly with returns, going from an investment that returns 200% to one that returns over ten times (150% annualized vs. 650% annualized) is significant. Doubling a return without doubling the holding period increases the annualized return dramatically.

1.5 Data

I use the VentureOne database maintained by the Dow Jones subsidiary VentureSource. It covers the venture capital market from 1987 to 2007 and tracks investments of $361 billion in 55,457 rounds and 16,849 companies. VentureOne collects their data on venture-capital backed companies with surveys of venture capitalists and entrepreneurial firms. The data lacks financings where corporations or institutions are the only investors in a particular company. For all financings that involve a venture capitalist, VentureOne claims near perfect coverage of 1992 – present. Smaller (in total assets) venture capitalists that invest alone in an entrepreneurial firm are less likely to be observed than the average size venture capitalist. However, if the small investor co-invests with larger venture capitalists already in the dataset, VentureOne starts to actively track the former's financings.

I corroborated 184 financings with two active venture capitalists to see if there are any missing rounds and found none.[6] Moreover, I only found a few instances (< 1%) where the numbers reported by VentureOne differed from the true value reported by the VC. In a similar study, Kaplan, Sensoy and Stromberg (2002) use detailed deal data to cross-check 143 financings in the VentureOne database. The authors find a bias toward reporting California-based companies and estimated that approximately 15% of all financings were missing. Overall, they conclude that VentureOne represents a relatively more reliable source of venture capital data than the major

[6]The two venture capital firms have more than $1 billion and less than $100 million in assets respectively.

alternatives.

CRSP and Global Financial Data provide the market return data. Using the investment and exit dates, I match the values of the S&P 500 and Wilshire 5000 index over a financing holding period. I settle on the Wilshire 5000 as the market factor because it contains a more diverse set of firms in terms of both size and industry, but results are similar with the S&P 500 as the pricing factor. Next, I describe the collection and features of each data set: the exit, holding period and returns data.

1.5.1 Exit data

Over their lifetime, venture capital-backed firms have multiple investments or staged financings. After a sequence of financings and several years, the firm has an IPO, acquisition or shuts down. Firms founded in the last few years are much less likely to have such exits simply because there has not been enough time.

Table 1.2 shows that the average firm has over two financing events. It takes an average of 2.8 financing rounds for firms to go public or be acquired. Bankruptcies occur more quickly, with an average of 2.2 financing rounds until exit. Firms go bankrupt an average of 5.6 years after founding, while newly-public firms are 7 years at the IPO.

Table 1.3 shows the distribution of exit types for financings, where exits are defined on a round-to-round basis rather than investment-to-liquidation. Over 85% of financings have an "exit" event. The statistics in Table 1.3 differ from the proportion of firms that are publicly-held or bankrupt in Table 1.5. Some 10% of financings exit via a bankruptcy or acquisition, while 16% have yet to exit as of the end of the sample. Standard financing exits account for 61% of all exits and include such events as a first round financing "exiting" in the second round.

1.5.2 Holding periods

The 20 years of data include over 37,000 non-exit, standard financing events with relevant censored and non-censored exit times. Table 1.4 presents basic statistics on the holding periods. On average, entrepreneurial firms receive new capital every year and a half. Figure 1.2 shows the estimated survivor function with a rapidly increasing probability of exit for the first two years after the investment. Entrepreneurial firms without new rounds as of the end of the sample have censored holding periods. For all variables that require a start and end time, the last date in the sample – 12/31/2007 – is used as the end point.

1.5.3 Returns

A venture capitalist can liquidate her investment in several ways. IPOs and acquisitions represent explicit transfers of ownership to either the public or another corporation. The VentureOne database includes excellent information on the former. I use the market capitalization of the firm at offering as the sale price for any financing event exiting via IPO and if reported, the acquisition price either in shares of the buying firm or cash. Unfortunately, acquisition prices are only available for about 30% of all acquired firms. The other possible exit outcome is bankruptcy. The VentureOne database does not include explicit dates for these events, but does include dates when the firm's records were last updated. Updates for all firms occur quarterly, so I use these dates for bankruptcy exits. Over 200 entrepreneurial firms in the database have not had a new financing in over 5 years and lost contact with VentureSource. To identify any possible bankruptcies (or other exits) for this set of firms, I tracked each of them using a combination of web searches and phone calls. The final database represents a clear picture of the venture capital market for 1987 - 2007.

Round to round returns require either an exit with a known valuation or two subsequent financings with reported valuations. In particular, the post-money valuation ($Post$) of the financing of interest and the pre-money valuation (Pre) of the subsequent round are required to calculate a return. The log return for firm i's j'th financing is

$$\ln(R_{\tau_{ij}}) = \ln(\frac{Pre_{\tau_{ij+1}}}{Post_{\tau_{ij}}})$$

Out of business outcomes result in near to complete loss of capital. The latter cannot be used in a log returns model, so I follow Korteweg and Sorensen (2009) and the results of Cochrane (2005)'s selection model. I assume that the final exit value is 25% of the dollars invested if the investment fails. Robustness checks for this out of business cutoff demonstrate some sensitivity to results for cutoff values less than 10%, which logged are extremely negative. However, the basic results hold for a wide range of out of business cutoffs.

Table 1.6 summarizes round-to-round returns data for non-bankrupt firms. Due to missing data, only some 10,000 of 32,000 exits have known returns. Both arithmetic and log returns are large. Annualization has a dramatic impact on mean arithmetic returns, with an average 8548%. The value increases when I include those financings that exited in less than 1 month. IT firms have higher returns than health care firms, while "real" exits like IPOs or acquisitions result in higher mean returns than other round-to-round returns. Finally, the 89% return to private financing implies that the average new capital infusions represents a large increase firm valuation.

Table 1.7 summarizes returns when the bankruptcy outcomes are included.

1.6 Estimation

Sample selection and endogeneity hinder unbiased estimation of risk and return parameters. Wooldridge (2002) presents a 3-stage estimator for just this problem. Let the population outcome equation be:

$$y_1 = z_1\delta_1 + \alpha_1 y_2 + u_1$$

with endogenous y_2 defined as

$$y_2 = z\delta_2 + v_2. \tag{1.17}$$

where z includes z_1. In the context of the returns model, y_1 is

$$r^i_{\tau_{ij}} = (\gamma_k + r^f)(\tau_{ij+1} - \tau_{ij}) + \beta_k(r^m_{\tau_{ij}} - r^f(\tau_{ij+1} - \tau_{ij})) + \varepsilon_{k,\tau_{ij}}$$

and the endogenous variable y_2 is the investment holding period $\tau_{ij+1} - \tau_{ij}$.

Equation (1.17) is a simple linear projection of the endogenous variable on a set of instruments z. In venture capital, observation of $(r_{\tau_{ij}}, \tau_{ij+1} - \tau_{ij})$ (i.e. (y_1, y_2)) depends on the outcome of a third random variable y_3. Observable returns and holding periods occur when a firm has a financing event. Define this variable in the standard selection equation probit setting:

$$y_3 = 1\{z\delta_3 + v_3 > 0\}$$

For the venture capital setting with three possible outcomes, the y_3 model will be the ordered probit in equation (1.13) defined by the variable:

$$Y^*_{ij} = \theta Z_{ij} + v_{ij}$$

Wooldridge shows that identification of the model requires the following assumptions:

1. (z, y_3) is always observed. (y_1, y_2) is observed when $y_3 = 1$.

2. (u_1, v_3) is independent of z

3. $v_3 \sim N(0, 1)$

4. $E[u_1|v_3] = \rho v_3$

5. $5.E[\mathbf{z}'v_2] = \mathbf{0}$ with $z\delta_2 = z_1\delta_{21} + z_2\delta_{22}, \delta_{22} \neq 0$.

Estimation of this model follows two simple steps:

1. Estimate $\hat{\delta}_3$ from a probit of y_3 on z using all available observations. Calculate the inverse Mills term for each observed $y_{1i}, \hat{\lambda}_{i3}$.

2. Estimate $y_{i1} = \mathbf{z}_1\delta_1 + \alpha_1 y_{i2} + \rho\hat{\lambda}_{i3} + r_i$ with the selected sample using 2SLS with instruments $(z_i, \hat{\lambda}_{i3})$.

Two issues remain. First, identification of the population parameters requires two separate instruments: one each for the endogenous variable and selection model, a potentially high hurdle for venture capital data. Second, Wooldridge stresses that "all exogenous variables should appear in the selection equation, and all should be listed as instruments"[7] for the 2SLS linear projection. For the venture capital returns model, this requirement conflicts with unobserved explanatory variable market return for those firms that do not have new financing events.

1.6.1 Applying the model to venture capital

The selection and endogeneity problems in venture capital data conform to the Wooldridge three-stage model. I make several modifications to the model for the venture capital data:

1. The endogenous variable y_2 is holding period $t_{ij} - t_{ij-1}$ in months. I thus estimate a duration model rather than a standard linear projection.

2. The selection equation for y_3 must account for multiple exit types: exit, bankruptcy and still private. Thus, the selection model is an ordered probit as in (1.13).

3. A fairly large set of regressors clearly impact both the exit type and the timing of the exit. These include firm age, location and basic investor characteristics. Excluding these regressors from the outcome equation – the returns model – requires some strong assumptions. I rely on the theory behind CAPM and only include the pricing factors in the returns model. Basic results are unchanged when I exclude all these variables from the estimator.

4. The other exogenous variable in the outcome/returns model – the market return $\ln \frac{V^m_{t_{ij}}}{V^m_{t_{ij-1}}}$ – is only observed when a financing occurs. Therefore, I cannot explicitly include it in

[7] page 569

the set of exogenous variables z. I use the market return as of the end of the sample as a replacement for this variable when the end point is unknown.

1.6.2 Instruments

The last identification condition of the three-stage model requires two instruments: one each for the duration and sample selection model.

Selection Model

Identification of the ordered probit stage of the estimator requires a financing-level variable that predicts exit events but does not belong in the returns model. Using the Census Bureau's database on business ownership, Fairlie and Robb (2008) show that the best indicator of entrepreneurial success is startup capital. For the sample selection instrument I propose the lag of the sum of the firm's capital stock. Let k_{ij} be the capital raised in firm i's j'th financing. Then the capital stock raised as of the j'th financing is:

$$K_{ij} = \sum_{l=1}^{j-1} k_{il}$$

This value will be zero for first financings, however, this lack of variability is not an issue because of the lack of sample selection for these events. All firms have a first financing event.

The likelihood of a new financing event – and thus a return observation – depends on the underlying health of the firm, itself closely related to the current capital stock. All else equal, I argue that the probability of a new financing (other than still private or bankruptcy) increases in the past capital stock, but the unobserved firm quality that correlates with IPO exits does not correlate with past capital stock. My focus on the exit event of the current financing rather than the firm as a whole helps to reinforce the exclusion restriction. Firm quality is presumably fixed, while the likelihood of a new financing event changes with time. A relatively large past capital stock indicates the firm can survive longer than average and also shows its investors' confidence that the expected return to investment was greater than their cost of capital. Moreover, I rely on the theory behind CAPM outcome equation which implies that only some pricing factors belong in the returns model. Table 1.8 shows the characteristics of this instrument across the firm development stage. Total capital raised increases as the firm develops, with significant variation within firm development stages.

Duration Model

The duration model requires a variable that correlates with durations but can be excluded from the returns model. The speed at which a similar firm in the same industry exited in the past should be indicative of how the current firm will exit, but not the return earned for the financing event. This variable predicts the state of the VC exit environment but does not correlate with firm quality. Aggregating at the industry may appear to introduce variation that could impact the return. However, given the unique features of entrepreneurial firms, their general industry label (e.g. Information Technology) rarely describes their business model.

Using the full sample of observed holding periods across four industries, I compute the average duration of all past financings in each industry. Let i represent an entrepreneurial firm and $\tau_i j$ be the calendar date of that firm's j'th financing. Define N_m as the set of financing events in industry m that occurred (i.e. exited) at least a month prior to τ_{ij}. Then the proposed instrument is calculated for industry m as follows:

$$D_{\tau_{ij},m} = \frac{1}{\#\{N_m\}} \sum_{(k,l)\in N_m, \tau_{kl}<\tau_{ij}} \tau_{kl} - \tau_{kl-1} \tag{1.18}$$

Note that the instrument varies for each financing event with a unique date and industry. Table 1.9 shows the basic characteristics of holding periods by each of the four major industries before and after 1998 (the beginning of the boom period). Holding periods have fallen since 1998 and have sufficient variation across industry. The instrument (1.18) averages these holding periods for each financing event date, while the lag ensures that it satisfies the exclusion restriction.

1.6.3 Modeling holding periods

Accurate modeling and estimation of VC holding periods may uncover features of the dynamics behind VC investments. Cumming (2006) demonstrates that total industry capital and entrepreneurial firm stage both explain cross-sectional differences in durations. Lunde, Timmermann and Blake (1999) study the closure rate of mutual funds and find that funds on the extreme ends of the age distribution are the least likely to close. Cochrane (2005) illustrates the importance of the time-to-exits or holding periods in accurately capturing sample selection in VC returns. His model's fit relied on its predictions of observed exit types over time, effectively estimating a competing risk model of venture capital exits.

The endogenous variable in the returns model is investment duration. Simple OLS will not suffice. Moreover, the estimation of the duration of financing events must capture right-censoring. Fortunately, there exist a wide variety of econometric models to estimate the impact of covariates on durations, which include fully parametric approaches and semi-parametric approaches like the Cox proportional hazard model. A popular hazard rate parametrization – the log-logistic – takes the following form:

$$\lambda(t;x(t)) = \frac{\exp(x(t)\kappa)\nu t^{\nu-1}}{1+\exp(x(t)\kappa)t^{\nu}}$$

where $x(t)$ are the time-varying covariates, t is the holding period and $\lambda(\cdot)$ is the instantaneous probability of a failure at time t, conditional on survival up to t. There are several other parametric hazards available. I show below that the log-logistic fits the data the best. However, it is important to note that fit or accurate prediction is not an end for this stage of the estimation. Rather, identification simply requires that the instrumental variable produce predicted holding periods through this model whose variation is exogenous to the observed return.

The endogeneity correction requires an estimate of fitted holding periods. Parametric hazards give way to more sensible predicted values, so I focus on this set of models. Finally, I capture the richness of the exit types by using a competing risk model with continuous time durations. Observed returns stem from new financing events or exits such as IPOs and acquisitions. The model separates the two types of "risks" in order to better control for the unobserved heterogeneity. Combined with the sample selection model detailed above, the first two stages of the three-stage model are complete.

1.6.4 Mixture model estimation

The last estimation step of the 3-stage estimator is the returns equation. The Wooldridge (2002) formulation does not impose any functional form on the outcome equation, so a mixture model in the final stage is available. The sample selection and duration model steps produces Mills terms and predicted holding periods for each observed return. These outputs are incorporated in the mixture returns model (1.11), which reduces to single-state model when $k = 1$. Estimators of mixture models include the EM algorithm presented in Hamilton (1990) and Everitt and Hand (1981) or Bayesian methods presented in Fruhwirth-Schnatter (2006) and McLachlan and Peel (2000). I use the EM algorithm for all estimations.

1.6.5 GLS and holding periods

Recall the discrete model of venture capital returns:

$$r^i_{\tau_{ij}} = (\gamma_k + r^f)(\tau_{ij+1} - \tau_{ij}) + \beta_k(r^m_{\tau_{ij}} - r^f(\tau_{ij+1} - \tau_{ij})) + \varepsilon_{k,\tau_{ij}}$$

where $\varepsilon_{k,\tau_{ij}} \sim N(0, \sigma_k^2(\tau_{ij+1} - \tau_{ij}))$. The variance of returns is proportional to the endogenous holding period. If interest lies in efficient estimation and retrieval of the true conditional volatility σ_k, then one might think to follow the standard GLS procedure and divide all variables by the square root of the holding period. I show in the Appendix that such an adjustment leads to biased parameter estimates because the holding period is endogenous. Fortunately, the 2SLS estimator presents an alternative: the square root of the predicted holding period from the first stage regression. The following steps produce the modified GLS correction:

1. Estimate the duration model for the holding periods.
2. Compute the predicted holding periods for all observed returns: $(\tau_{ij+1} \hat{-} \tau_{ij})$.
3. Divide all variable in the second stage returns regression by $\sqrt{(\tau_{ij+1} \hat{-} \tau_{ij})}$.
4. Estimate the mixture returns model with the modified variables in step 3.

1.6.6 State probabilities

I allow the mixture state probabilities to depend on entrepreneurial firm size. Ideally, any covariate includes in the probability structure should not belong in the outcome (i.e. returns) model. Fortunately, the lagged capital stock from the selection model is both a proxy for entrepreneurial firm size and presumed exogenous in the log market model. So I let the covariates Z in equation (1.3) be the same lagged capital stock K_{ij} instrument from the ordered probit estimator. The results below are insensitive to simply using a dummy variable for stage, which is equal to one if the entrepreneurial firm is in the early stages of its development.

1.7 Results

1.7.1 Sample selection and duration results

Recall that the exit indicator takes the following form:

$$Y_{ij} = \begin{cases} 0 & \text{if bankruptcy} \\ 1 & \text{if no exit} \\ 2 & \text{if new financing event} \end{cases} \tag{1.19}$$

I include the log market return, holding period in months and dummies for firm development stage and firm industry in the ordered probit estimation (1.13). Table 1.10 presents the results. I do not include time dummies as they perfectly predict outcomes of 1987 - 1991 financings. The last three columns give implied marginal effects at the means of the independent variables. An increase in the market return lowers the probability of bankruptcy and no exit, while it increases the probability of a positive exit. A firm that moves from an early stage of development to a later stage sees a decrease in the probability of a positive exit because nearly all firms have at least two financing events when they are in the early development stages and bankruptcies typically occur after such time. Finally, the marginal effect signs for past capital raised show that an increase in total capital stock increases the probability of a good outcome and decreases the probability of a bad outcome. Thus, the t-stat of 3.8 shows that the instrument passes the relevancy test.

Hazard model choice

I run and compare five hazard function specifications. Although Cochrane (2005) does not explicitly label his selection function as a hazard function, his model for new financing events mimics an exponential hazard with a log-logistic functional form. Simply, time does not impact the probability of exit, while log firm value affects the rates of bankruptcy and new financing rounds.

Table 1.11 shows that the log-logistic formulation best fits the data using either the AIC or BIC statistic. In unreported results, the weibull, exponential and gompertz each have unintuitive and unrealistic signs and sizes for the coefficient estimates and hazard ratios. I settle on a log-logistic hazard with time-varying covariates and standard errors clustered at the firm level.

Duration model results

The duration model exploits the same set of variables included in the ordered probit with the additional historical duration instrument. I utilize all the available information about exits: censored and uncensored holding periods. A "failure" or "end of spell" occurs when a financing has a subsequent exit event. That event could be an IPO, a new round of financing or a bankruptcy. Figure 1.3 shows the estimated, non-monotonic hazard. The probability of a new financing increases for the first two years and falls thereafter. Table 1.12 presents the parameter estimates of a log-logistic hazard with the historical industry durations and Mills terms as instruments. An increase in the market return dramatically increases the probability of a financing event. The coefficient on the Mills term is difficult to interpret as it is only included for identification purposes. Finally, the instrument's relevancy is confirmed by its positive sign and significant coefficient estimate.

Implied hazard functions aid in interpretation of coefficient estimates. Figure 1.4 shows the difference in hazard rates between early stage firms and non-early stage firms. Younger, less developed firms have new financing events more quickly. I posited that an above average historical duration for the firm's industry would lead to a lower holding period. Figure 1.5 confirms that the estimated hazard is lower for those firms with an above average historical industry duration. The predicted holding periods from the duration model are now incorporated into the final stage of the 2SLS estimator.

1.7.2 Single-state estimates

Table 1.13 presents the full single state model parameter estimates with a one and three-factor model. I focus on the three-factor model throughout. The OLS column shows that ignoring the known form of the returns volatility and sample selection results in a huge volatility estimate and arithmetic alpha. The log intercept and alpha have no time dimension, so are difficult to interpret. The GLS column corrects all observed variables by dividing them by the square root of the (endogenous) holding period. With a more accurate estimate of volatility, it falls almost ten-fold. This decrease in turn lowers the implied arithmetic alpha to 60%. These estimates still suffer from both sample selection and endogenous holding periods.

Recall that sample selection produces too high an alpha and the endogenous holding periods amplify the problem by introducing downward bias in the systematic risk estimate. Comparing column 5 and column 7 of Table 1.13 shows that the inclusion of both the Mills term and fitted holding periods has an impact on parameter estimates. Systematic risk increases from 1.6 to 1.9, while the arithmetic alpha falls to 40%. With a significantly smaller volatility, one might think that a mixture model is no longer required. However, the returns model may still be misspecified if the true process follows a mixture.

Comparison to earlier results

Although estimated over 1987 - 2000, Cochrane (2005) presents a benchmark to compare these single-state estimates. Recall that his final model included a measurement error process, a single factor and a parametric selection function. Table 1.14 shows that despite a similar arithmetic alpha and log returns volatility, the new model and data predict a significantly lower mean return than earlier results. Of course, the additional post-Nasdaq years contribute to this difference.

Predicted returns and pdf

Figure 1.6 plots the kernel estimator of observed log returns against the predicted pdf using the three-factor, single-state model. The differences between the GLS without selection corrections and the full model is volatility. As expected, inclusion of the Mills and endogeneity corrections puts less weight on the right tail and shifts the estimated returns distribution to the left. Overall, the selection and endogeneity corrections have the desired impacts on parameter estimates. I now estimate a mixture model for the last stage of the estimation.

1.7.3 Mixture step

Before estimating the full mixture model, I must choose the number of states and the underlying distribution for each state. The BioMix story and VC expectations suggest three mixture states for venture capital returns: “winners,” “failures” and “break-even”. Outliers computed from the residuals of the single-state estimator presented in Table 1.15 illustrate that extremes are in both the left and right tails.

Choosing the number of states

Testing for the number of states is a difficult problem. Selecting one or two states has been addressed by Cho and White (2007), however, choosing more than two states is an unresolved problem. McLachlan and Peel (2000) summarize the literature and available test statistics. They show that the penalized likelihood statistics AIC and BIC are often helpful, but tend to overestimate the number of states. Biernacki, Celeux and Govaert (2000) present a integrated classification likelihood (ICL) that suffers from less over-fitting problems than AIC and BIC. McLachlan and Peel (2000) show that ICL penalizes complex models and mixtures with significant overlap across states. Naik, Shi and Tsai (2007) present a test statistic that simultaneously selects the number of states and variables in a mixture regression. The returns model presented above gives a theoretical motivation for including all the pricing factors, so I focus on selecting the number states. Fortunately, the large sample of 12,000 returns mitigates the small sample problems of these test statistics. Table 1.16 presents the AIC, BIC and ICL statistics for two to five states.

The standard choice of using the lowest value AIC or BIC suggests that 4 or 5 states fit the data, while the ICL implies two states. However, I settle on three states for two reasons. First, the AIC and BIC tend to overfit the number of states. Also, recall that I assumed normal states within the mixture for simplicity and to retain mappings from log to levels. If some of the state densities are in fact non-normal (e.g. Student t)[8], then the AIC and BIC will overfit, while ICL is consistent (see Schannter p. 215). Next, the conclusions implied by the 4 and 5 states are very similar to those of three states and several of the state pdfs have significant overlap. In particular, the tail states are approximately the same in terms of risk and return with additional states, while the "middle" of the returns distribution is broken up into more and more states. A three-state world is also confirmed by an additional test.

I also test the null hypothesis of only two states (versus three) using the bootstrapped likelihood ratio test proposed by McLachlan (1987) and conclude that three states fir the data. This modified likelihood ratio statistic takes standard form $-2\ln\lambda$. I run 200 bootstraps and the estimate mixture model for both state types. The assumption of different variances within states means that the estimation must also sample hundreds of possible initializations to find the largest local maximum. The result is a set of 200 test statistics which form the empirical distribution of the likelihood ratio. The value of the likelihood ratio test statistic$-2\ln\lambda$ for the original sample is .94. The statistic compares to the 93rd percentile of the bootstrapped test statistic distribution. Although this result does not pass the 5% rule, combined with the results of the AIC statistics and the economic motivation, I settle on three states. Even if the true number of states is four, little information is lost imposing three states.

1.7.4 Mixture model results

I estimate the three-state mixture on the three-factor returns model with the Mills terms and fitting holding periods from the first estimation stages. For comparison, Table 1.17 presents the parameter estimates for each mixture state. Column 1 presents the single-state model. Several specifications consistently produce a negative but insignificant beta estimate for one mixture states so I fix one state's beta at zero. This value is more sensible and actually increases the AIC and BIC statistics.

Across mixture states, the coefficient estimates on the pricing factors vary significantly. The market loading ranges from 3.6 to 1.7, while the HML factor is as low as -2.7. The pattern of mean log returns by state matches the Mills coefficient estimates. The state with the lowest

[8] See Giacomini, Gottschling, Haefke and White (2008) for a t-mixture alternative.

predicted mean return also has the lowest Mills coefficient, suggesting that positive selection is relatively weaker conditional on that state. Next, the state-level predicted means closely match the "winners" and "failures" story posited above. One state has an alpha of 101%, a mean return of 185% and a prior state probability of 13%. In contrast, the "failure" state has a low mean of -202%, a mixing weight of 25% and an statistically insignificant alpha. The highest probability state produces a mean return of 22% and alpha of 30%, numbers very similar to those found for Cochrane (2005). Figure 1.7 displays the three state outcomes and the full pdf.

The mixture reveals distinct risk features of investment outcomes. The "winning" outcome has no systematic risk and its returns behave like growth stocks. The "failure" state has significant systematic risk and the expected returns look like small-cap stocks. An analysis of posterior probabilities reveals that many of the returns labeled "failures" were financed at the top of the Nasdaq bubble. These investments all failed when the market crashed. The introduction of the mixture also dramatically lowers the predicted mean returns, which falls to -11% in the three-state model from 4% in the single-state model. In contrast to a single-state estimator with normality, a mixture invites skewness and kurtosis. Compared to the single-state estimates I find a fatter left tail, skewness of -.2 and excess kurtosis of 4.4.

Computing arithmetic returns at the state-level is straightforward and follows from the log-normal assumption. The predicted means in Table 1.18 follow the same basic pattern as log returns, but we see that the log volatility dominates in the "winners" outcome. The predicted arithmetic return of 1300% stems from volatility and confirms the basic results in Cochrane (2005). The population arithmetic return is the linear combination of the state-means, however, there is no clear way to compute the total arithmetic volatility. Using the linear combination of state-level volatilities suggests a total volatility of 1100%. I believe these unreasonable numbers stem from the fact that I model log returns rather than arithmetic. It is doubtful that a mixture of normals for log-returns translates into a mixture of log-normals for arithmetic returns.

1.7.5 Comparing to single state

Figure 1.8 plots the full mixture pdf against the single-state estimate and kernel of observed returns. The most striking difference is in the left tail: the mixture model reveals a strong mode around -200% annualized log returns. The single-state model misses this feature of the distribution. This stark change likely stems from the conditioning selection correction and the size-dependent state probabilities. The selection problem presumes that there are too few bad returns relative to the good outcomes. If the instrument is working, the Mills term by state adjusts the means by state. Thus, conditional on the "failure" state, the Mills term effectively pushes down the mean and increases the relative likelihood of the state occurring. More importantly, the differences between the two models illustrates that volatility is not an informative measure of return outcomes.

The mixture and single-state model produce volatility estimates of 104% and 99%, however, the left and right tails on the former are fatter. The mixture has a skewness of -.2 (statistically significant) and an excess kurtosis of 4.4. Semi-variance is 50% larger than the population variance, indicating significant downside risk. Figure 1.9 shows the implied cdf for the single-state and mixture estimates. It illustrates that the mixture predicts 50% more occurrences of capital loss greater than 50%. By assumption, the single-state mixture with normality lacks any skewness or kurtosis. If the mixture represents the true returns distribution, the skewness and kurtosis demonstrate that simple volatility underestimates both the frequency of extreme outcomes and the magnitude of negative tail events. Simply, describing VC risk and return requires more than detailing the first two moments.

1.7.6 Stage and outcomes

Recall that I let the size of the entrepreneurial firm as proxied by the lagged capital stock impact the probability a return is in a given state. In unreported results, the coefficient on lagged capital stock is significant at the 5% level for each state. Thus, entrepreneurial firm size predicts state. The functional form of the state probabilities present ex-ante predictions of state membership given a firm's lagged capital stock. Figure 1.10 plots the predicted probability of each state implied by the state probability estimates. For firms with little or no capital stock — early-stage financings — the probability of a "winner" is about 30%. This likelihood is five times larger than for investments in firms that have raised over $10 million. In fact, the state probabilities say — ex-ante — that as a firm raises venture capital the returns distribution moves from a three-state mixture to a two-state. The stark difference in ex-ante probability of a winner based on firm size illustrates that mixture states map to (or correlate with) firm size. The state probabilities also allow for investigation of analysis of risk and return features as an entrepreneurial firms raises capital.

For a given entrepreneurial firm size, the state probabilities give the ex-ante likelihood of each mixture state. The characteristics of the states, however, are fixed. Figure 1.11 shows the implied changes in beta and alpha as firms raise capital. In contrast to Cochrane (2005), the mixture model predicts that the beta increases as firm develop. Entrepreneurial firms in the later stages of development are also nearer exits like acquisitions and IPOs. These outcomes are much more likely when the public markets are doing well. I find that this increase is not solely due to an decrease in return volatility from small to large firms, but rather from an increase in raw correlation between market and VC returns. Similarly, the arithmetic alpha falls as firms develop, suggesting much of the alpha in venture capital returns comes from early-stage investors. These investors take the most risk and also contribute more human capital to their investments than late-stage investors. Finally, Berk et. al. (2004) predict that risk premiums earned on investments in R&D projects (i.e. firms) should fall the project nears completion. Figure 1.12 shows a stark prediction from the mixing probabilities that confirms this hypothesis for VC returns. The ex-ante mean log return falls from 25% to -25% as one goes from minimal capital stock to over $50 million.

1.8 Comparing to public markets

Cochrane (2005) concludes that alphas and mean returns of VC investments resemble those of a micro-cap Nasdaq index. I now ask whether those same public indices are approximated by the mixture distribution that I found for VC returns. If not, then although basic means and average risk characteristics are similar, the skewness and multimodal features are unique to VC investment returns.

I construct the deciles of the Nasdaq index as detailed by Cochrane (2005). For comparison, I regress the log return to each public stock that matches the cutoff criteria on a constant, the excess log market return and the log FF factors. I strongly reject the multi-state model for all but the smallest decile. For this decile, the ICL statistics suggests a single state and the BIC maxes at 2. Given the overfit problems of BIC, this is a weak endorsement for a mixture model of small decile Nasdaq stocks. Moreover, Figure 1.13 shows the two states have significant overlap, while one has a volatility of 280%. These results imply that two states may be too many for this set of stocks. Figure 1.14 compares the single-state micro-cap distribution with that of VC returns and illustrates how downside risk and kurtosis are unique to latter. The two-state mixture for the smallest decile has an insignificant kurtosis and skewness. In contrast to venture capital returns, the microcap index volatility is informative about the relevant risks. Investors in venture capital find unique risk features unavailable in the standard benchmark.

The benchmark microcap index is not the only possible comparison asset. Harvey and Siddique (2000), Harvey and Siddique (1999) and Hwang and Satchell (1999) show that some public stock returns have negative skew and excess kurtosis. However, Kim and White (2004) show that estimators of both moments are sensitive to outliers. For example, the negative skew found in the daily S&P 500 index falls falls ten-fold when the 1987 market crash (one day) is excluded. The authors present robust estimators of skewness and kurtosis from the statistics literature. They estimate these alternative measures to the S&P 500 and find insignificant skew and diminished kurtosis even when outliers are included. These results suggest that the skewness and kurtosis of VC returns are likely not just unique when compared to the microcap index.

1.9 Robustness checks

1.9.1 Out of business returns

One important assumption for calculation of the out of business outcomes was the percent capital returned to original investors. I used 25% throughout the results discussed above as it was motivated by reality, how the rest of the literature dealt with these outcomes and the results of Cochrane (2005). Sensitivity analysis of this assumptions suggests that a wide range of values give the same basic results and implications, but at some point the log of a very small number generates an unrealistic negative left tail. Three basic changes occur as the cutoff value falls:

- β increases
- α falls
- Mean log returns fall dramatically

Table 1.19 shows the change in non-annualized log return for various levels of the cutoff. The mean falls dramatically: moving from a 15% to 10% cutoff, lowers the mean log return 42%. Moving the cutoff from 20% to 15% lowers the mean log return 50%. Surprisingly, these dramatic changes in mean returns has a small impact on single-state estimates. The beta estimate increases and the alpha estimate falls as the cutoff falls. However, the range of the latter is 1.8 - 2.1. Because the mixture model can fit unique tail returns processes, lowering the cutoff should change the left "failure" return process. I find that as the cutoff falls below 15%, the mean of the failure state falls, while the probability of the state decreases. The "winner" state also shifts: the mean increases and the state probability falls. As I lower the cutoff, the number of states moves towards four as the two tail states further separate. The ICL criterion suggests 4 states, while the AIC and BIC continue to imply 4 or 5. Overall, the mixture shape is sensitive to the smallest values of the cutoff criterion. The mean of the left tail state falls dramatically, while the risk characteristics like beta and the Fama and French loadings are constant. For example, the 4-state mixture with a 15% cutoff changes has a volatility of 113%, a mean log return of -40% and a alpha of 44%. Two states only differ in their intercept term. I conclude that cutoffs below 15% result in dramatically lower mean log returns and higher volatilities, but the current cutoff of 25% adequately represents the data and follows current practice.

1.9.2 State-dependent coefficients

Other than fixing one of the mixture state betas to equal zero, I allow all other coefficients on the pricing factors to differ across states. For example, I let $\beta_1 \neq \beta_2 \neq \beta_3$. Perhaps the Fama and French factor loadings are same across state, while the log market model intercept differs. Moreover, I argue that the "failure" and "winner" states have distinct systematic risks. I test whether the major coefficient estimates differ across state again using the BIC test statistics. I fix the states at three, so the information criterion does not suffer from the overfit problems. Table 1.20 shows that fixing coefficients for all market loadings leads to worse fit. The Mills term differs across states, confirming that selection effects depend on the return level. I conclude that the heterogeneity in the standard market and FF loadings across states is real.

1.10 Conclusion and further work

I present a new model of venture capital risk and return whose estimates demonstrate that normality is a poor approximation for investment outcomes. Mixture states that approximate the non-normality map to typical entrepreneurial firm outcomes. Negative skewness and excess kurtosis characterize a returns distribution where volatility underestimates left tail outcomes. I formulate a tractable, flexible estimator that corrects for sample selection and endogenous holding periods. The corrections require two instrument variables and have the expected impact on parameter estimates. The conclusions about non-normality and risk suggest that the research should move towards studying the optimal asset allocation decisions of the well-diversified, wealthy investors in venture capital. It is possible that the issues of weakly informative volatility may not inform their portfolio choices, however any preference for symmetric risk could alter allocation decisions.

The paper can be expanded in several ways. The market model setup may not fit VC returns. The basic derivation of all asset pricing models requires a "small" change in one's portfolio. As Cochrane explains, "a venture capitalist [...] must take all or nothing of a project" rather than a small, but diversified change in their portfolio.[9] The 3-stage model requires full observability of all exogenous variables, so I create market returns for financings without exits. Further work could test other assumptions for this variable. More pricing factors could enrich the model, but additional parameters may hinder estimation.

[9] Cochrane, John, Asset Pricing, Princeton University Press, 2005. page 37.

1.11 Tables and Figures

Table 1.1: Returns and durations

	Mean holding period	Median holding period	Observations
Bankruptcies	24.7 months	13.1 months	3636
0 < multiple < 2	15.5 months	13.8 months	7059
2<= multiple < 10	13.7 months	11 months	3214
multiple > 10	17.2 months	11.1 months	138

Includes all financing events with known dates. A holding period is defined as the time between two financing rounds or a financing round and an exit. Multiple is the gross increase in value of an entrepreneurial firm between two financing events. 5912 observations lack an exit date and are thus excluded from the table.

Table 1.2: Statistics on financings per entrepreneurial firm (with exits)

	Mean	Median
Full sample, 1987-2007		
Number of non-exit financings	2.5	2
Total financing events, including exits	3.1	3
Number of rounds for firms with IPO or acquisition	2.8	2
Number of rounds for bankrupt firms	2.2	2
Number of non-exit VC financings	2.9	3
Years to bankruptcy	5.6	5.6
Years to IPO	7	4.8
Years to acquisition	6.7	5.4

Counts the number of financing events per entrepreneurial firm with an exit by the end of the sample. Exits include IPOs, acquisitions

and bankruptcies. Non-VC rounds include corporate rounds and debt rounds.

Table 1.3: Exit type distribution for round-to-round returns, by financing

Exit type	**Percent of financings with exit type**
IPO	3.8%
Acquisition	9.7%
Bankruptcy	9.6%
Standard financing	61%
No exit	15.9%

Tabulation of exits for individual financing rounds. Includes all standard, non-debt venture capital rounds as of December 2007.

Table 1.4: Historical holding period across industry (in years)

Mean holding period	18.8 months
Median holding period	15.2 months
Number of financings	37,395
Number financings with exits	32,377

Holding period is the time between financing rounds. Averaged across all financing events with and without exits. Averages are across industry and financings. Industries are "Information Technology," "Healthcare," "Business and Consumer" and "Other."

The sample includes all venture capital rounds as of December 31st, 2007.

Table 1.5: Exit type distribution for entrepreneurial firms

Exit type	**Percent of financings with exit type**
IPO	3.8%
ACQ	9.7%
Bankruptcy	9.6%
Standard financing	61%
No exit	15.9%

Tabulation of exits for individual financing rounds. Includes all standard, non-debt venture capital rounds as of December 2007.

Table 1.6: Round-to-round return characteristics, non-bankruptcies

	Arithmetic	Log	Obs.
Mean return (non-annualized)	108%	39%	10421
Median return (non-annualized)	50%	40%	10421
Mean annualized return	8548%	62%	10354
Median annualized return	141%	35%	10354
σ	252%	84%	10421
annualized σ	836267%	130%	
Mean return IPO/Acquisition	248%	93%	1171
Mean return private financing	89%	33%	9250
Mean return for IT firm	117%	91%	5753
Mean return for biotech firm	77%	35%	3157

Includes all venture capital rounds with holding periods greater than 1 month.

"Mean return IPO/Acquisition" is the return for a financing that exits via an IPO or acquisition.

"Mean return private financing" is the return with an "exit" via a standard financing round.

Table 1.7: Round-to-round return characteristics, all types

	Arithmetic	Log	Obs.
Mean return (non-annualized)	.72	-.067	12018
Median return (non-annualized)	.26	.23	12018
Mean annualized return	$2.1*10^{27}$	.326	12018
Median annualized return	.22	.109	12018
σ	232%	134%	12018
annualized σ	$2.4*10^{29}$	238%	12018
Mean return for IT firm	.81	-.056	6628
Mean return for bankruptcy	.55	-1.21	2820
Mean return for biotech firm	0	.07	3426

Includes all venture capital rounds with holding periods greater than 1 month, including out of business outcomes. "Mean return for bankruptcy" is the return for a financing that exits via bankruptcy."Mean return private financing" is the return with an "exit" via a standard financing round.

Table 1.8: Average historical capital raised by firm development and industry (millions)

Stage	Average	Standard deviation
Early	\$8.62	17.9
Mid-stage	\$20.8	24.1
Late	\$39	43.8
Information Technology	\$21.7	34
Healthcare	\$19.9	30
Consumer	\$19	30

Means are computed across all financing rounds that are of the particular stage and industry. "Early" stage includes the Series A financings and restart rounds that are 1st or Seed rounds. "Mid-stage" are all 2nd and 3rd rounds and those "Corporate" rounds that occur when a firm is 2 to 5 years old. "Late" is the remaining set of financing rounds not defined as early or mid-stage.

Thus, one firm will have multiple, distinct historical capital measures.

Table 1.9: Average historical historical holding period by industry (in years)

Industry	Average	Standard deviation
pre-1998		
IT	1.8	.12
Biotech	1.6	.12
Consumer	1.9	.14
Other	2	.1
post-1998		
IT	1.6	.09
Biotech	1.7	.08
Consumer	1.5	.1
Other	1.9	.1

Tabulates the time between financing rounds by industry and time period. A new financing round can be an exit or a standard financing.

Table 1.10: Ordered probit results

Variable	**Coefficient**	M.E.: Bankruptcy	M.E.: no exit	M.E.: non-bankruptcy
past capital raised (millions)	.0128 (3.75)	-.0019 (.0005)	-.0018 (.0005)	.0037 (.001)
log market return	1.63 (31.98)	-.241 (.0071)	-.24 (.008)	.4813(.0148)
holding period	-.022 (-38.30)	.0032 (.0032)	.003 (.0001)	-.0064 (.0001)
stage (=1 if late stage)	-.1805 (-4.72)	-.0373 (.003)	-.03595 (.0029)	.0732(.006)
cutoff 1 (s.e.)	-1.57 (.026)			
cutoff 2 (s.e.)	-.939 (.025)			
Observations	37530			
Time dummies	N	N	N	N
Industry dummies	Y	Y	Y	Y
Interactions	N	N	N	N
pseudo-R^2	0.0527			

Dependent variable is 2 if financing had an non-bankruptcy exit as of the end of sample, 1 if no exit and 0 if bankruptcy exit.

Data includes all standard venture capital rounds that impact dilution. “M.E.” is marginal effects. t-statistics in parentheses, except for marginal effects,which are s.e.. Cutoffs are the α_1 and α_2 from the ordered probit specification.

Table 1.11: Selection of parametric hazard function

	Log-logistic	Weibull	Log normal	Exponential	Gompertz
AIC	**31475.388**	32772.11	32747.179	40201.231	37595.124
BIC	**31696.094**	32992.816	32967.885	40413.448	37815.83

Summary statistics from various duration models. Includes all censored and non-censoring holding periods for all standard venture capital rounds

Table 1.12: Log-logistic duration model estimates

Independent variable	**Coefficient** (t-statistic)	**Coefficient (t-statistic)**
log market return	2.31 (93)	2.46 (84)
mills	5.94 (103)	6.6 (89)
log historical industry duration	.5 (11.7)	.37 (8.5)
past raised capital (millions)	.003 (21.5)	.003 (21)
stage (=1 if late stage)	.32 (52)	.31 (45)
constant	-.36 (-10)	-.53 (-13)
Observations	37222	37222
Number of "failures"	32042	28564
Time dummies	N	N
Failure	New financing or bankruptcy	New financing
Industry dummies	Y	Y
Interactions	N	N

Standard errors are clustered at the firm level. Industry dummies are included in each regression but not reported. For the "New Financing" failure, the model treat bankruptcy exits as censored.

Table 1.13: Single-state estimates

	OLS	OLS-3	GLS	GLS-3	Full	Full-3
γ	-.0177(.0006)	-.01(.0008)	-.006(.0006)	.002(.0008)	-.007(.0002)	-.008(.0004)
β	2.4(.06)	1.6(.07)	2.6 (.06)	1.6(.08)	1.7(.04)	1.9(.06)
SMB		-.44(.09)		-.47(.1)		1.14(.07)
HML		-1.16(.08)		-1.5(.08)		-.12(.07)
α	824% (40)	814% (32)	60% (4.9)	70% (5.4)	40% (5)	40% (3.8)
Mills					1.3(.012)	1.4(.01)
σ	411%	406%	116%	114%	98%	99%

Standard errors in parentheses, clustered at the entrepreneurial firm. Estimates of equation (1.11) for $k = 1$ with a single-factor and three-factors (e.g. "OLS-3") using 12,007 returns to new financings and out of business outcomes. The market factor is the Wilshire 5000, while the SMB and HML are the standard FF factors "small minus big" and "high minus low". OLS does not include sample selection corrections and does not correct for volatility heterogeneity. GLS divides all variables by the square root of the observed holding periods. Full includes the Mills term from the ordered probit selection model, the fitted holding periods from 2SLS and divides all variables by the square root of the predicted holding periods. Alpha is computed using (), while the volatility estimate in columns 6 and 7 follow ().

Table 1.14: Single-state estimates and Cochrane (2005)

	Cochrane (2005)	Full
β	1.2	1.7 (.04)
α	35% (5.7)	40%(3.8)
$E[\ln R]$	15%	-12%
$\sigma(\ln R)$	91%	99%
$E[R]$	61%	38%
$\sigma(R)$	110%	103%

Notes: "Cochrane round-to-round" is from Table 4 of Cochrane (2005) and is estimated on a 1987 - 2000 round-to-round returns with the Nasdaq as the market factor (for proper comparison). Column 2 presents the full single-factor, single-state model estimates with the Wilshire 5000 as the market factor. $E[\ln R] = ga\hat{m}ma + \bar{\mu_{rf}} + \hat{\beta}(\bar{\mu}_m - \bar{\mu}_{rf})$ and $E[R]$ follows from the log-normal assumption.

Table 1.15: Return Outliers: Both large and small

log return	holding period (months)
1.2	.13
-5.4	5.9
4.6	3.02
-2.3	2.03
0	.1
2.8	2.5
1	.2
-4.2	1.2
2.8	2.5
2.7	6.5
-3.6	2.6
3.3	7.8
2.8	3.7
3.3	4
2.6	2.5

Summary of log returns for the observations (from the selected sample)

with the largest residual in the 3-factor, single-state regression.

Table 1.16: Assessing the number of mixture states

States	AIC	BIC	ICL
2	-11838.54	-11735.03	-5529.421
3	-12256.77	-12094.11	-4279.314
4	-12678.06	-12456.25	546.809
5	-12845.59	-12564.64	3452.8016

Notes: Test statistics for various mixture formulations. Each mixture model estimated with 3 factors.

Table 1.17: Mixture Results: Three states

	Single-State	Mixture		
		Prob	Estimate	
α	39% (1.2)	14%	101%(11)	42%(3)
		61%	30%(6)	
		25%	7%(3)	
		Prob	Estimate	
β	1.86 (.06)	14%	0	1.9(.08)
		61%	1.7(.1)	
		25%	3.6(.2)	
		Prob	Estimate	
SMB	1.14 (.07)	14%	.14(.05)	1.2 (.1)
		61%	.9(.1)	
		25%	2.4(.3)	
		Prob	Estimate	
HML	-.12 (.06)	14%	-2.4(.2)	.05 (.1)
		61%	.28(.08)	
		25%	.9(.3)	
		Prob	Estimate	
E[ln R]	3%	14%	185%	-11%
		61%	22%	
		25%	-202%	
		Prob	Estimate	
σ(ln R)	99%	14%	128%	104%
		61%	90%	
		25%	96%	

Notes: Mixture estimates from EM algorithm of a 3-factor model with the Fama-French factors. Each sub-row is a state-coefficient/parameter. The final column represents the "average" or population estimate that is the weighted average of the state-level coefficient estimates. Standard errors for population parameters derived from the delta method.

Table 1.18: Implied arithmetic means

	"Winners"	"Break-even"	"Failures"	Population
$E[R]$	1340%	87%	-79%	219%
$\sigma(R)$	3000%	207%	20%	1300%

Note: Each state arithmetic return is calculated using $E[R] = \exp(E[\ln R] + .5\sigma^2) - 1$, while volatilities are $\sigma(R) = (E[R]+1)(\exp(\sigma^2) - 1)$

Table 1.19: Out of business cutoff and mean log returns

Cutoff	$E[\ln R]$	$\sigma(\ln R)$
.1	-17.2%	159%
.15	-12%	148%
.2	-8.4%	140%
.25	-5.7%	134%
.3	-3.3%	130%

Notes: Mean log returns are non-annualized percents. "Cutoff" is the assumption of the value of an

investment at an out of business exit as a proportion of the original capital invested.

Table 1.20: BIC criterion for fixed coefficients across states

	Fixed	Unrestricted
β	-12053.29	-12099.38
SMB	-12082.65	-12099.38
HML	-11757.03	-12099.38
Mills	-12080.13	-12099.38

Notes: The table reports the BIC for each restriction. The second row fixes all betas to be identical across states. "Unrestricted" is the BIC from the 3-state mixture with beta = 0 for one state.

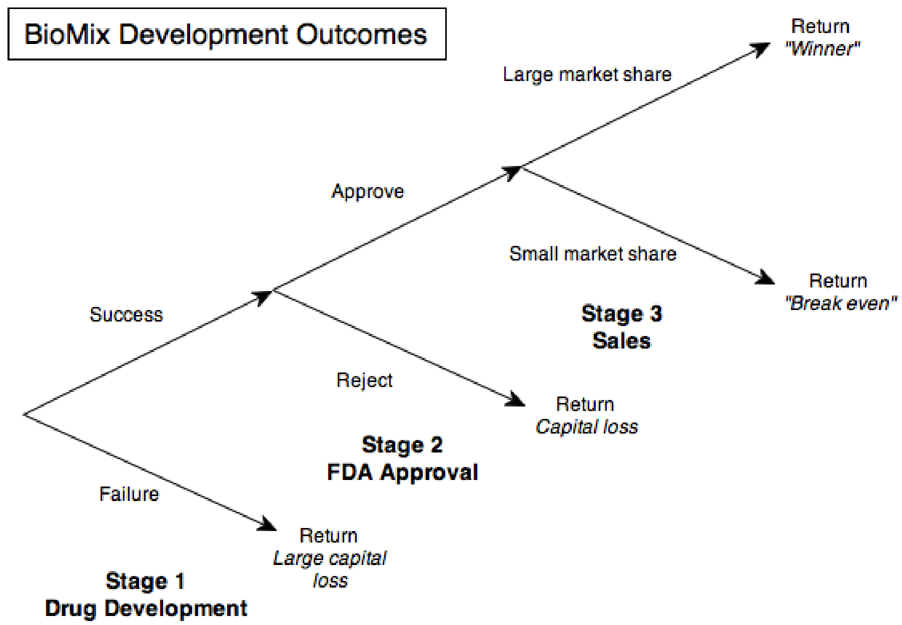

Figure 1.1: Fictional development of an entrepreneurial firm: BioMix

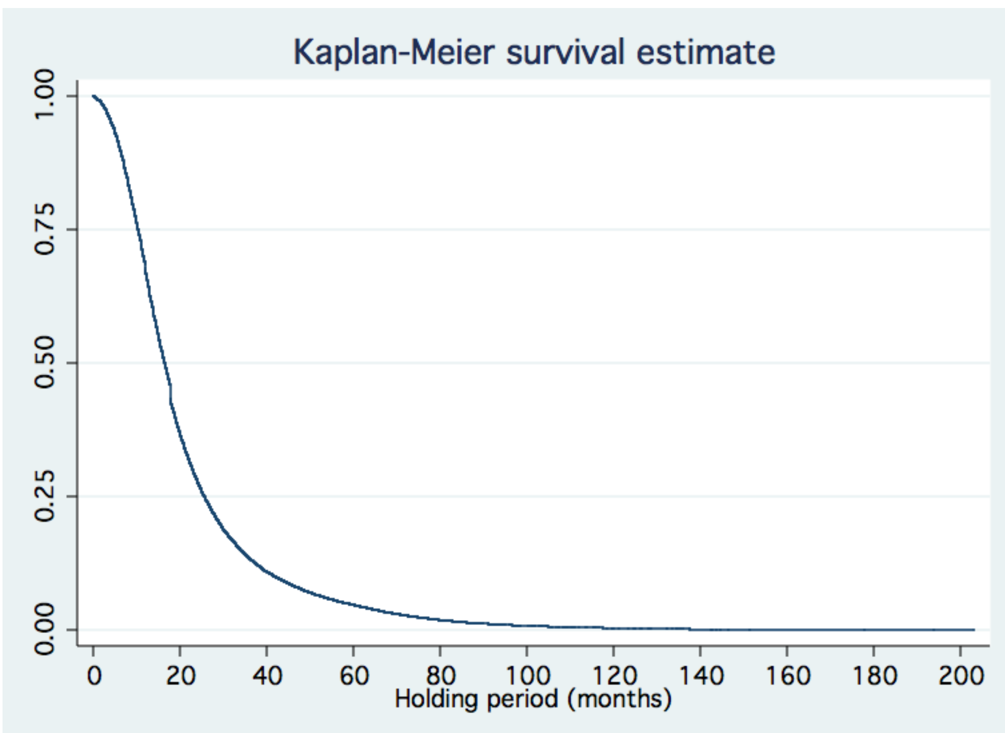

Figure 1.2: Survivor function estimate for investment holding periods

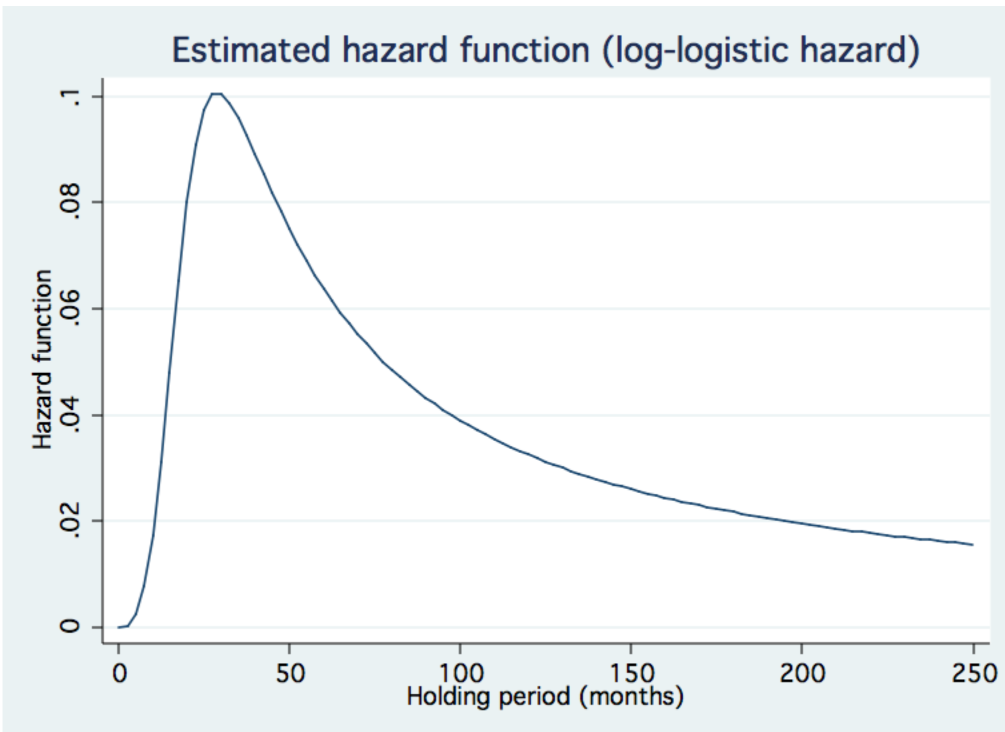

Figure 1.3: Estimated hazard

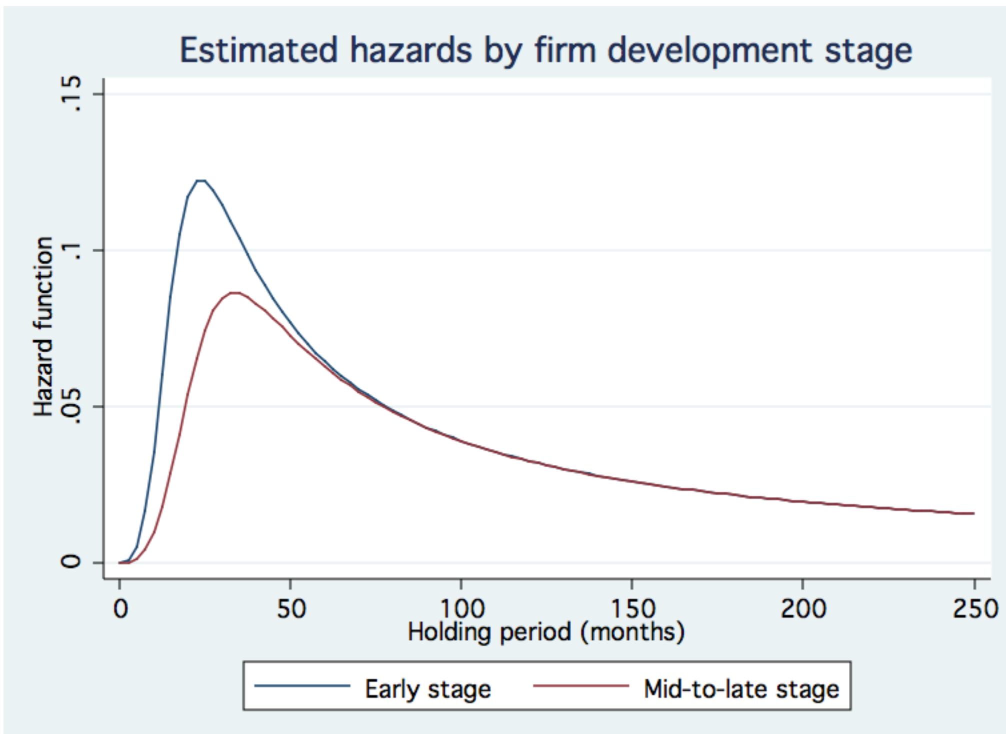

Figure 1.4: Estimated hazards by development stage

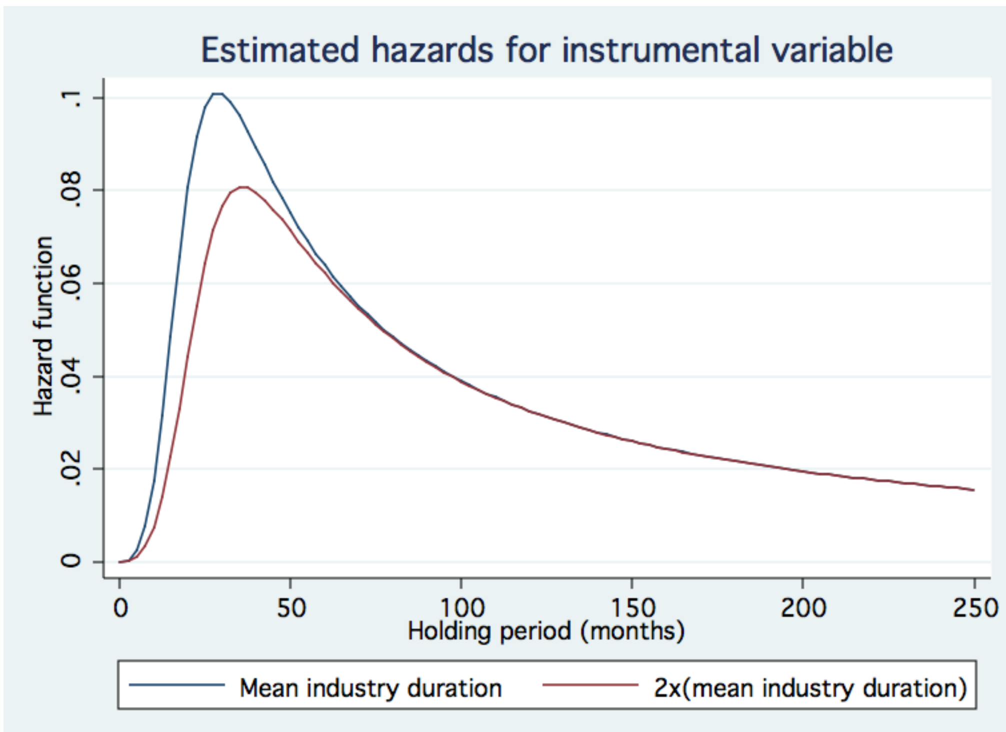

Figure 1.5: Estimated hazards for instrument (historical industry duration)

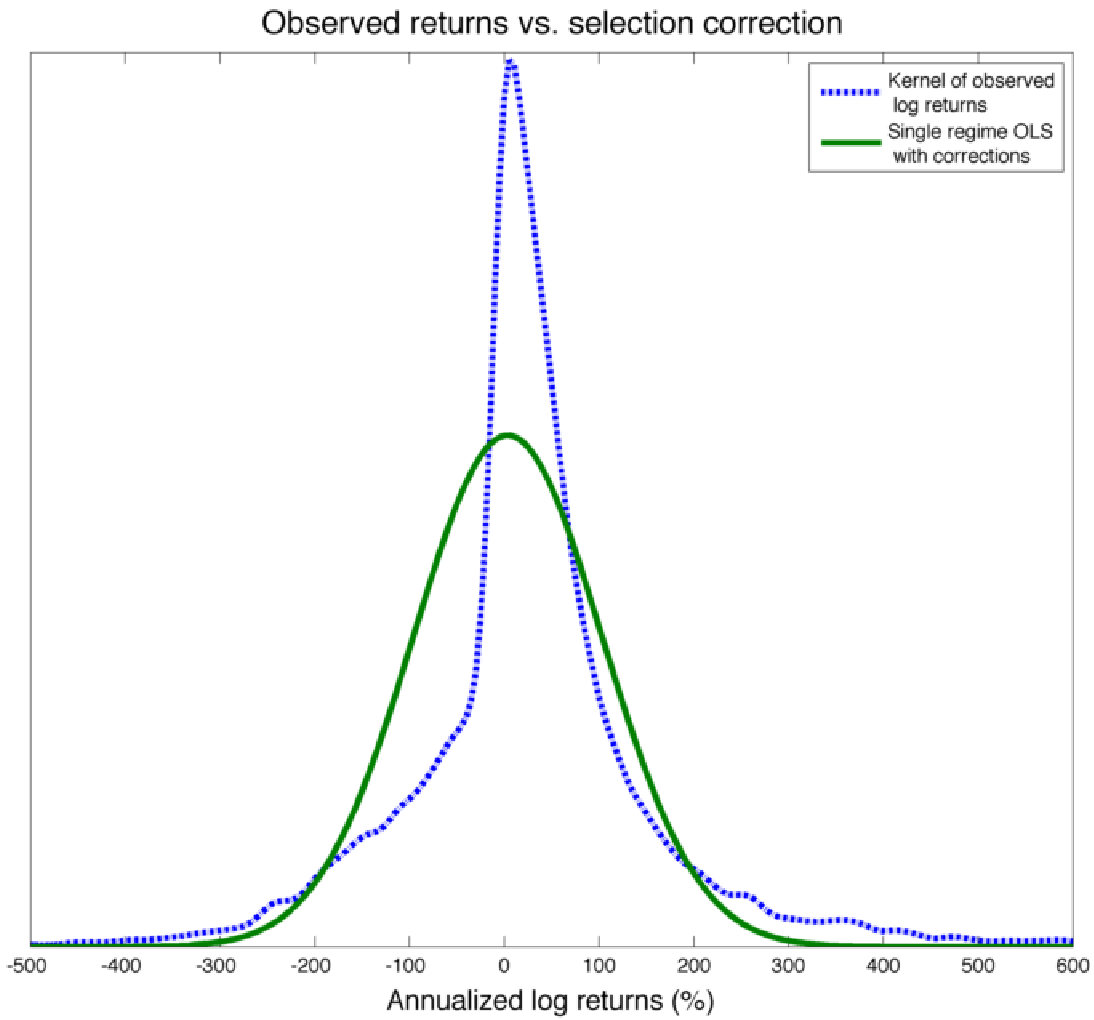

Figure 1.6: Kernel and full selection corrected pdf: Log returns

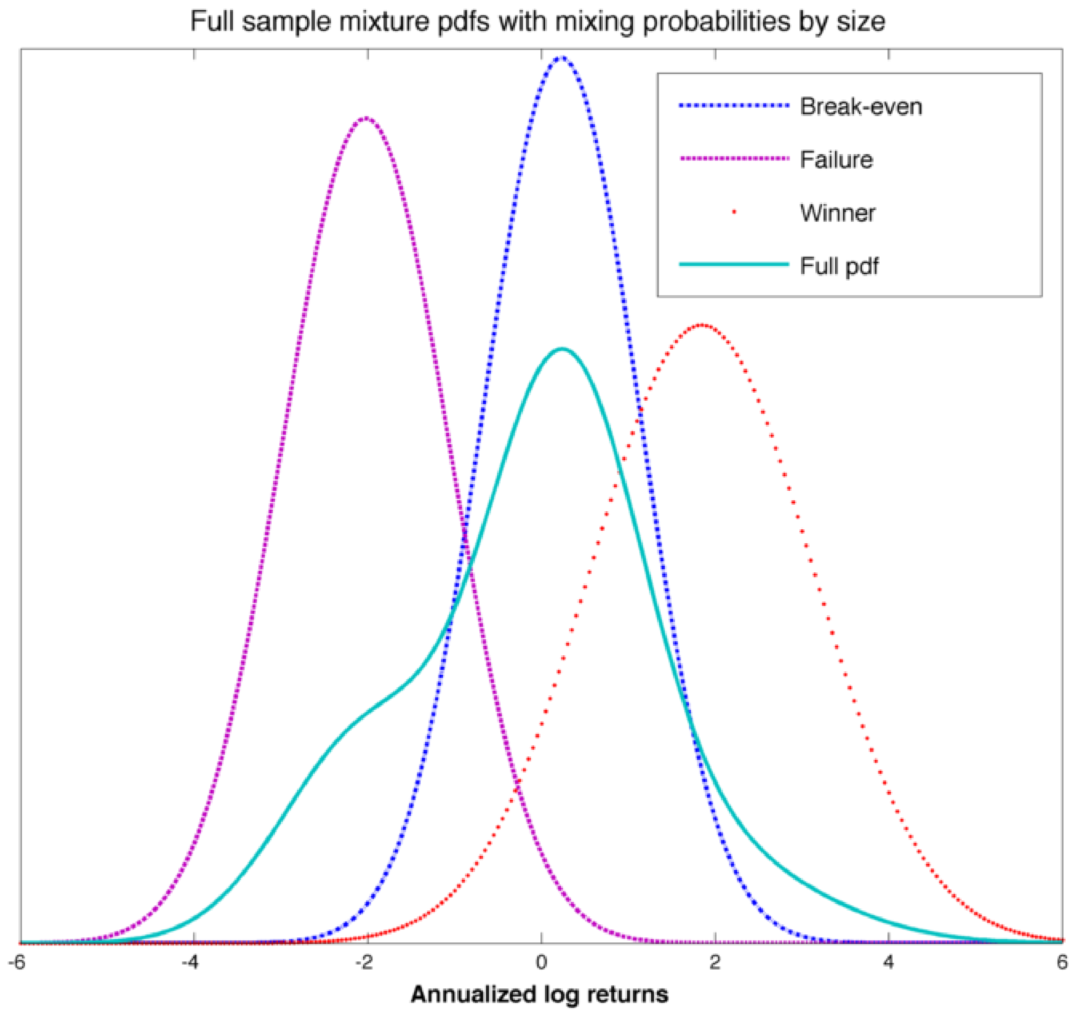

Figure 1.7: Full mixture and mixture states

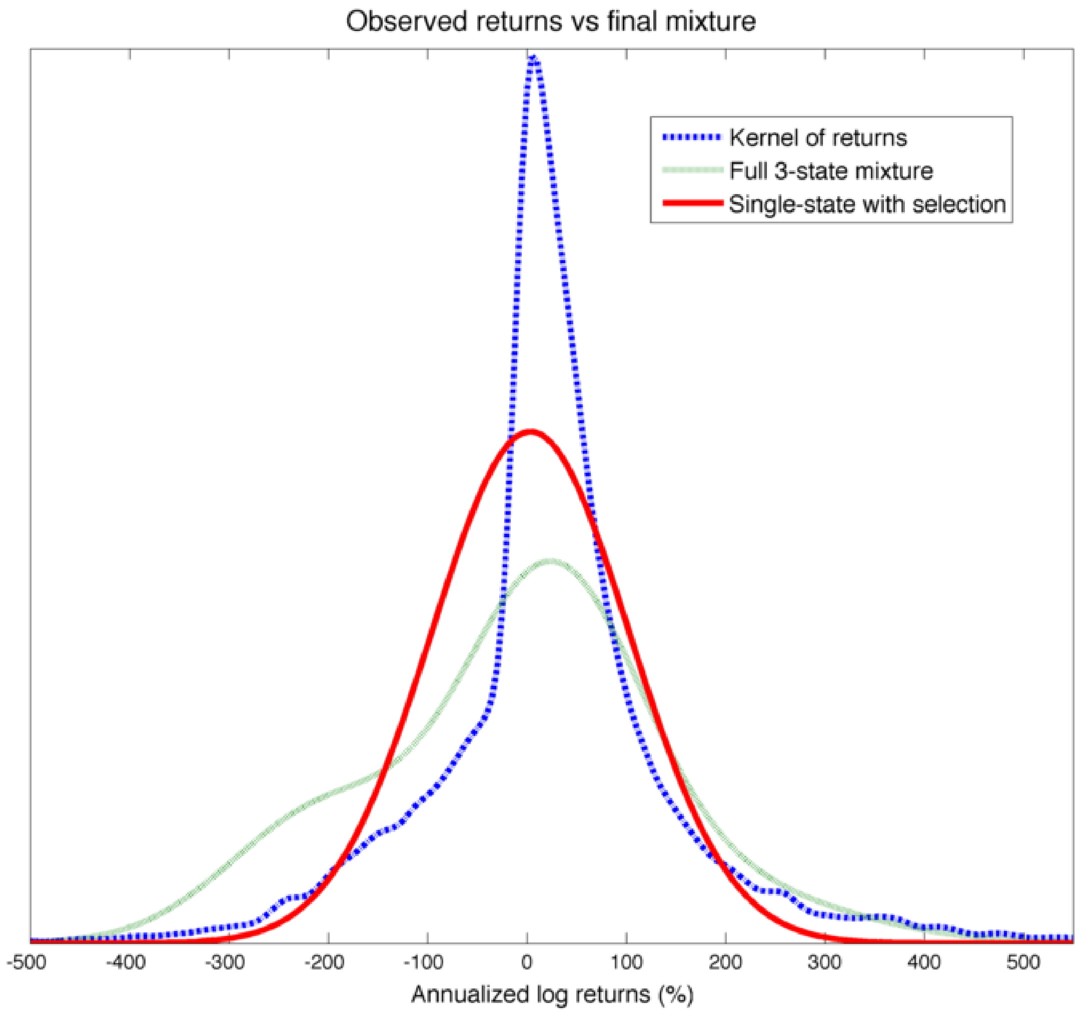

Figure 1.8: Progression from single-state to mixture

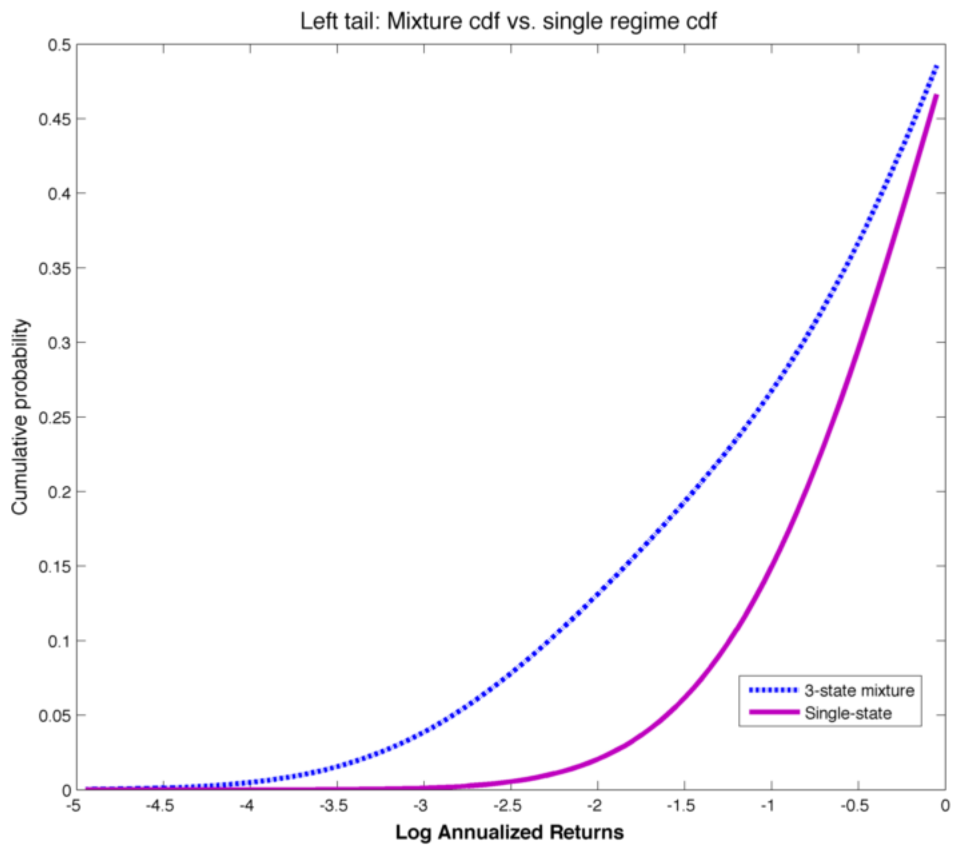

Figure 1.9: Left tail cdfs

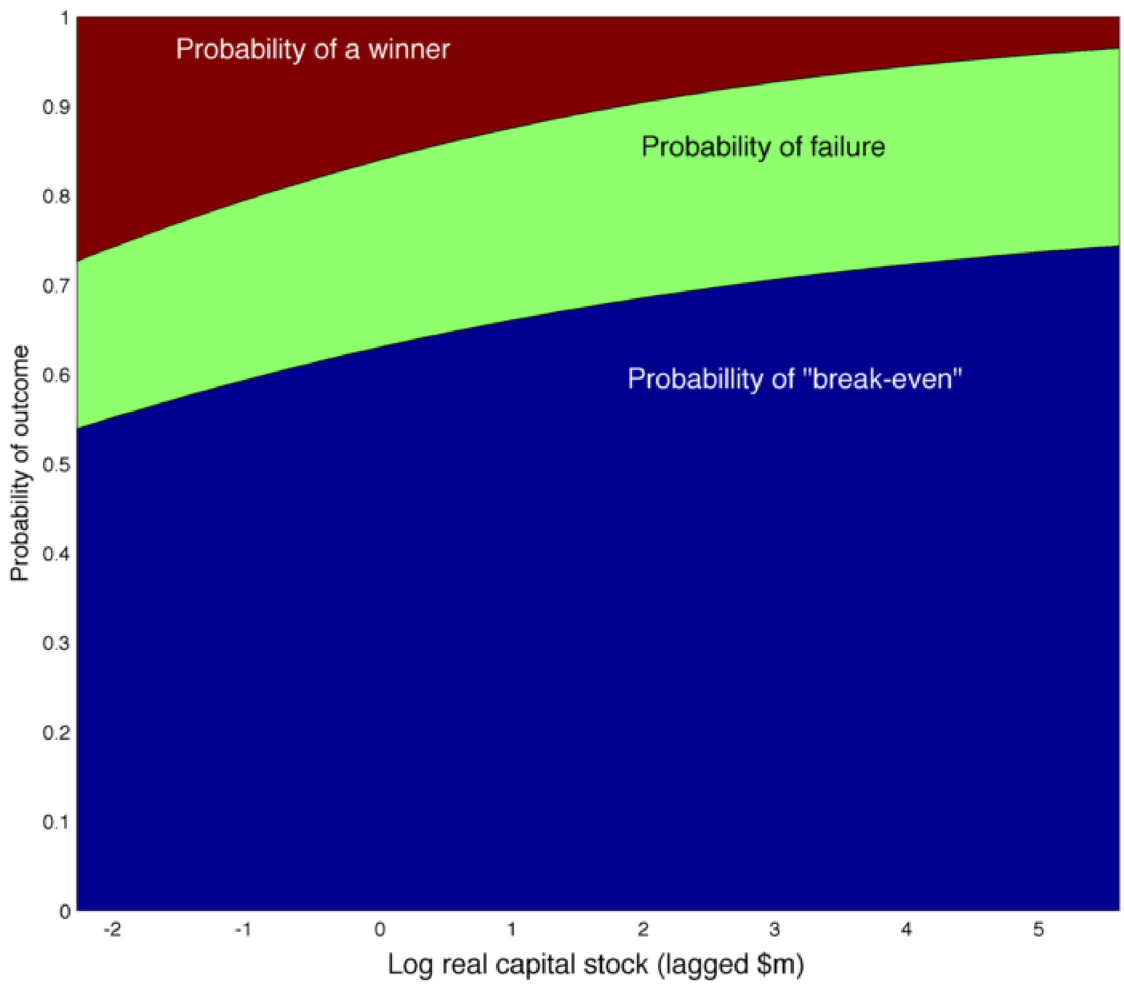

Figure 1.10: Ex-ante state predictions by size

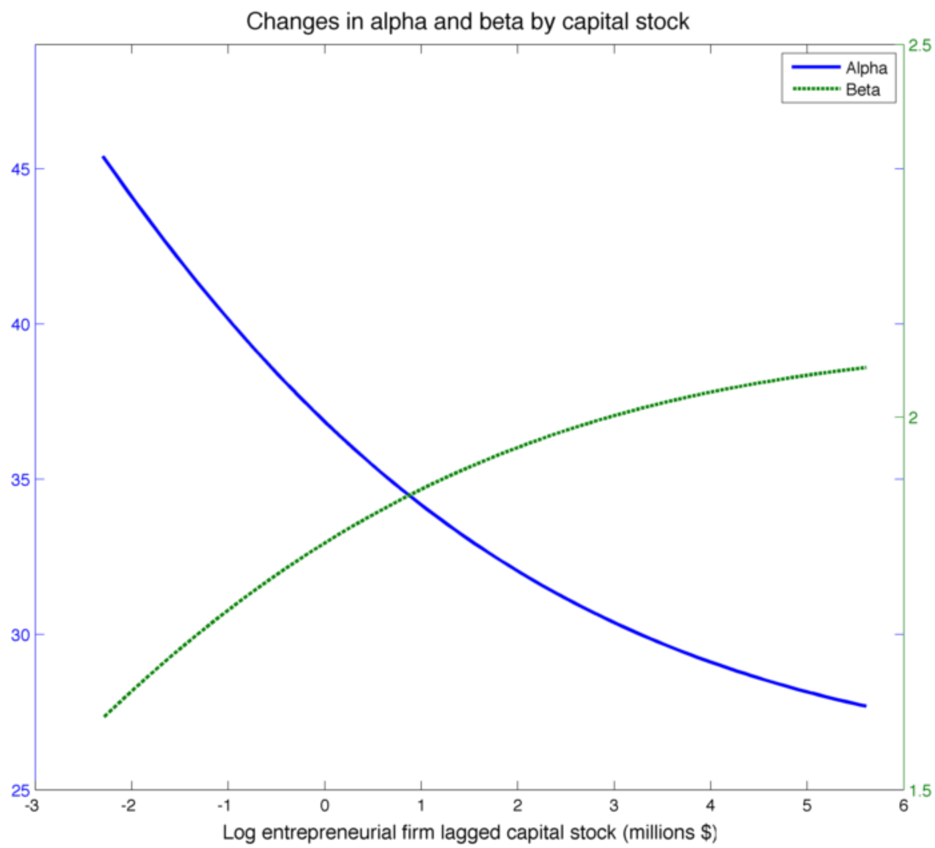

Figure 1.11: Alpha and beta by entrepreneurial firm size

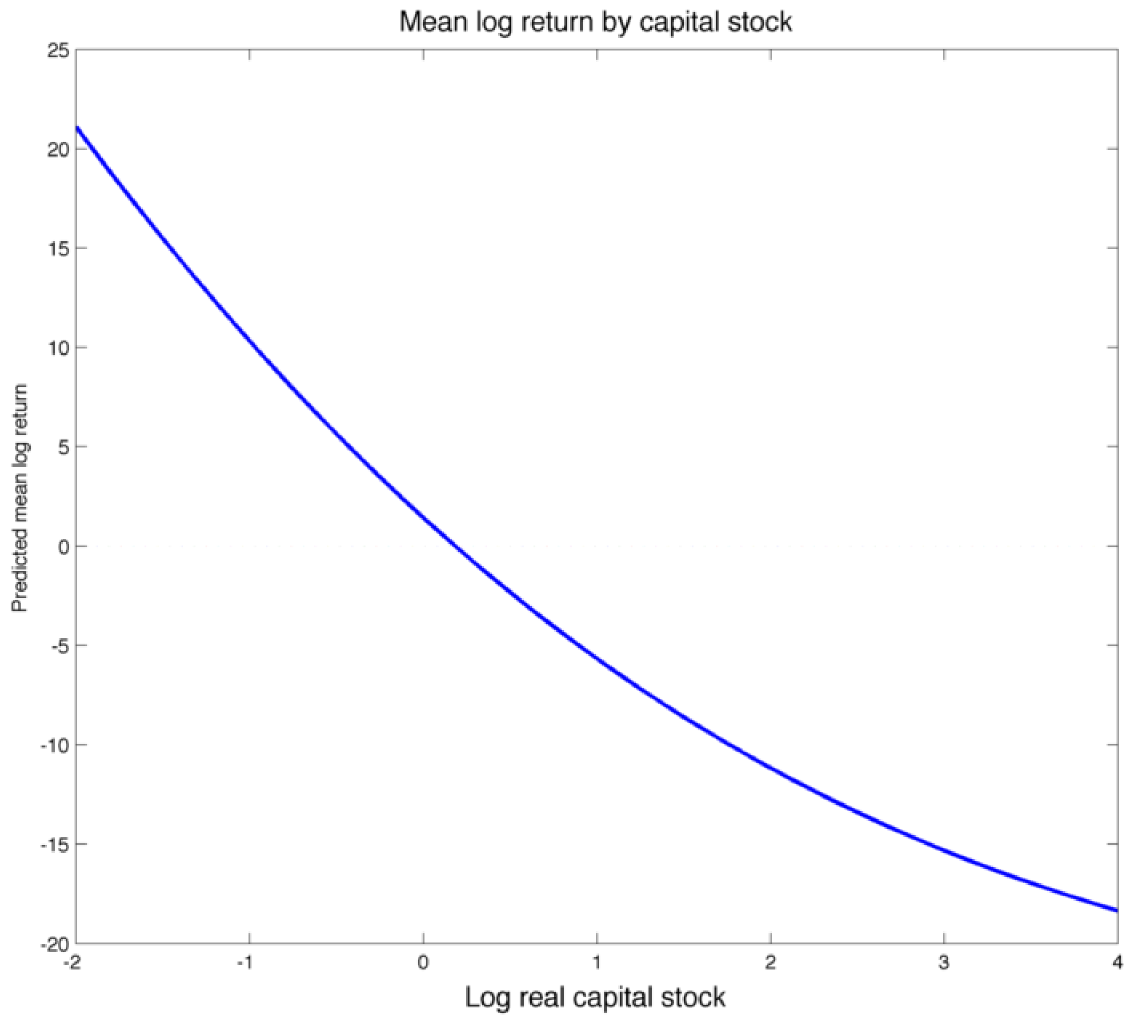

Figure 1.12: Predicted mean log returns by capital stock

Notes: predictions of mean log returns by the multinomial logit mixing probabilities. Capital stock is the lagged capital raised as of time t deflated by CPI.

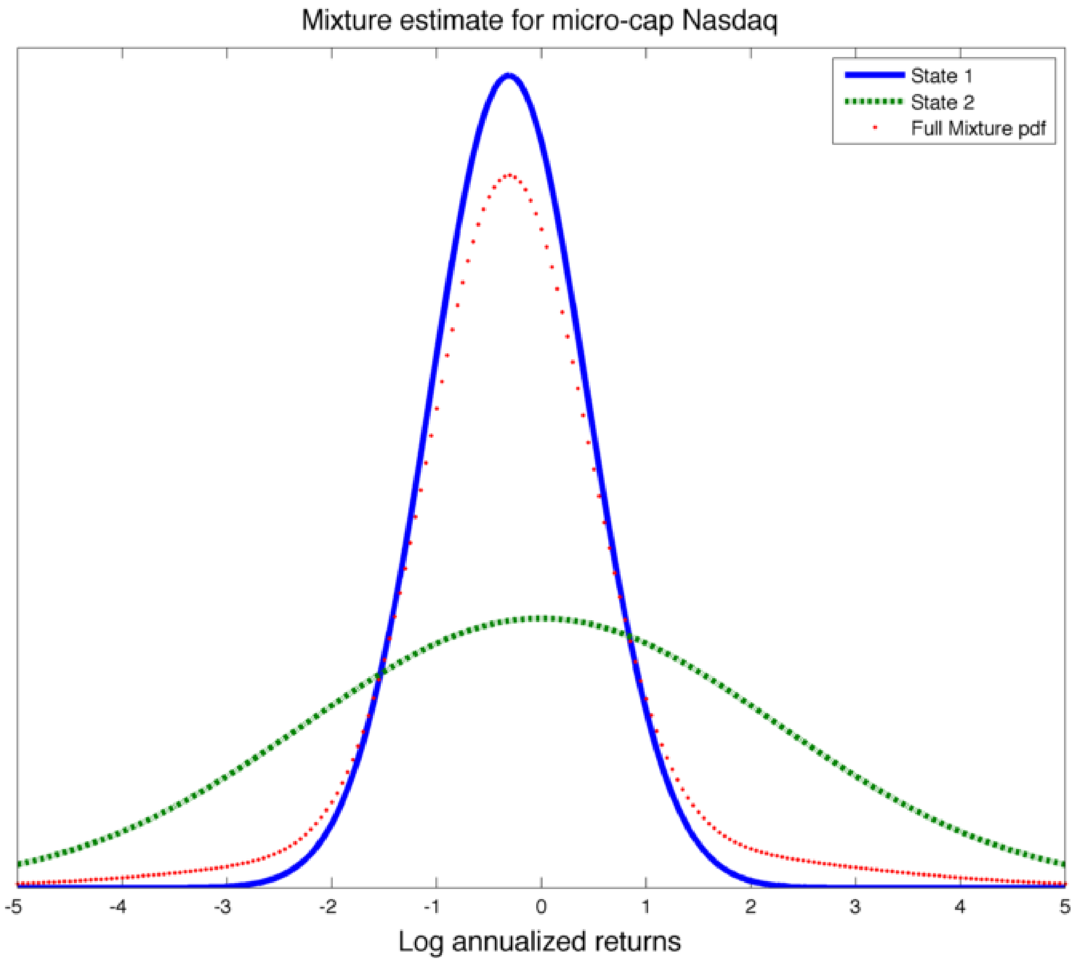

Figure 1.13: Micro-cap Nasdaq mixture

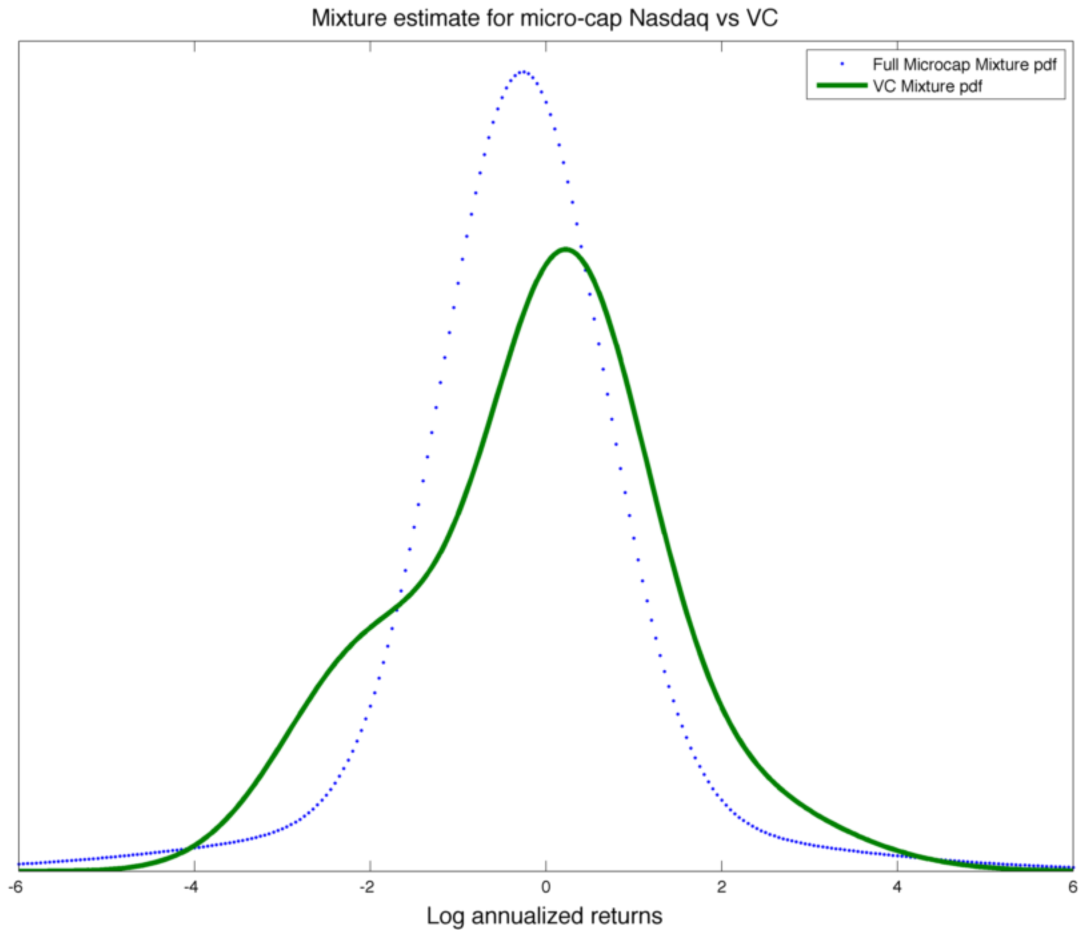

Figure 1.14: Micro-cap Nasdaq mixture vs VC returns mixture

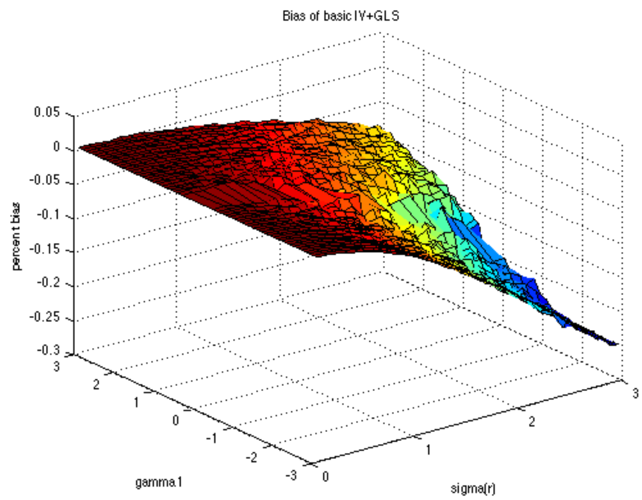

Figure 1.15: Bias of IV+GLS of β_1 with endogenous denominator

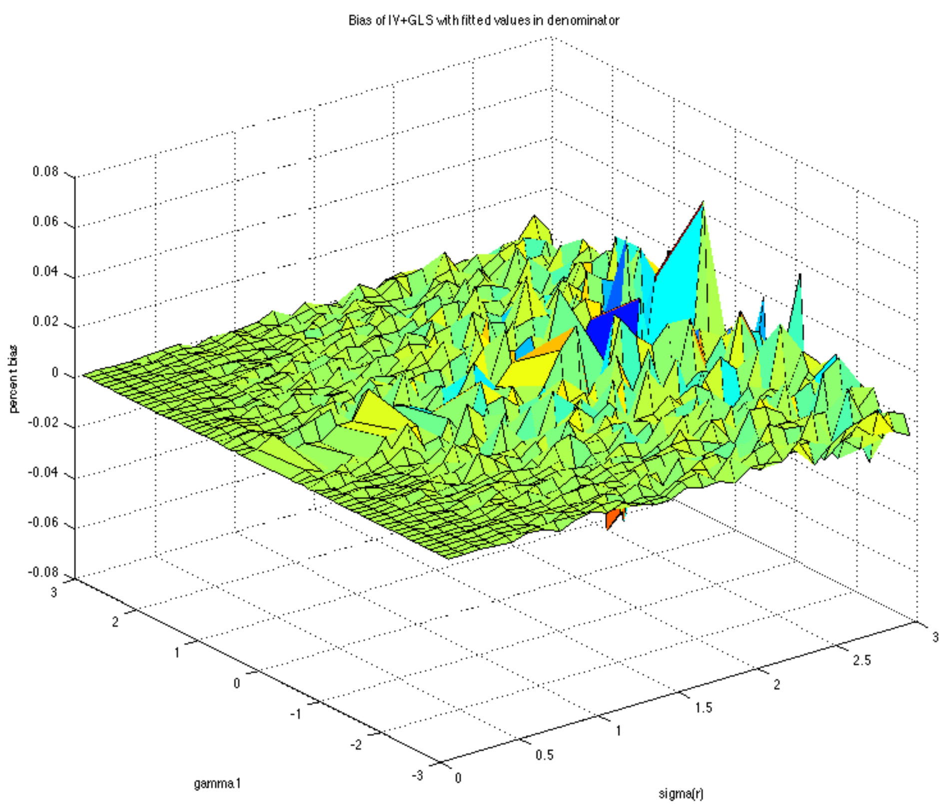

Figure 1.16: Bias of IV+GLS of β_1 with fitted denominator

1.12 Appendix

1.13 Estimating volatility

The size of the market model alpha hinges on the underlying volatility estimate, itself affected by corrections for sample selection and endogenous holding periods. For the standard Heckman selection correction, the coefficient on the Mills term is[10]

$$\beta_{Mills} = \rho\sigma$$

where σ is the true volatility of the returns and ρ is the sample selection correlation from assumption A4 in the 3-stage model. Observed volatility differs from σ because of sample selection. The conditional variance for each return j with the simple selection correction is

$$s^2 = \sigma^2(1 - \rho^2(\lambda(z\delta_3)(\lambda(z\delta_3) - z\delta_3))).$$

The σ falls out of the residual sum of squares from the first stage selection regression:

$$\sigma^2 = \frac{1}{N}s^2 + \hat{\hat{\delta}}\hat{\beta}^2_{Mills}$$

where

$$\hat{\hat{\delta}} = \frac{1}{N}\sum_{i=1}^{N}\hat{\lambda}(z_i\hat{\delta}_3)(\hat{\lambda}(z_i\hat{\delta}_3) + z_i\hat{\delta}_3)).$$

As Greene (2003) shows, the $\delta_i \in (0,1)$. If $\rho > 0$ (so that $\beta_{Mills} > 0$ and the data suffers from positive sample selection), then the conditional volatility estimate under-estimates the population volatility. The 2SLS step impacts the s^2 estimate by requiring the non-fitted holding periods in the error term estimation, slightly changing the estimate. I take this final estimate of s^2 and the new estimate of $\hat{\beta}_{Mills}$ to get the underlying volatility σ. The adjustments for selection and endogeneity result in a new mapping from the log market model parameters to the arithmetic alpha:

$$\alpha = \hat{\delta} + \frac{1}{2}\hat{\delta}(\hat{\delta} - 1) + \frac{1}{2}(\frac{1}{N}s^2_{2SLS} + \hat{\hat{\delta}}\hat{\beta}^2_{Mills}) \tag{1.20}$$

[10] I closely follow the discussion in Greene (2003).

1.14 GLS with endogeneous variables

I discuss below a generalized model of an endogenous variable that is also explicitly impacts the variance of the outcome equation.

1.14.1 Simple model

The following discussion borrows from Hamilton (1994). Suppose the outcome equation of interest is

$$y_i = \beta_0 + \beta_1 x_{1i} + \beta_2 x_{2i} + \varepsilon_i$$

and let x_1 be endogenous. There exists a variable x_3 that is exogenous in the outcome equation and correlated with x_1. Write

$$x_{1i} = \gamma_0 + \gamma_1 x_{3i} + \gamma_2 x_{2i} + u_i$$

Define $z' = (1, x_2, x_3)$. Then the estimate of $\gamma = [\gamma_0, \gamma_1, \gamma_2]$ is

$$\hat{\gamma} = \left[\sum_{i=1}^{N} z_i z_i'\right]^{-1} \left[\sum_{i=1}^{N} z_i x_{1i}\right]$$

From this estimate define

$$\hat{x} = [\hat{\gamma}' z, x_2]$$

The standard 2SLS estimator for $\beta = [\beta_1 \beta_2]$ is

$$\beta_{2SLS} = \left[\sum_{i=1}^{N} \hat{x}_i x_i'\right]^{-1} \left[\sum_{i=1}^{N} \hat{x}_i y_i\right]$$

1.14.2 Why GLS is biased

Suppose that we utilize the information that $\varepsilon \sim N(0, \sigma^2 x_1)$ and divide all the regressors in the second stage by $\sqrt{x_{i1}}$. The derivation below shows that this leads to a biased estimate of β.

$$\tilde{\hat{x}}_i' = [\hat{\gamma} z_i / \sqrt{x_{1i}}, x_2 / \sqrt{x_{1i}}]$$

$$\tilde{x}_i = x_i/\sqrt{x_{1i}}$$

So the 2SLS-GLS estimator is

$$\beta_{2SLS-GLS} = \left[\sum_{i=1}^{N} \tilde{\hat{x}}_i \tilde{x}_i'\right]^{-1} \left[\sum_{i=1}^{N} \tilde{\hat{x}}_i \tilde{y}_i\right] = \left[\frac{1}{N}\sum_{i=1}^{N} \tilde{\hat{x}}_i \tilde{x}_i'\right]^{-1} \left[\frac{1}{N}\sum_{i=1}^{N} \tilde{\hat{x}}_i (\tilde{x}_i \beta + \tilde{\varepsilon}_i)\right] \tag{1.21}$$

$$= \beta + \left[\frac{1}{N}\sum \tilde{\hat{x}}_i \tilde{x}_i'\right]^{-1} \frac{1}{N}\sum_{i=1}^{N} \tilde{\hat{x}}_i \tilde{\varepsilon}_i \tag{1.22}$$

This estimator is biased because

$$\lim_{N\to\infty} \frac{1}{N}\sum_{i=1}^{N} \begin{bmatrix} \hat{\gamma} z_i / x_{1i} \\ x_{2i}/x_{1i} \end{bmatrix} \varepsilon_i = \lim_{N\to\infty} \frac{1}{N}\sum_{i=1}^{N} \begin{bmatrix} \hat{\gamma} z_i \\ x_{2i} \end{bmatrix} \frac{\varepsilon_i}{x_{1i}} \neq 0$$

as $E[x_1 \varepsilon] \neq 0$.

GLS with fitted values

I now repeat the exercise above, but replace the term $\sqrt{x_{1i}}$ with the fitted value from the first stage regression, $\sqrt{\hat{x}_{1i}}$. Note that

$$\hat{x}_{1i} = \hat{\gamma} z_i$$

We have

$$\lim_{N\to\infty} \frac{1}{N}\sum_{i=1}^{N} \begin{bmatrix} \hat{\gamma} z_i / \sqrt{\hat{x}_{1i}} \\ x_{2i}/\sqrt{\hat{x}_{1i}} \end{bmatrix} \tilde{\varepsilon}_i = \lim_{N\to\infty} \frac{1}{N}\sum_{i=1}^{N} \begin{bmatrix} \hat{\gamma} z_i \\ x_{2i} \end{bmatrix} \frac{\varepsilon_i}{\hat{x}_{1i}} \tag{1.23}$$

$$= \lim_{N\to\infty} \frac{1}{N}\sum_{i=1}^{N} \begin{bmatrix} \hat{\gamma} z_i \\ x_{2i} \end{bmatrix} \frac{\varepsilon_i}{\hat{\gamma} z_i} \tag{1.24}$$

$$= \lim_{N\to\infty} \frac{1}{N}\sum_{i=1}^{N} \begin{bmatrix} 1 \\ x_{2i}/\hat{\gamma} z_i \end{bmatrix} \varepsilon_i = 0 \tag{1.25}$$

where the last step follows from $E[\varepsilon] = E[x_2 \varepsilon] = 0$. So the GLS correction should use the fitted values of the endogenous variable from the first stage regression. Next, I run some simple simulations showing the bias of each estimator.

1.14.3 Simulation results

The model presented above is simulated using N random draws S times. The simulation works as follows:

1. Generate N draws of $r \sim N(0, \sigma_r^2)$.
2. Generate N draws of $u = \sigma_u * r$
3. Generate N draws of $z = \mu_z + \sigma_z Z \qquad Z \sim N(0,1)$ and $x_2 = \mu_2 + \sigma_2 X_2, X_2 \sim N(0,1)$.
4. Compute $x_1 = \gamma_0 + \gamma_1 x_3 + \gamma_2 x_2 + u$ where γ is fixed.
5. Generate N draws of $\varepsilon = \sigma_\varepsilon x_1 E \qquad E \sim N(0,1)$
6. Compute $y = \beta_0 + x_1\beta_1 + x_2\beta_2 + \varepsilon$
7. Run OLS of y on a constant, x_1 and x_2. Save $\hat{\beta}$.
8. Run 2SLS. Compute $\hat{x}_1 = \hat{\gamma}_0 + \hat{\gamma}_1 x_3 + \hat{\gamma}_3 x_2$ from OLS of x_1 on a constant, x_3 and x_2.
9. Run OLS of y on a constant, $\hat{x}_1$ and x_2. Save $\hat{\beta}_{IV}$.
10. Compute $\tilde{y} = y/\sqrt{x_1}$, $\tilde{c} = 1/\sqrt{x}$, $\tilde{x}_1 = \hat{x}_1/\sqrt{x_1}$ and $\tilde{x}_2 = x_2/\sqrt{x_1}$.
11. Run OLS of $\tilde{y}$ on $\tilde{c}$, $\tilde{x}_1$ and $\tilde{x}_2$. Save $\hat{\beta}_{IVGLS}$.
12. Compute $\bar{y} = y/\sqrt{\hat{x}_1}$, $\bar{c} = 1/\sqrt{\hat{x}_1}$, $\bar{x}_1 = \hat{x}_1/\sqrt{\hat{x}_1}$ and $\bar{x}_2 = x_2/\sqrt{\hat{x}_1}$.
13. Run OLS of $\bar{y}$ on $\bar{c}$, $\bar{x}_1$ and $\bar{x}_2$. Save $\hat{\beta}_{IVGLS2}$.

Repeat these steps S times. We then have S estimates of $(\hat{\beta}, \hat{\beta}_{IV}, \hat{\beta}_{GLS}, \hat{\beta}_{GLSIV})$. We are ultimately interested in any bias of these estimators. First, we know that the standard OLS estimate of β will be biased. I am interested in the the bias of β_1 and β_2 for a range of γ_1 and σ_r. These two constants measure the relevancy of the instrument and the covariance of the two error terms. The fixed parameters are

$$\beta_1 = 1.5 \quad \beta_2 = 4 \quad \mu_z = 1 \quad \mu_{x_2} = 2.5 \quad \sigma_{x2} = 2.4$$

$$\sigma_z = 1.1 \quad \sigma_\varepsilon = .6\sigma \quad \gamma_2 = 2.2 \quad \sigma_u = .5$$

Finally, I set $N = S = 1000$. Figure 1.15 shows that the bias of the IV estimator increases (in absolute terms) as the variance of r increases, while for very large γ_1, the bias is minimal.

Figure 1.16 shows the bias of the adjusted IV+GLS estimator that uses the fitted values of the endogenous variable in the denominator. The most significant absolute bias occurs when the instrument is weak: $\gamma_1 \approx 0$. Overall, using the fitted values for the GLS correction eliminates most of the pervasive bias.

2 Entrepreneurial Activity of Venture Capitalists

Abstract

Each year, about 15% of new venture capital firms are formed by venture capital partners at existing firms. This paper investigates the consequences of these employee spinoffs for parent firms and the characteristics of their founders. As predicted by the spinoff formation model of Cabral and Wang (2009), high type partners and low type partners at failing parent firms are the most likely to leave and start a new venture capital firm. After accounting for the endogeneity of the *timing* of spinoff formation, estimates reveal a large, negative impact of spinoffs on parent firm performance. The direction of the endogeneity bias suggests that spinoff founders time their exits to coincide with success at the parent firm. The negative impact of spinoffs shows that individual venture capital partners can play a crucial role in the performance of their firms. Thus, findings on venture capital firm characteristics such as performance persistence (Kaplan and Schoar (2005)) or social networks (Hochberg, Ljungqvist and Lu (2007a)) may be a partner-level phenomenon.

2.1 Introduction

For many industries, a significant source of new firms are spinoffs: those started by former employees at existing firms. Approximately 15% of all new venture capital firms are spinoffs. New firms reshape the distribution of capital to entrepreneurs and alter the competitive environment between investors. New venture capitalists can also change the mix of industries that receive capital. For example, new firms may increase the shift of money from biotech to information technology. Interest in the causes and consequences of new venture capital (VC) firm formation extends beyond these market effects. Analysis of human-capital intensive firms differs from the popular study of capital and technology-intensive sectors.[1] In particular, intangible assets such as social network status and industry expertise will influence VC spinoff formation. Results on venture capital spinoffs can extend to industries such as hedge funds, investment banks and law firms. Next, existing studies of VC firm and fund performance aggregate away individual employee input associated with the firm's investments. Any detrimental impacts of partner exit can illustrate the role that individuals rather than firms play in observed outcomes. Last, endogeneity can plague any study of the impact of spinoffs on parent firms. Employees may time their exit based on their parent's performance or the market, masking any real impact from the researcher.

This study answers two questions about spinoff formation in the venture capital industry using a unique panel database of the employment histories of venture capital partners. First, what employee and parent firm characteristics predict spinoff? A model of spinoff formation by Cabral and Wang (2009) presents a set of testable hypotheses about who starts a spinoff firm and how parent type interacts with the decision. After identifying the features of spinoff founders, I next ask what, if any, are the consequences of spinoff formation on parent firms. A simple estimator allows for testing of several spinoff impact hypotheses, which range from no impact to a large, negative impact. An accurate answer to this question must address endogenous timing of spinoff formation that hampers unbiased estimation.

Several empirical papers investigate the causes and consequences of spinoff formation. Campbell, Agarwal, Ganco and Franco (2009) use one of the most detailed datasets available in the literature and ask similar questions about spinoff formation in the US legal services industry. They find that an increase in employee quality lowers the probability of exit to spinoff, while conditional on exit, high type employees are most likely to start a new firm. An analysis of the consequences of spinoffs on parents reveals that exit to start-ups (i.e. spinoffs) lowers a

[1] See Klepper (2009) for a survey.

parent's revenue per worker. The paper does not address the endogeneity of spinoff timing and the confidentiality constraints result in significant aggregation of key independent variables and employee types. In contrast, the data analyzed here includes information on all the active employees of venture capital firms, particularly partners whose exit is most likely to have an adverse impact on the parent firm. Phillips (2002) finds negative performance effects spinoffs in the legal industry, however the data only include a general failure indicator. Finally, Gompers, Lerner and Scharfstein (2005) test two models of "entrepreneurial spawning," one of which implicitly predicts significant spinoff formation in the venture capital industry. They show that a strong predictor of spawning – a parent firm's exposure to venture capital funding – fosters an environment of entrepreneurial learning. Venture capitalists act as mentors or teachers of entrepreneurship, while many started their careers as entrepreneurs outside of venture capital. Entrepreneurial activity of venture capitalists should follow.

Motivated by a model of spinoff formation by Cabral and Wang (2009), I first study the characteristics that predict what types of venture capital partners leave their firm to form a spinoff. Their model predicts that high type employees will always find it advantageous to attempt a spinoff, while low type employees will only do so if they see their current firm failing. Analysis of who leaves and who stays requires a set of comparable non-spinoff founders. To ensure that each partner is in a very similar decision-making setting, the data pools co-workers at parent firms. The estimator addresses any parent firm heterogeneity with fixed effects. As predicted by the Cabral and Wang model, venture capital partners in the top quartile of IPO rates (high types) and those in the bottom quartile (low types) working at soon-to-fail parent firms are most likely to leave and start a spinoff. Next, I investigate the impacts of spinoffs on the parent firms.

The paper's second major contribution is an analysis of spinoff impacts on parent firms that exploits a rich panel of investment outcomes. The finding that high quality partners sort into spinoffs and the low quality partners spinoff when their parent firm is failing implies that one should observe a fall in a parent's post-spinoff performance. The high-type partner may take with her knowledge gained at the parent firm, deal flow or her social network and transfer it to the spinoff. A low-type partner leaves when performance is falling or has begun to fall. In contrast to earlier studies of spinoff impacts (see Phillips (2002), Wezel, Cattani and Pennings (2006)) and similar to Campbell et al. (2009), the data include outcome variables that allow for identification of parent performance over time. A panel estimator of IPO probabilities shows that parent performance is lower for two years after spinoff formation. Of course, if spinoff founders time their exit based on parent performance or the market, then the negative impact is not causal. A third contribution of this paper is the explicit accounting of this endogeneity with an instrumental variables estimator. Using a proxy for entry costs as an instrument for the spinoff event, the IV estimates reveal a stronger negative impact than found with OLS. The corrected estimates predict a 50% fall in the probability a parent's post-spinoff investments go public. These adverse consequences are not mechanically driven by the low type partners leaving failing firms, nor are they driven by unobserved parent heterogeneity.

The discovery of positive endogeneity bias reveals how the typical high-type venture capital partner times her spinoff. She exits as the parent is doing well rather than at the peak of its performance. Any simple analysis of post-spinoff performance that ignores this endogeneity will thus understate impacts. There are several possible explanations for the adverse impact on parent firms. First, the sorting of spinoff founders shows that the best partners often leave and thus take their human capital with them. Similarly, Ljungqvist et al. (forthcoming) show that entry costs are lower if a new VC firm has connections to incumbent VC firms. A potential spinoff founder may have to build a social network – along with a history of investment success – before leaving their parent firm. Such networks are a key asset of most venture capital firms (see Hochberg et al. (2007a)), so any transfer of the spinoff founder's network from parent could harm its performance. Preliminary estimates show that spinoff founders and their former co-workers have many similar social network characteristics at spinoff. Spinoff founders do differ in their "closeness centrality": relatively more social paths between venture capitalist pass through the average spinoff founder. Finally, I test the Klepper and Sleeper (2005) hypothesis that spinoffs compete with parents and a similar idea that spinoff formation coincides with an increasingly competitive environment. Including controls for market competition among VC firms does not alter the estimates.

The paper proceeds as follows. Section 2 surveys the theoretical and empirical literature on spinoffs. Section 3 details the venture capital firm and Section 4 describes the data source and data collection. I define spinoffs in the venture capital industry in Section 5, followed by a summary of spinoff and parent firms in Section 6. Next, Section 7 details the motivating model of Cabral and Wang (2009). Section 8 presents the results of which partners leave to start their own firms. Section 9 presents the model and empirical results of spinoff impacts on parents. Robustness results follow in Section 10 with a short discussion of further work in Section 11.

2.2 Previous studies

A rich theoretical literature models the causes and consequences of spinoff formation. Klepper and Sleeper (2005) present a model where spinoffs inherit important characteristics of the parent firm. Tested on a data from the laser industry, they find that more successful firms have higher spinoff rates, while firms where knowledge is more capital-based have lower spinoff rates. Similarly, Franco and Filson (2006) posit that workers acquire knowledge at parent firm and then attempt to imitate that technology at a new firm. They test this “knowledge diffusion” hypothesis on spinoff data from the hard drive industry. Hellmann (2007) lets workers create new innovations at the firm and asks how ownership of such ideas impacts new firm creation, while Braguinsky and Oyama (2007) present a matching model where high-quality workers sort into self-employment. Cabral and Wang (2009) combine a model of heterogeneous entry costs between insiders (i.e. existing industry workers) and a learning process for new workers. Finally, Thompson and Klepper (2006) formulate a theory that can capture the wide array of empirical regularities found in the spinoff literature. The authors posit that a model with “strategic disagreements” can explain much of the findings.

Many authors investigate the causes and consequences of spinoffs across a variety of industries. A few studies investigate the individual characteristics that predict entrepreneurial activity such as spinoffs. Groysberg, Nanda and Prats (2009) study the mobility of research analysts at investment banks and find those in the upper tail of ability are most likely to start their own firms. Phillips (2002) studies 50 years of mobility among Silicon Valley law firms and hypothesizes that spinoffs are a transfer of resources from the parent to the new firm. He shows that type of employee that leaves alters any impact on parent performance. For example, he shows that spinoffs formed from failing firms have shorter lifetime that other spinoffs. Elfenbein, Hamilton and Zenger (2009) find that the smaller firms spawn more new firms. They argue the results may result from heterogeneity in the kind of workers that reside at small versus large firms. Unlike many empirical studies of spinoffs, Hirakawa, Muendler and Rauch (2010) use a representative database of firms across all industries. The authors can compare de novo entrants and spinoffs and find that the latter start larger and survive longer. Several authors study the impacts of spinoffs on parent firms. Thompson and Klepper (2006) find a negative impact and argue that it stems from the loss of a quality employee. Klepper and Sleeper (2005) show that spinoffs produce similar products to their parents and thus attribute some of the negative performance impacts to increased competition. The learning model of Cabral and Wang (2009) suggests that negative impacts depend on the parent type, but any such impacts stem from the loss of a good employee (on average). Studying the Dutch accounting industry, Wezel et al. (2006) study competitive changes due to mobility of employees among firms and illustrate that spinoff location choice alters the impact on parent performance.

2.2.1 Parallel study

This paper is similar to recent work by Campbell et al. (2009) that studies spinoff formation in the legal services industry. Using a panel of employment histories from the Census, the authors ask what employee characteristics lead to exit and how exits impact parent firms. The data includes earnings at both the individual and firm level, which the authors use as a performance measure. They find that employee mobility to new startups has a negative impact on parent firm performance and that high type workers (as proxied by earnings) are less likely to leave the firm to either start a new firm or move to an existing one. However, high-earners at law firms are often the partners that own the firm and thus have limited mobility options. Only when conditioning on ability do they find that worker quality positively correlates with spinoff formation. The results indicate that much of the mobility between law firms and to new laws firms comes from the low-tenure summer law students or new partners.

This study differs from Campbell et. al. in several ways. Despite the level of detail, the restrictions on the data used in Campbell et. al. require significant aggregation of the mobility measures. This paper uses data on all active employees at venture capital firms and tracks the firm's investment outcomes over time. Performance data only requires that a VC partner sit on an entrepreneurial board, which is standard practice for almost all venture capitalists. Also, I address the *endogeneity* of spinoff timing and present an unbiased estimate of the impact of spinoffs on parent firm performance.

2.3 The venture capital firm

Venture capital (hereafter VC) firms are partnerships, structured much like law firms. Metrick (2007) describes the structure of VC firms and the compensation of its employees. There are three roles at a VC firm: Associates, Partners and Managing Partners roles at a VC firm. Associates do not lead investments nor take any share of the profits earned by the firm. These employees typically perform the due diligence and screening of entrepreneurial firms. Some Associates are on the Partner track, while others are not expected to move up within the firm. Partners are the lowest level that earn a share of management fees and profits. Most partners (expect Venture Partners) sit on entrepreneurial boards and lead investments. Compared to the highest partner-level, Partners receive the smallest share of the profits. Finally, Managing partners receive the largest share of both the fees and carry and manage the firm's "best" deals. These partners are typically labeled "key man" at the firm, which are the individuals that cannot legally leave the firm to start a new firm. LPs define a small set of partners in this way so that the basic composition of the VC firm does not change over time. Thus, those employees that leave VC firms to start new firms are often either Partners or Associates.

2.4 Data

The paper uses the VentureOne database provided by the Dow Jones subsidiary VentureSource. The sample covers the venture capital market from 1987 to 2007 and tracks investments of $361 billion in 55,457 rounds and 16,849 companies. VentureOne collects their data on venture-capital backed companies with surveys of venture capitalists and entrepreneurial firms. The data lacks financings where corporations or institutions are the only investors in a particular company. For all financings that involve a venture capitalist, VentureOne claims near perfect coverage of 1992 – present. Smaller (in total assets) venture capitalists that invest alone in an entrepreneurial firm are less likely to be observed than the average size venture capitalist. However, if the small investor co-invests with larger venture capitalists already in the dataset, VentureOne starts to actively track the former's financings. For this study, I focus on the rich data available on members of the entrepreneurial board.

For each entrepreneurial company in the VentureOne database, there includes a list of "current" (as of 2007) and former venture capitalist board members. I had to make significant changes to the data on board members due to a mismatch of individuals and venture capital firms. Simply, the raw database does not accurately track who works where over time so if a partner leaves her firm to join another, then the firm-partner pair is incorrect. A supplementary database provided by VentureSource along with the list of investors by entrepreneurial company corrects these issues. The final database is the first of its kinds that tracks the employment histories of venture capital partners. For this study, I must label those partners that started a new firm and also founded the firm; a feature unavailable in the data.

I compiled a list of venture capital firm and partner names and conducted a web search for their online biographies. The vast majority of venture capitalists list their full employment and educational histories on their websites. For example, most venture capital firms have a "Team" or "About Us" page that details each partner at the firm. I scraped this data from over

500 prospective venture capital spinoffs and identified whether the partner was listed as a founder or co-founder at the firm. Then, the list of spinoff firms and their founders are merged with the rich outcome data on financing events. For each entrepreneurial firm, the data include the dollars invested, the venture capitalist investors and the exit types. Exits include initial public offerings, shut-downs and acquisitions. The panel of employment histories is built on the financing event by matching individual partner with her venture capital firm and in turn the financing event. Table 2.1 details the major parts of the data.

The "Fraction IPO" are the proportion of entrepreneurial firms that via initial public offering by 2007. The pre-2002 equivalent considers only those firms that we founded prior to 2003, which represents an important sub-sample in the analysis below. The average standard VC (i.e. non-corporate) has held 18 board seats. The data on board seats includes over 13,000 of the 16,849 total entrepreneurial firms. Among the 1632 VC firms, an average of two VC partners (which may be at the same VC firms) sit on these entrepreneurial boards.

2.5 Defining spinoffs

A new VC firm is a spinoff if it has at least one founder that previously worked at an incumbent VC firm. The list begins with all new firms founded from 1992 - 2007. A new firm is observed after it makes its first investment and receives a board seat. This requirement limits the set of new firms slightly because not all venture capital investors receive board seats when they invest. Second, board seat activity identifies all those employees that sat on a entrepreneurial board within a year of the firm's founding and the set of possible spinoff founders.

The condition that the potential founders sit on a board seat excludes individuals who start new firms and simply act as a CEO or manager. Also, many firms founded during the dot-com boom simply supplied capital to cash-hungry entrepreneurial firms. Without board seats, many of these VC firms will not be counted in my tally. With this list of original employees, online biographies identify firm founders.

Last, a spinoff founder must have past employment at another VC firm. These spinoff founders could be past associates, partners or managing partners at their previous job. From this set I eliminate serial founders and label all firms as spinoffs or non-spinoffs and all active partners (i.e. those that sit on entrepreneurial boards) as spinoff-founder or non-spinoff-founder. Figure 2.1 presents the number of new firms and new spinoffs by year. On average, 15% of all new firms are spinoffs each year, while the sharp increase in both firm types follows the increase in dollars invested during the boom era of 1998 - 2000.

2.5.1 Dating spinoffs

Dating spinoff formation is not straightforward. Although the year founded and first observed financing date of each VC firm is known, these are typically not the dates the founders begin working at the firm. The founder's last observed financing and board seat at the parent firm is another alternative for spinoff formation date. In discussions with venture capitalists, I learned that the real founding date is typically in between these two dates. Starting a new firm requires at least several months of fund-raising, while leaving the parent firm demands some spinning down of board member responsibilities. Those same conversations revealed that the latter requirement is relatively more flexible and suggests that the real founding date of the spinoff firm is nearer to the last investment at the parent. The analysis below sets spinoff founding dates as the last investment made at the parent firm.

2.5.2 Spinoff founders

Table 2.2 presents statistics on spinoff founders and all other VC partners. It is difficult to create a comparison group for these founders because all other founders lack history in the database. Across the sample period, partners that started new firms have more board experience and have been venture capitalists longer. Such differences stem from the fact that spinoff founders have – by definition – at least two industry jobs. Spinoff founders and others have indistinguishable success rates as proxied by IPO outcomes, while the former invest in more early stage investments than the average partner.

2.6 Spinoff and parent firms

Table 2.3 compares spinoff firms to all types of other, non-parent firms like banks, corporations and standard venture capitalists.[2] The second column is the best comparison because the spinoff definition only includes standard venture capital firms. Spinoff firms and other non-parent firms differ little in age, but many more of the former were founded during the boom years of 1998 - 1999.[3] Difference in year founded will be important when addressing the endogeneity of spinoff formation timing. Spinoff firms also have higher survival rates than the average VC, but similar initial assets.

Table 2.4 details the characteristics of parent firms and non-spinoff firms. There are a

[2] See Ewens (2010b) for an analysis of spinoff versus de novo entrants.
[3] This apparent contradiction is reconciled with different survival rates.

total of 232 parent firms with at least one spinoff. Many parents had multiple spinoff events over the 20-year sample. Compared to non-spinoff firms, parents are older and larger, which is somewhat expected because spinoffs are more likely with more employees. Parent firms do not distinguish themselves with higher success or exit rates. Last, some 70% of parent firms are standard venture capitalists, while the remaining are either corporations or other private equity firms.

2.7 Cabral and Wang (2009)

The Cabral and Wang (2009) (hereafter Cabral and Wang) model of spinoff formation motivates much of this paper's analysis. Firms in their model are comprised of a manager and an employee. Each type of worker can be one of two types — high (H) or low (L) — that in combination determines the profits of their firm. Firms can be on of four types: HH, HL, LH or LL. The employee and manager only learns of their type after joining the firm. New employees enter every period and an exogenous process shutdowns a proportion of existing firms. Existing employees also make exit decisions in each period. The decision on whether to start and manage a new firm depends on entry costs, outside options, parent type and whether the employee works at an incumbent firm. Employees that leave their existing firm to start a spinoff – i.e. insiders – face lower entry costs than new employees to the market. The model gives predications about who spins off a new firm and what the impacts of those spinoffs are on the parent firm.

The first set of predictions from the Cabral and Wang model concerns what types of employees decide to attempt a spinoff.

Hypothesis 1: High type employees will attempt to spinoff [Type I Spinoff]

Hypothesis 2: Low type employees will attempt to spinoff if they know their firm will exit. [Type II Spinoff]

The model also implies impacts on survival rates of parent firms post-spinoff.

Hypothesis 3: Parent firms of type HH see no change in survival rates.

Hypothesis 4: If a firm is not of type HH, it has a lower survival rate post spinoff.

Hypothesis 5: A firm's survival rate conditional on spawning a low-type manager is lower than its survival rate conditional on giving birth to a high-type manager.

The final three hypotheses are somewhat extreme in the venture capital market. Complete shutdown of venture capital funds would take a prolonged period of time as funds are legally structured to last 8 - 12 years. Next, partners at venture capital firms are part owners of the firm. Thus, the division of employee and manager does not directly apply. This difference from the economic model suggests that the loss of a VC partner is much like the loss of a co-manager. In the following empirical results, I will focus on simply searching for impacts of spinoffs on parent performance. The lack of firm shutdown as a response to the loss of a partner means that the impact analysis will have to use more subtle measures of firm performance over time.

2.8 Who spins?

2.8.1 Hypotheses

The Cabral and Wang model has two clear implications for who leaves an existing firm to start a new firm.[4] In the context of venture capital firm spinoffs, I test two hypotheses:

1. High type partners are more likely to start a new spinoff firm.

2. Low type partners only attempt to start new firms if their parent firm is about to fail.

2.8.2 Data construction

Accurate analysis of who stays and who leaves requires grouping spinoff founders with non-spinoff founders that face the same decision-making environment: their co-workers. First, I identify all spinoff firms and parent firms as described above. Next, I construct the list of employees at each parent firm as dated by the investments made. Entrepreneurial board activity identifies who works where and when, however some partners are inactive for years prior to each spinoff. The final sample only includes partners at a parent firm that sat on an entrepreneurial board within three years of the spinoff date.[5] Labeling partners high or law uses their history of entrepreneurial investment outcomes. A partner must have at least two such investments to be included in the sample, so the final set of partners includes only active VC partners at each parent firm. These restrictions drop those VC employees such as Associates that do not sit on entrepreneurial boards. Similarly, if a VC works as an executive at a VC firm but does not sit on boards and then starts a firm, they will lack prior activity. However, such a partner is unlikely to leave as an executive at firm A and then later start sitting on entrepreneurial boards at firm B.

The Cabral and Wang theory posits two types of employees at a firm: high and low. The entrepreneurial company on which a VC partner sat on the board can end up going public,

[4]The Cabral and Wang model posits behavior about spinoff attempts rather than successful attempts. The data that I use throughout will only contain successful spinoff attempts.

[5]Results are insensitive to the cutoff, particularly using 2 or 4 years.

get acquired or go out of business. I use the IPO event as the distinguishing characteristics of outcomes for VC partners and compute the fraction of investments that have an IPO for each of the active partners at a parent firm. Call this partner i's IPO rate and define a "high type" partner as one that has an IPO rate that is in the top quartile of all IPO rates for relevant partners in the sample. "Low types" are those partners that have IPO rates in the lower quartile of the sample distribution.[6]

A particular parent firm may have multiple spinoffs over time. Each one resets a firm as a new parent, increasing the sample size. Finally, parent types must be labeled for the test of Type II spinoffs. If the parent fails within three years of spinoff formation, it is labeled as an "exit" (i.e. type LL).

2.8.3 Data summary

Tables 2.6 and 2.7 describes the characteristics of parent firms in the regression sample, while Table 2.5 presents the full set of parents. The restricted sampled include all parents that have at least two active employees within three years of spinoff formation. All measures are computed as of the spinoff formation. Table 2.7 includes the same VC firm multiple times if the parent had more than one spinoff over the sample period. All the conditions set above (e.g. at least two investment for each partner) eliminate many parent firms. Comparing the two tables shows that parents in the regression sample are younger, invest in more entrepreneurial companies and have higher survival rates than the average parent firm. If such observable differences correlate with the type of partner that decides to spinoff, the results below are not completely general.

Table 2.8 details the characteristics of partners at parent firms prior to spinoff formation. Unconditionally, there is also little difference in age, experience and IPO rates between spinoff and non-spinoff founders. Also, the conditions for regression analysis do not create any observable differences between partners included and excluded from the regression.

2.8.4 Model

The dependent variable for the analysis - $Spin_{ij}$- is equal to 1 if partner i and parent firm j leaves to start a new VC firm. Independent variables include partner age or experience and fixed effects for parent firms (at each spinoff). To test for Type I and II spinoffs, I use the continuous measure IPO rate with a terminal date equal to the spinoff date. The indicator for

[6] Results are insensitive to using the bottom and top third of the distribution.

high type - H_{ij}- equals one when the partner's IPO rate is in the top quartile over the whole sample period. Type II spinoffs occur when a low type partner leaves a failing parent. Define the low type variable L_{ij} equal to 1 if the partner's IPO rate is in the bottom quartile of IPO rate. Finally, the model includes an interaction term of type and a dummy E_{ij} for whether the parent failed within 3 years of spinoff. The reduced-form model with parent fixed effects is

$$Spin_{ij} = \alpha_0 + \alpha_1 H_{ij} + \alpha_2 L_{ij} + \alpha_3 L_{ij} E_j + \alpha_4 H_{ij} E_j + \alpha_j + \alpha_5 X_{ij} + \varepsilon_{ij} \tag{2.1}$$

where X_{ij} are partner characteristics at spinoff. For example, a high type partner that spins-off from a surviving parent will have $H_{ij}, Spin_{ij} = 1$ and $L_{ij}, E_j = 0$. Note that a time series is not available, so the fixed effect α_j absorbs all parent characteristics (including the Exit indicator). The Cabral and Wang model implies:

- $\alpha_1 > 0$
- $\alpha_2 < 0$
- $\alpha_3 > 0$
- α_4 ambiguous, likely zero

2.8.5 Results

Tables 2.9 and 2.10 present the logit and probit results with the respective fixed or random effects controls. The first columns of each table show the simple relationship between high type partners and spinoff formation. Relative to all other partner types, venture capitalists in the top quartile of performance have a higher probability of starting a new firm (compared to the whole sample). Column two introduces a new indicator for a partner in the bottom quartile. This variable and the high type indicator are closely related, however, the raw correlation is only -21% so multicollinearity is not a severe issue. The coefficient on the high type variable is still positive (Type I spinoff), but now only significant at the 10% level. Column 3 also introduces the interaction of the type variables and an indicator for whether the parent firm exited as of the end of the sample. Recall that the Cabral and Wang model predicts that the low type coefficient should be negative, while the interaction of low type and exited should be positive. Table 2.9 and 2.10 confirm this theoretical implication. The interaction term for low type and exited is positive and significant at the 5% level (Type II spinoff).

The last column in Tables 2.9 and 2.10 include two versions of fixed effect model for limited dependent variable. The logit specification uses the conditional logit (Chamberlain (1980)), while the probit specification uses a random effects framework discussed in Wooldridge (2002). With parent fixed effects, “high type” is now defined within a parent firm. The low type partner at a parent firm still has a lower probability of starting a new spinoff and conditioned on parent exit, the probability increases. The coefficient on the interaction term α_3 dwarfs α_2, confirming the if-and-only-if result from the Cabral and Wang hypothesis 2. For both the logit and probit specifications, high type partners still start more spinoffs, but only at the 10% level. The estimates suggest a direct relationship between a VC partner’s type both within firm and across the population as predicted by the Cabral and Wang model.[7]

2.8.6 Robustness

The results presented in Table 2.10 are similar when the sample includes the set of partners that were active 2 and 4 years before spinoff formation. As the window expands however, the results concerning high type partner exit disappear because the inclusion of more inactive partners weakens statistical power. Results are the same when the parents in the sample only have two active employees, but requiring at least five employees weakens the results due to a small sample size. Coefficient signs are the same throughout these specifications despite statistical insignificance.

2.9 Impact of spinoffs on parents

Both Type I and Type II spinoffs occur in the venture capital industry. There are several reasons why the exit of a VC partner to a spinoff could harm the parent firm’s performance. The exiting partner could take with her a social network built through her investment activity. Several studies have found that one of the most important determinants of VC firm performance is its position in the social network (see Hochberg et al. (2007a)). The loss of a VC partner can also result in a loss of industry experience unique to the individual. For example, the partner may have focused her investments in a particular niche sector that no one else at the parent firm understands. Also, the relatively small size of venture capital firms (4 to 5 partners) suggests that partner exit would alter the hierarchy and decision-making capabilities of the parent firm.

The loss of a partner could also proxy for a change in the parent’s competitive environment. The decision to leave and start a new firm is a function of the entry cost (presumably lower

[7] Note that although it seems mechanical that low type partners will leave from low firms (all partners at low firms are low), the fixed effects model ensures that we are studying difference among partners within firms. The results in fact show that low type partners at non-exited parents have a lower probability of leaving that those at failing parents.

for high type partners) and the probability the new firm will succeed. New firms are founded during times of growth and entry from other non-spinoff firms. Table 2.3 shows that many firms were founded during the hot market of 1998 - 1999. Any observed impact of spinoff formation on parent investment performance could simply relate to the change in competitive landscape. The likelihood that a quality partner leaves also suggests that the new spinoff firm will directly compete with the parent firm. The first step in the empirical exercise will attempt to separate out any such endogeneity in the *timing* spinoff formation.

2.9.1 Data construction

An analysis of the impact of spinoffs on parent firms requires a time series of performance. Some parent firms have multiple spinoffs over their lifetime, so I first expand the sample to effectively create new parent firms for each spinoff event. Without rich returns data, the literature has settled on the IPO event as a suitable measure of investment performance. A time series of investment outcomes (= 1 if IPO) is constructed with dates equal to the first investment in the entrepreneurial company. Controlling for firm age, time effects and simple investment characteristics, better parents have more IPOs. The investment outcomes for the pre-spinoff analysis are only those investments made by the parent firm for which the future spinoff founder did not sit on the board. This restriction helps to ensure that the parent investments were those where the spinoff founder's impact was not direct. The key independent variable is an indicator for the spinoff event.

For every investment outcome event and time period, I create a variable that indicates whether the parent firm had a spinoff occur in the recent past. Figure 2.2 depicts when this variable is "turned on" along with the relevant analysis time frames. Let $t_{i,spin}$ be the date of parent i's spinoff (each spinoff at a VC firm is a new parent). The period of spinoff impact equals a time period of length s post-spinoff. One would expect that any impact of spinoff formation on parent firms would take time as the investment cycles for entrepreneurial firms can be 2 - 5 years. Within those s years, parents with less than two entrepreneurial investments are excluded. After $t_{i,spin} + s$, the dummy for spinoff formation turns to 0 again and the parent's performance is tracked until T_2 years post-spinoff. I also restrict the time period of analysis to the largest of T_1 years prior to spinoff formation and the first observed investment made by the spinoff founder at the parent firm.

Several time-varying entrepreneurial and VC characteristics are available for each investment. One of the leading indicators of whether a investment made by a given VC will go

IPO is the stage of the first investment. Investments made when the entrepreneurial company are very young (i.e. Seed or Series A rounds) are the least likely (all else equal) to go public. Regressions include a dummy for this scenario. Note that if two different parents invest in the same entrepreneurial company at different stages, they will have different values for this variable. Next, the cyclical and boom/bust feature of the VC investment environment necessitates the inclusion of year dummies. Finally, the experience of the parent firm in either years or total dollars invested is an important time-varying characteristic that could impact the likelihood of an IPO. All estimators detailed below will include these variables.

2.9.2 Basic model

Examining the impact of spinoffs on parent performance use the IPO event for each investment made by the parent within $(t_{i,spin} - T_1, t_{i,spin} + T_2)$ time period. IPO_{ijt} is equal to one if parent firm i's investment in entrepreneurial firm j at time t exited via an initial public offering. The indicator HS_{ijt} defines whether a spinoff occurs and is equal to 1 from time $t_{i,spin}$ to $t_{i,spin} + s$ (see Figure 2.2. The full reduced form model is thus:

$$IPO_{ijt} = \alpha_0 + \alpha_1 HS_{ijt} + \alpha_2 t + \alpha_3 X_{1it} + \alpha_4 X_{2ijt} + \varepsilon_{ijt} \tag{2.2}$$

where t is a vector of year dummies, X_{1ijt} includes VC experience and X_{2ijt} includes entrepreneurial companies variables like an indicator for the stage of the investment. The sample only includes investments made up and through 2002 so that the investment has time to exit (IPO or otherwise).

2.9.3 Endogenous spinoff timing

Spinoff founders may time their exit – H_{ijt} – based on the past and expected performance of their parent firm (i.e. IPO_{ijt}). The resulting endogeneity will bias estimate of α_1 in equation (2.2) in several ways, each detailed in Table 2.11. The Cabral and Wang model predicts that low type partners will leave to start a new firm if their parent firm is about to fail. This "jumping ship" scenario result in an upward bias in the OLS estimate of spinoff impacts on parent performance. The Cabral and Wang model also implies that high types will leave once they learn their type, but *independent* of their parent type. VC partners could use their parent firm's success to sell themselves to new clients and the parent's clients (see e.g. Rauch and Watson (2007)). In this scenario, partners leave when the parent firm is in the middle or near the peak of its success ("growth timing") and a simple estimator would underestimate the impact of spinoff formation on parent performance. The summary statistics on spinoff firms indicate that many formed during the boom-era of 1998-1999 when most existing firms had high success rates. This fact points to another source of bias: high type partners time their exit when market entry costs are lowest. Such costs may be lower when excess money flows into the market and in turn, competition is increasing for the parent firm. An OLS estimate of the impact will attribute lower performance to the spinoff event, when in fact increased competition is to blame.

Unobserved heterogeneity can also bias estimates. Unobserved differences between parent firms could induce spinoff formation and also impact the likelihood of an IPO event. For example, the theory that low type partners can only leave failing firms suggests that the unobserved parent type is correlated with the decision to exit. The unobserved heterogeneity has an unambiguous impact on the spinoff dummy variable.

2.9.4 Instrumental variable

Any endogenous timing of spinoff events embodied in the series of H_{ijt} can be solved with an instrumental variable. An instrument should predict the timing of a spinoff for a parent firm but not belong in the outcome equation (2.2). A VC partner's outside options such as starting a new firm or exiting the industry depend on the available capital and the state of the IPO market, which influence entry costs. The Cabral and Wang model lets the entry costs of outsiders – new employees – exceed that of incumbent employees. In venture capital firms, not all partners decide to start a spinoff, so entry costs should differ within insiders. The proposed instrument for the endogenous spinoff variable H_{ijt} proxies for the entry costs faced by insiders at a parent firm.

The range of entrepreneurial industries receiving venture capital changes over time. For example, clean energy and green technologies saw a large increase in funding starting in 2006. The dollars for these new firms shifted away from existing sectors in information technology and biotechnology, but also came from new VC firms. The growth of a new entrepreneurial industry is an excellent environment for new venture capital firms. The instrument for the timing of spinoff formation summarizes the composition of industries in a parent's peers' portfolios. For each time t, I track the portfolio of past investments made by VC firm i in each of the twenty entrepreneurial industries. Let N_{it} be the total number of entrepreneurial investments made by firm i as of t and n_{ijt} be the number of investments in industry j (K total). The "industry diversity" measure for a VC firm i at time t is fashioned after the Herfindahl index:

$$ID_{it} = \sum_{j=1}^{K} \frac{{n_{ijt}}^2}{N_{it}^2} \tag{2.3}$$

Suppose a VC firm starts its life investing in only two industries. Its ID_{it} will be $1/2$. If the firm branches out into a new sector and by the next time period is equally investing in three separate industries, then ID_{it} will be 1/3. This measure of industry diversity will converge to $1/K$ as the firm diversifies equally among all industries. The instrument builds on the ID_{it} of all the parent's peers.

In almost all non-seed financing events, a syndicate of least two VCs contribute capital to an entrepreneurial company (see Lerner (1994)). Define P_{it} as the set of parent i's co-investors in all their syndicates up to time t. The peers' investment decisions or portfolio composition proxy for the entry cost for a potential spinoff founded by one of the parent's partners. Simply, if the peers' portfolios shift into a new industry, new VC firms should find it easier to gather capital than when the composition of industries contract. The simplest characterization of a parent's peers' portfolio diversification averages their ID_{it} for each time t**:**

$$PID_{it} = \frac{1}{P_{it}} \sum_{p=1}^{P} ID_{pt}. \tag{2.4}$$

This variable represents the average industry diversification of a parent's peers and should predict the likelihood a partner at the firm will leave to start a new firm.

Why should the instrument predict spinoffs?

The instrument captures the change in a set of VC firms' preferences over available entrepreneurial industries. An increase in the number of industries in a parent's peers' portfolios (i.e. a drop in PID_{it}) implies that firms similar to the parent firm are investing in new industries. A significant increase in the amount of industries invested in signals a change in the entrepreneurial environment. New VC firms such as spinoffs should find it easier to enter the market when entrepreneurial firms in relatively new industries require capital. The ease stems from a lack of flexibility at incumbent VC firms to dramatically shift their investment focus to new opportunities. Conversely, an increase in PID_{it} implies that the number of unique industries a parent's peers invest in decreases. A fall in industry diversification correlates with a decrease in investment opportunities and a worse environment for new firm formation. Thus, there should be a negative relationship between PID_{it} and the probability of a spinoff at time t.

Exogeneity

The PID_{it} variable satisfies the exogeneity condition for several reasons. The instrument measures the composition of VC portfolios, while the dependent variable is the outcome of an individual entrepreneurial investment. The level of the instrument says little about the characteristics of the entrepreneurial company nor the chances it will go public. Next, the averaging over a large set of peers with a lag partially ensures that the level of the instrument is unrelated to the individual entrepreneurial outcome IPO_{ijt}. The ID_{it} of a parent's peer also excludes all the parent's investments. One possible source of instrument endogeneity could stem from its correlation with the IPO market. For example, a diversifying landscape where the average VC firm is spreading their investments into multiple industries may precede the growth of a particular hot market for IPOs. Fortunately, the correlation between the sample of PID_{it} and the time-matched Nasdaq return (a good proxy for IPO probabilities) is less than 10%.[8] Also, the regression specifications include year dummies.

Summary of instrument

Table 2.13 shows the characteristics of the industry diversity instrument for all the VCs firms in the sample. It is bounded by one, with a significant proportion of VCs with unity over time. As the measure approaches one, a VC firm is focusing its investments on one particular industry. Figure 2.3 plots the time series of this measure (with missing quarters filled in) for four random firms. A clear monotonic relationship appears which should occur as VCs expand their investment reach and as the number of available industries increases. The instrument used in all analyses is the average industry diversity of all a parent's peers (defined above) as of each quarter. Figure 2.4 plots four random parent firms' PID_{it} and shows that averaging over peers removes much of the monotonicity in the raw measures and thus its correlation with time.

2.9.5 Data summary

After restricting the set of parents using the rules set out in Figure 2.2, 143 parents remain. Tables 2.16 - 2.18 details the characteristics of parents for each regression specification. The data requirements differ for each, so the set of parents changes slightly. There is very little difference across the samples or with each and the full sample in Table 2.5.

[8]The correlation between between the average PID_{it} across firms and the Nasdaq is also small.

2.9.6 Basic Results

Due to the binary nature of the endogenous regressor and a binary dependent variable, a simple linear probability in a 2SLS framework will not achieve consistency. (See Wooldridge (2002)) Thus, the estimator is either a probit or logit with corrections for endogeneity and unobserved heterogeneity. Table 2.12 presents the simple probit and logit results for the basic model of spinoff impacts. One can think of these estimators as similar to a pooled OLS where the multiple observations per parent is ignored.

For each specification, the coefficient on the HS_{ijt} variable is significant and negative. The coefficient on parent age is insignificant in each column, however, it is an important control variable because spinoff founders may require time to build their human capital. In unreported marginal effect estimates, a spinoff event lowers the probability of an IPO outcome by 20% (from 26% to 23%). These uncorrected results indicate that spinoff formation is correlated with lower probabilities of IPO for parent firms. Of course, this could be due to the endogeneity of spinoff formation.

2.9.7 IV Results

If the dummy variable for spinoff formation is endogenous, the estimation problem is one of an binary dependent variable and binary endogenous variable. Wooldridge (2002) discusses a IV estimator that uses a probit model for both the "first" stage and the outcome equation. Table 2.14 presents the results of this bivariate probit estimator. The first stage results presented in the bottom section show that the instrument is relevant and has the expected sign. An increase in the diversity of a parent's peer's portfolios increases the likelihood of a spinoff. After addressing the endogeneity, the coefficient on HS_{it} in the third column is still statistically negative and reveals positive endogeneity bias.

Using the coefficient estimates from the probit+IV, I calculate the change in predicted probability of an IPO for a parent firm. The IV framework results in a slightly different interpretation of coefficients because the HS_{it} variable in the outcome equation is no longer binary, but rather a predicted probability from the first stage regression. Nonetheless, moving from a predicted probability of a spinoff of 25% to 75% lowers the probability of an IPO for the parent firm from 26% to 13%. This compares to a marginal effect of 26% to 23% predicted by the standard probit (going from no spinoff to spinoff). I conclude that the endogeneity bias for the HS_{it} is positive: the average spinoff founder appears to leave her parent firm when things are going well.

Interpretation

The analysis of who leaves to start a spinoff revealed that high type partners leave, so it should not be surprising that there is a negative impact on the parent. However, the implied marginal effects of the IV results show that the endogeneity bias is severe and positive. Thus, the exit of a VC partner to a spinoff has a significant impact on parent performance and that impact is under-estimated when the endogenous timing is ignored. The IV-corrected estimates effectively answer the question: "What if you randomly chose a time to remove a partner from the parent firm?" Note that the randomization is not over partner type, so most will be high type venture capitalists. Table 2.11 presents several hypotheses about the possible bias. Empirically, the "growth timing" phenomenon – where a VC partner exits when the parent firm is in the middle of success – dominates. The endogeneity correction also addresses the hypothesis that spinoffs are timed to periods of increased new firm growth and competition. Thus, the impact on parent performance is not related to changes in market conditions.

Other explanations

Endogeneity of the instrumental variable could generate the observed changes in coefficient estimates. As the instrument value falls, the diversity of a parent's peer's portfolios increases. Omitted variables in the outcome equation (2.2) that are not captured with the control variables or year dummies could correlate with these changes. For example, there may be some time-varying market characteristics that change the likelihood of an IPO. If these characteristics are correlated with the changes in VC portfolio diversification, then the instrument may violate the exogeneity condition. Inclusion of the year dummies throughout the regressions should alleviate this problem, particularly for the boom era. Much of the difference in the IPO market are closely related to the cyclicality in the VC investment environment, which the year dummies address. Moreover, the strength of the relevancy in first-stage results (i.e. p-value for coefficient on peer diversity) suggests that any violation of instrument exogeneity would have be extremely severe. I conclude that the changes due to the endogeneity corrections are real.

2.9.8 Fixed effects

Although estimates address the potential endogeneity of spinoff formation, results may be confounded by unobserved parent heterogeneity. For example, Sorensen (2007) shows that an important distinguishing feature of VC firm performance stems from differences in "deal quality." Such a measure is unobserved and possibly correlated with independent variables. A consistent estimator that incorporates a binary dependent variable and a binary endogenous regressor in a panel setting is difficult. Work is in progress on implementing the Carrasco (2001) estimator which will address all the empirical issues. A simple first approximation to the potential bias generated by unobserved heterogeneity can be found by estimating FE or RE regressions without the IV corrections.

Table 2.15 presents the results of each fixed effects model compared with the simple pooled logit and probit estimates. The coefficient on HS_{it} remains statistically negative in both the probit and logit frameworks. Moreover, the marginal effects implied by the estimates (unreported) are nearly identical to the simple logit or probit without parent fixed or random effects. The evidence indicates that unobserved heterogeneity does not drive the uncorrected negative relationship between spinoffs and parent performance.

2.10 Robustness checks

The negative impact of spinoffs on parent firm performance is robust to several different specifications.

2.10.1 Failed parents

The strong negative impact of spinoffs on parent firm performance may stem from low type partners leaving failing firms. When failed firms are excluded from the sample, the basic results are the same. Table 2.19 shows that the coefficient on the HS_{it} variable falls for the survivors sub-sample, but the differences are statistically insignificant. The strong negative impacts are not driven by failing parent firms.

2.10.2 Competition

The results thus far have little to say about the source of the negative impact of spinoff formation. Klepper and Sleeper (2005) find that some of the impact of spinoffs on parent performance is due to increased competitive pressure from the new spinoff firm and other new firms founded at the same time. I test this hypothesis with a competition measure motivated by the “money chasing deals” concept (see Gompers and Lerner (2000)). The IPO event dependent variable should correlate with the number of VCs per active entrepreneurial firm, which alters investment valuations and the number of marginal entrepreneurial firms the receive financing. A spinoff is more likely to occur during times of increased new firm growth; an environment of degrading parent performance because of increased competition. The competition variable – displayed in levels in Figure 2.5 – measures the annual growth in the number of VC firms to number of financing events for each quarter. The variable increases as the number of active VCs to entrepreneurial firms increases. Table 2.20 shows the results of the basic impact regressions with the additional "growth in VCs per deal" variable. The impact of a spinoff is still statistically negative, indicating that the source of the fall in performance is not solely due to increased competition.

2.11 Further work

Work is in progress on estimating a full fixed effects, IV and binary dependent variable model following Carrasco (2001). The paper has yet to identify the cause of the lower post-spinoff performance. Post-spinoff changes in the parent's social network could also explain some of the observed impacts. I posited above that one possible intangible asset transfer from the parent to spinoff was the network of connections made by the spinoff founder. If this is true, we might expect some structural break in the parent's network evolution post-spinoff. I have yet to condition the spinoff event on the type of founder. Work continues on adding an interaction term that indicates whether the exiting employee was a high type at spinoff formation. Next, more robustness checks are required to test the sensitivity of results to the cutoff time (T_1 and T_2). Last, I only consider investments made up to 2002 so that there is ample time for outcomes to occur. However, many of the spinoffs occurred in 1999 - 2000. Given that the HS_{it} variable equals one for at least 2 years (i.e. s), this means that it will not switch back to zero for parents that had late-sample spinoffs. I plan to focus on the sub-sample of parents that had spinoffs at least prior to 2000 so that this important HS_{it} variable can switch back to zero for the majority of parent firms.

2.12 Conclusion

I find that high type venture capital partners or low type partners at failing firms are the most likely to start a spinoff firm. Entry costs for venture capital firms thus depend on past success and possibly network status. As expected, there are adverse effects on the parent firms that lose such partners. A robust analysis of such impacts reveals that endogeneity bias is severe and positive. Spinoff founders, particular high types, leave their parent firm when times are good and take important, intangible assets with them. Standard estimators that attempt to isolate spinoff impacts will thus underestimate these effects. The results are not driven by an increase in competitive pressures, nor the mechanical failing of parent firms post-spinoff. The positive endogeneity bias illustrates that even parent firms could underestimate the impacts of losing a quality employee. Finally, the negative impacts of partner exit to a spinoff show that any cross-sectional study of venture capital firm performance may in fact be studying the differences in those firms' partners.

2.13 Tables and Figures

Table 2.1: Summary statistics for board member data

Variable	Mean
Entreprenurial companies	13724
Total VC partners	8733
Fraction IPO	0.12
Fraction Acquired	0.28
Fraction Out of Business	0.2
Fraction Private	0.41
Fraction IPO (pre-2002)	0.15
Fraction Acquired (pre-2002)	0.34
Fraction Out of Business (pre-2002)	0.26
Fraction Private (pre-2002)	0.25
Total VC firms	2773
Total Standard VC firms	1632
Board seats per VC (all)	13.31
Board seats per VC (standard)	18.59

Table 2.2: Summary of spinoff founders and other partners (at least 4 board seats)

	Non-spinoff founders	Spinoff founders	Total
Years sitting on boards	7.366	10.71	7.682
	(4.696)	(5.003)	(4.825)
Total boards	8.897	11.49	9.142
	(6.097)	(7.366)	(6.272)
Fraction IPOs	0.108	0.128	0.110
	(0.155)	(0.136)	(0.154)
Year first board seat	1996.2	1994.1	1996.0
	(5.150)	(5.189)	(5.191)
Fraction early stage	0.642	0.645	0.642
	(0.237)	(0.215)	(0.235)
Observations	2788	291	2552.0
	(0)	(0)	(730.6)

Note: Includes all spinoff founders and all other partners.
Mean of each variable with standard deviation in parentheses.

Table 2.3: Spinoff and non-spinoff firms.

	Non-spinoffs	VC non-spinoffs	Spinoffs	Total
Year founded	1992.3	1996.6	1999.1	1995.0
	(19.03)	(6.197)	(3.757)	(13.56)
Total assets (millions)	2026.8	280.1	223.0	1039.5
	(15206.4)	(4081.2)	(362.5)	(10479.8)
Percent exited	0.128	0.232	0.113	0.176
	(0.334)	(0.422)	(0.317)	(0.381)
VC Age	5.578	6.146	6.676	5.944
	(4.636)	(4.672)	(3.423)	(4.574)
Fraction standard VC	0	1	1	0.562
	(0)	(0)	(0)	(0.496)
Observations	3843	1811	236	2563.8
	(0)	(0)	(0)	(1206.5)

Note: Includes all spinoff firms and non-parent firms.
VC-only firms excludes corporations, hedge funds, etc.

Table 2.4: Summary of parent firms and non-spinoffs as of exit or 2007

	Non-parents	VC non-parents	Parents	Total
Year founded	1992.3	1996.6	1991.7	1994.4
	(19.03)	(6.197)	(7.431)	(13.83)
Total assets (millions)	2026.8	280.1	775.6	1099.8
	(15206.4)	(4081.2)	(2499.4)	(10697.2)
Percent exited	0.128	0.232	0.281	0.187
	(0.334)	(0.422)	(0.451)	(0.390)
VC Age	5.578	6.146	10.82	6.123
	(4.636)	(4.672)	(4.954)	(4.800)
Fraction standard VC	0	1	0.675	0.529
	(0)	(0)	(0.470)	(0.499)
Observations	3843	1811	232	2656.1
	(0)	(0)	(0)	(1136.0)

Note: Compares parent firms and all non-spinoff firms.
Sample of VC firms excludes corporations, banks and other similar institutions.
Mean of each variable with standard deviation in parentheses.

Table 2.5: Characteristics of all parents

Variable	**Mean**	**Std. Dev.**	**Min.**	**Max.**
Year Founded	1986.81	11.58	1895	2003
Exited	0.3	0.46	0	1
CA or MA	0.43	0.5	0	1
Dollars invested (millions)	2090.22	3130.82	8.4	21655
Total financings	153.08	204.04	1	1377
Total entrepreneurial companies	48.34	68.48	0	412
Age (years) at spinoff	6.94	4.97	0.07	22.09
N		223		

Table 2.6: Parent characteristics from FE regression, multiple spinoffs

Variable	Mean	Std. Dev.	Min.	Max.	N
Year Founded	1984.05	9.73	1953	2003	131
Exited	0.08	0.27	0	1	138
CA or MA	0.53	0.5	0	1	138
Dollars invested (millions)	2369.48	2944.91	72.68	16442.13	138
Total financings	218.98	198.3	6	1149	138
Total entrepreneurial companies	76.34	59.9	0	348.24	138
Age (years) at spinoff	12.24	5.2	0.08	23.41	138

Table 2.7: Parent characteristics from FE regression, no duplicates

Variable	Mean	Std. Dev.	Min.	Max.	N
Year Founded	1984.96	10.24	1953	2003	76
Exited	0.09	0.29	0	1	80
CA or MA	0.5	0.5	0	1	80
Dollars invested (millions)	1882.36	2328.13	77	15334.79	80
Total financings	169.05	152.35	6	808.5	80
Total entrepreneurial companies	61.86	51.39	0	251.83	80
Age (years) at spinoff	11.31	4.89	0.08	22.09	80

Table 2.8: Who spins: Partner characteristic

	Non-spinoff founder	Spinoff founder	Total
Total investments	7.826	8.036	7.887
	(6.594)	(6.479)	(6.559)
Fraction IPO	0.199	0.254	0.215
	(0.221)	(0.234)	(0.226)
Fraction early stage	0.661	0.689	0.669
	(0.259)	(0.225)	(0.250)
Time as VC (years)	5.454	5.681	5.520
	(4.464)	(4.358)	(4.434)
Observations	1094	444	906.4
	(0)	(0)	(294.6)

Note: Compares spinoff founder characteristics to all co-workers.
Mean of each variable with standard deviation in parentheses.

Table 2.9: Which partner leaves the parent firm: Logit and FE

	Model 1	Model 2	Model 3	Conditional Logit
High type	0.838*	0.619^{+}	0.721^{+}	0.865^{+}
	(0.373)	(0.361)	(0.368)	(0.508)
Log number inv.	0.300*	0.286*	0.308*	0.365*
	(0.0933)	(0.0924)	(0.0935)	(0.106)
Low type		-0.301*	-0.355*	-0.352*
		(0.145)	(0.148)	(0.169)
Low Type X Exited			1.146^{+}	1.142*
			(0.623)	(0.517)
High Type X Exited			-0.445	0.00138
			(1.193)	(1.428)
Parent exited			-0.235	
			(0.463)	
Constant	-1.641*	-1.410*	-1.439*	
	(0.180)	(0.187)	(0.194)	
Observations	1377	1377	1377	1377
Pseudo R^2	0.010	0.013	0.018	0.022

Standard errors in parentheses

Dependent variable is equal to one if the VC partner left to start a new spinoff.

Models 1 - 3 are logit regressions without corrections for parent fixed effects.

High type is equal to 1 if the partner's IPO rate is above the 75th quartile and the *low type* variable is equal to 1 if the partner's IPO rate is below the 25th quartile. *Low Type X Exited* is the interaction of the low type variable and an indicator whether the parent firm subsequent failed (similar for *High Type X Exited*). The variable *Log number inv.* is the log of the number of investments made by the partner up to the spinoff formation and proxies for experience. Includes all parent firms founded prior to 2003 with at least three active employees (defined above) prior to spinoff formation. Standard errors are clustered at the parent level, where each new spinoff creates a new

$^{+}$ $p < 0.10$, * $p < 0.05$

Table 2.10: Which partner leaves the parent firm: Probit and RE

	Model 1	Model 2	Model 3	RE Probit
High type	0.502*	0.370^{+}	0.433^{+}	0.527^{+}
	(0.230)	(0.222)	(0.227)	(0.295)
Log number inv.	0.180*	0.174*	0.187*	0.198*
	(0.0560)	(0.0555)	(0.0562)	(0.0547)
Low type		-0.185*	-0.218*	-0.207*
		(0.0866)	(0.0882)	(0.0896)
Low Type X Exited			0.691^{+}	0.619*
			(0.370)	(0.244)
High Type X Exited			-0.284	-0.354
			(0.712)	(0.796)
Parent exited			-0.137	
			(0.269)	
Constant	-0.998*	-0.861*	-0.879*	-0.888*
	(0.106)	(0.108)	(0.112)	(0.130)
lnsig2u				-1.681*
				(0.248)
Observations	1377	1377	1377	1377
Pseudo R^2	0.010	0.014	0.018	

Standard errors in parentheses

Dependent variable is equal to one if the VC partner left to start a new spinoff. Models 1 - 3 are probit regressions without corrections for parent fixed effects. *High type* is equal to 1 if the partners IPO rate is above the 75th quartile and the *low type* variable is equal to 1 if the partner's IPO rate is below the 25th quartile.*Low Type X Exited* is the interaction of the low type variable and an indicator whether the parent firm subsequent failed (similar for *High Type X Exited*). The variable *Log number inv.* is the log of the number of investments made by the partner up to the spinoff formation and proxies for experience.Includes all parent firms founded prior to 2003 with at least three active employees (defined above) prior to spinoff formation. Standard errors are clustered at the parent level, where each new spinoff creates a new *parent.*

$^{+}$ $p < 0.10$, * $p < 0.05$

Table 2.11: Sources of bias in impact study

Source of timing bias	**Bias in spinoff impact**
"Growth timing": partners leave during good times	Positive
Partners "jump ship"	Negative
Partners leave at peak performance	Negative
Unobserved heterogeneity of parents	Ambiguous
Lowered entry costs and increased competition	Negative

Notes: Positive bias equates to underestimating the impact of a spinoff on parent performance. "Negative" bias implies that OLS would result in too high a negative impact. See Section 2.9.3 for details on sources of bias.

Table 2.12: Impact of spinoffs on parent performance

	OLS	Logit	Probit
Had Spinoff	-0.0165^{+}	-0.132^{+}	-0.0822*
	(0.00903)	(0.0695)	(0.0398)
Early stage	-0.134*	-0.875*	-0.516*
	(0.00870)	(0.0668)	(0.0362)
Age of parent	-0.00679	-0.0373	-0.0184
	(0.00779)	(0.0487)	(0.0286)
Observations	11877	11877	11877
Pseudo R^2		0.119	0.120

Standard errors in parentheses
Dependent variable is equal to 1 if the parent firm's investment (that was not associated with the spinoff founder) went IPO. Includes all parents that pass the conditions discussed above. *Had spin* is equal to one after the spinoff formation for *s* days after spinoff and zero otherwise. *Early stage* is equal to one if the time of the parent's first investment in the entrepreneurial company was at the Seed or Series A stage. All estimators include year dummies. Standard errors are clustered at the parent level, where each new spinoff creates a new *parent.*
$^{+}$ $p < 0.10$, * $p < 0.05$

Table 2.13: Summary of industry diversity instrument

Variable	**Mean**	**Std. Dev.**	**Min.**	**Max.**
Industry diversity	0.53	0.32	0.09	1
N		98030		

Table 2.14: Impact of spinoffs: IV regression

	OLS	Probit	Bi-Probit+IV
Had Spinoff	-0.0168^{+}	-0.0830*	-0.949*
	(0.00903)	(0.0399)	(0.195)
Early stage	-0.133*	-0.514*	-0.446*
	(0.00879)	(0.0367)	(0.0340)
Age of parent	-0.00540	-0.0132	-0.0220
	(0.00821)	(0.0303)	(0.0206)
First stage			
Peer diversity			-0.772*
			(0.245)
Age of parent			-0.0189
			(0.0190)
Early stage			-0.000609
			(0.0273)
Observations	11641	11641	10489
Adjusted R^2	0.118		

Standard errors in parentheses
Dependent variable is equal to 1 if the parent firm's investment (that was not associated with the spinoff founder) went IPO. Includes all parents that pass the conditions discussed above. *Had spin* is equal to one after the spinoff formation for s days after spinoff and zero otherwise. *Early stage* is equal to one if the time of the parent's first investment in the entrepreneurial company was at the Seed or Series A stage. *First stage* column reports the probit results of the first-stage of IV-probit estimator. All estimators include year dummies. Standard errors are clustered at the parent level, where each new spinoff creates a new
$^{+}$ $p < 0.10$, * $p < 0.05$

Table 2.15: Impact of spinoffs: Fixed effects regression

	Logit	Conditional Logit	Probit	RE Probit
Had Spinoff	-0.134*	-0.137*	-0.0830*	-0.0829*
	(0.0595)	(0.0655)	(0.0335)	(0.0350)
Early stage	-0.870*	-0.779*	-0.514*	-0.499*
	(0.0490)	(0.0531)	(0.0281)	(0.0295)
Age of parent	-0.0282	-0.218*	-0.0132	-0.0323
	(0.0344)	(0.0806)	(0.0201)	(0.0240)
Observations	11641	11441	11641	11641
Pseudo R^2	0.120	0.083	0.121	

Standard errors in parentheses

Dependent variable is equal to 1 if the parent firm's investment

(that was not associated with the spinoff founder) went IPO.

Includes all parents that pass the conditions discussed above. *Had spin*

is equal to one after the spinoff formation for *s* days after

spinoff and zero otherwise. *Early stage* is equal to one if

the time of the parent's first investment in the entrepreneurial

company was at the Seed or Series A stage. All estimators include

year dummies. Standard errors are clustered at the parent level,

where each new spinoff creates a new *parent.*

$^{+}$ $p < 0.10$, * $p < 0.05$

Table 2.16: Characteristics of parents in probit regression

Variable	Mean	Std. Dev.	Min.	Max.
Year Founded	1985.56	9.97	1945	2000
Exited	0.25	0.44	0	1
CA or MA	0.48	0.5	0	1
Dollars invested (millions)	2841.76	3584.41	79.95	21655
Total financings	208.87	229.74	8	1377
Total entrepreneurial companies	64.65	77.57	0	412
Age (years) at spinoff	7.95	4.77	0.07	17.93
N		143		

Table 2.17: Characteristics of all parents in IV regression

Variable	Mean	Std. Dev.	Min.	Max.
Year Founded	1985.67	10.21	1945	2000
Exited	0.23	0.42	0	1
CA or MA	0.49	0.5	0	1
Dollars invested (millions)	3037.36	3711.53	82.97	21655
Total financings	218.33	236.29	10	1377
Total entrepreneurial companies	66.66	79.19	0	412
Age (years) at spinoff	8.02	4.91	0.07	17.93
N		121		

Table 2.18: Characteristics of all parents in RE Probit

Variable	Mean	Std. Dev.	Min.	Max.
Year Founded	1985.51	10.16	1945	2000
Exited	0.23	0.42	0	1
CA or MA	0.48	0.5	0	1
Dollars invested (millions)	2980.68	3651.93	79.95	21655
Total financings	218.13	234.28	9	1377
Total entrepreneurial companies	67.13	79.33	0	412
Age (years) at spinoff	7.95	4.87	0.07	17.93
N		134		

Table 2.19: Impact of spinoffs: Non-exited firms

	All firms	Survivors	IV+Probit	IV+Probit Survivors
Had Spinoff	-0.0830*	-0.0862*	-0.949***	-1.131***
	(0.0335)	(0.0363)	(0.195)	(0.129)
Age of parent	-0.0132	0.0189	-0.0220	0.0126
	(0.0201)	(0.0233)	(0.0206)	(0.0230)
Early stage	-0.514***	-0.515***	-0.446***	-0.424***
	(0.0281)	(0.0305)	(0.0340)	(0.0340)
First stage				
Peer diversity			-0.772**	-0.576*
			(0.245)	(0.255)
Age of parent			-0.0189	-0.0172
			(0.0190)	(0.0209)
Early stage			-0.000609	0.00392
			(0.0273)	(0.0297)
Observations	11641	10083	10489	9037
Pseudo R^2	0.121	0.125		

Standard errors in parentheses
Dependent variable is equal to 1 if the parent firm's investment (that was not associated with the spinoff founder) went IPO. Includes all parents that pass the conditions discussed above. *Had spin* is equal to one after the spinoff formation for *s* days after spinoff and zero otherwise. *Early stage* is equal to one if the time of the parent's first investment in the entrepreneurial company was at the Seed or Series A stage. All estimators include year dummies. Standard errors are clustered at the parent level, where each new spinoff creates a new *parent*.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 2.20: Impact of spinoffs: Competition

	Probit	IV+Probit
Had Spinoff	-0.0832*	-0.941***
	(0.0335)	(0.194)
Age of parent	-0.0132	-0.0221
	(0.0201)	(0.0206)
Early stage	-0.514***	-0.448***
	(0.0281)	(0.0338)
Growth in Deals per VC	0.189	0.286
	(0.162)	(0.157)
First stage		
Peer diversity		-0.767**
		(0.244)
Age of parent		-0.0195
		(0.0190)
Early stage		-0.00139
		(0.0273)
Growth in Deals per VC		0.254*
		(0.123)
Observations	11641	10489
Pseudo R^2	0.121	

Standard errors in parentheses
Dependent variable is equal to 1 if the parent firm's investment
(that was not associated with the spinoff founder) went IPO.
Includes all parents that pass the conditions discussed above. *Had spin*
is equal to one after the spinoff formation for s days after
spinoff and zero otherwise. *Early stage* is equal to one
if the time of the parent's first investment in the entrepreneurial
company was at the Seed or Series A stage. *Growth in Deals per VC*
is the annual change in the ratio of active VCs per investments by quarter.
All estimators include year dummies. Standard errors are clustered at
the parent level, where each new spinoff creates a new *parent*.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

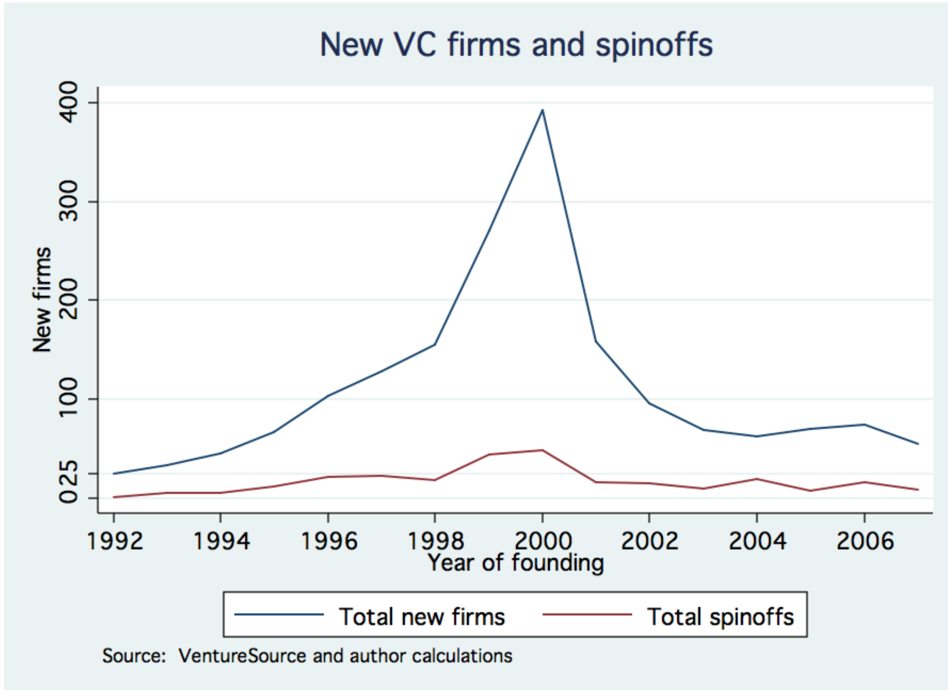

Figure 2.1: New firms and spinoffs over time

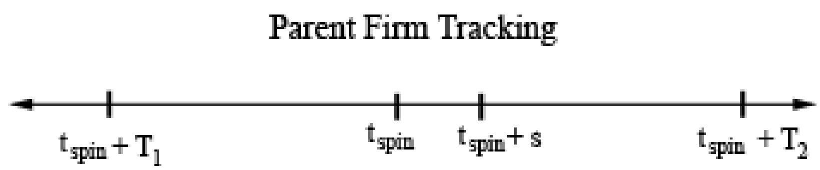

Figure 2.2: Timeframe of spinoff impacts

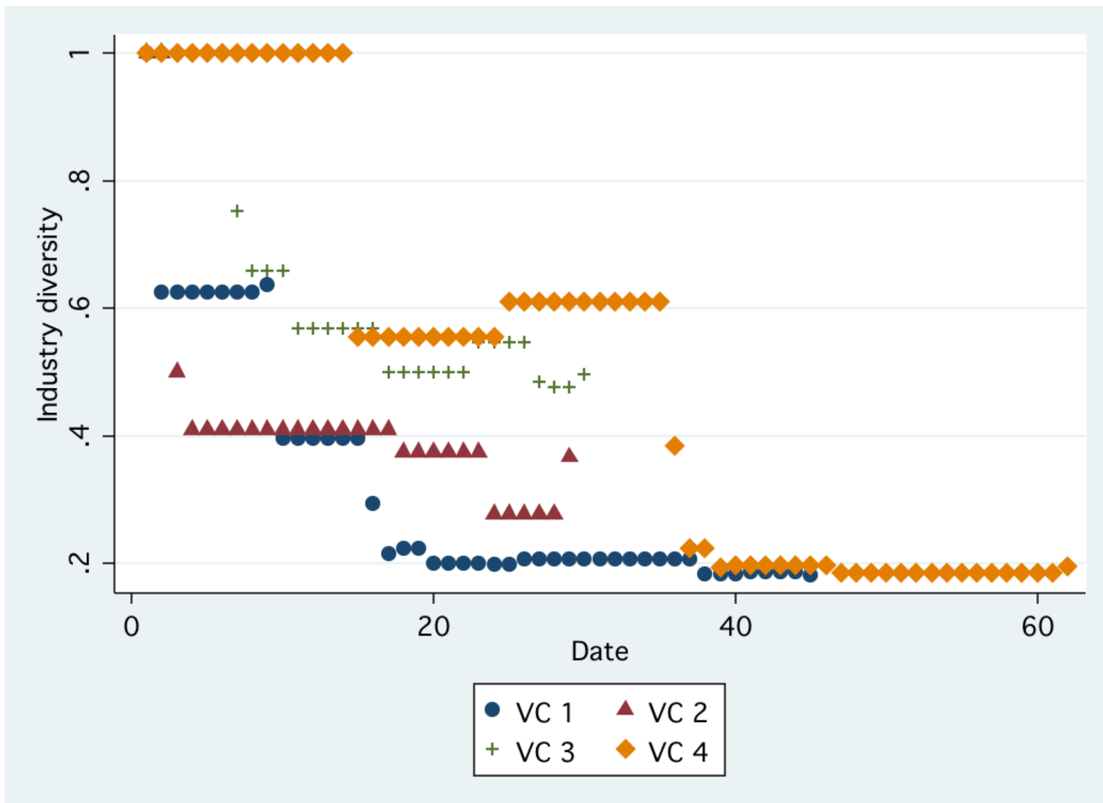

Figure 2.3: Sample instrument variables

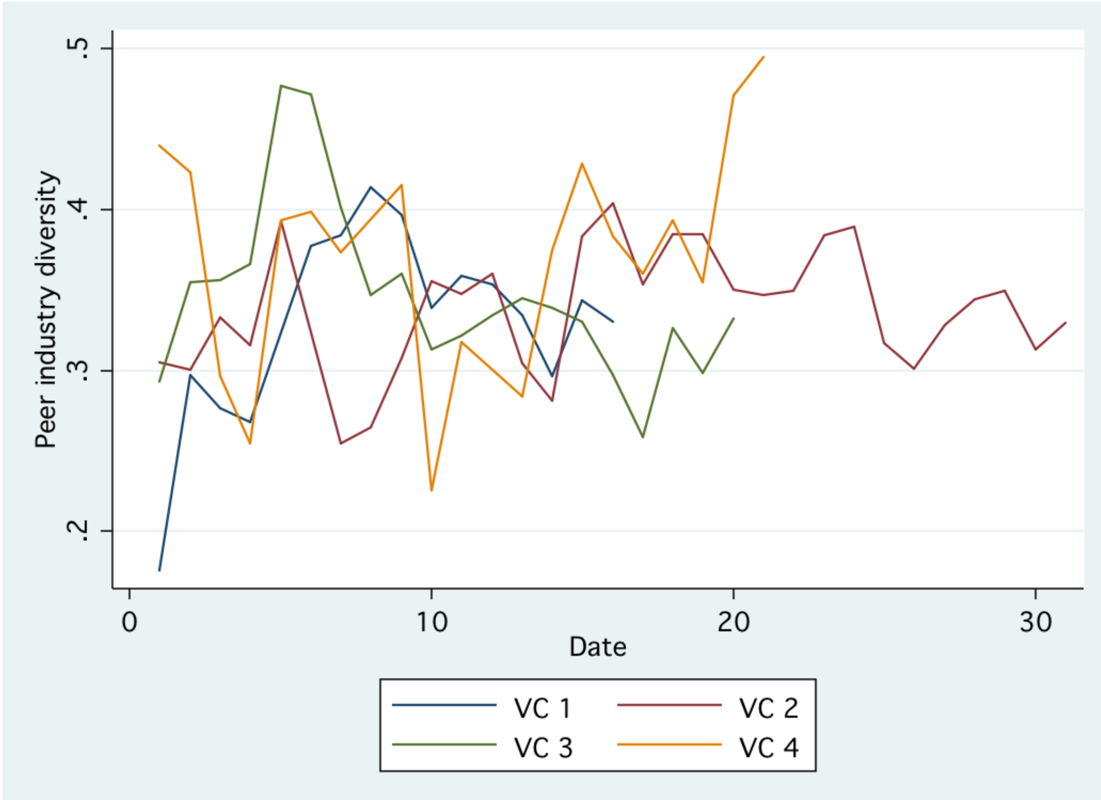

Figure 2.4: Sample instrument variables

2.14 Appendix

2.15 Appendix

2.15.1 Dating entrepreneurial outcomes

Exits of a venture capitalist's investments can take three to five years to occur. So when a spinoff founder makes her last investment at her parent firm and starts the spinoff months later, another investment made around the same time by a co-worker may still be private. Are these outcomes assigned to the parent before or after the spinoff? If the outcome maps to the pre-spinoff parent, then any input the spinoff founder had in that entrepreneurial investment was instrumental in its outcome. Conversely, I could assign outcome of entrepreneurial investment based on their exit dates. In this example, if the investment was pre-spinoff and IPO occurs post-spinoff then the outcome would be associated with the post-spinoff parent. In this analysis, I use the investment date in the entrepreneurial company as the cutoff. I do this for two reasons. First,

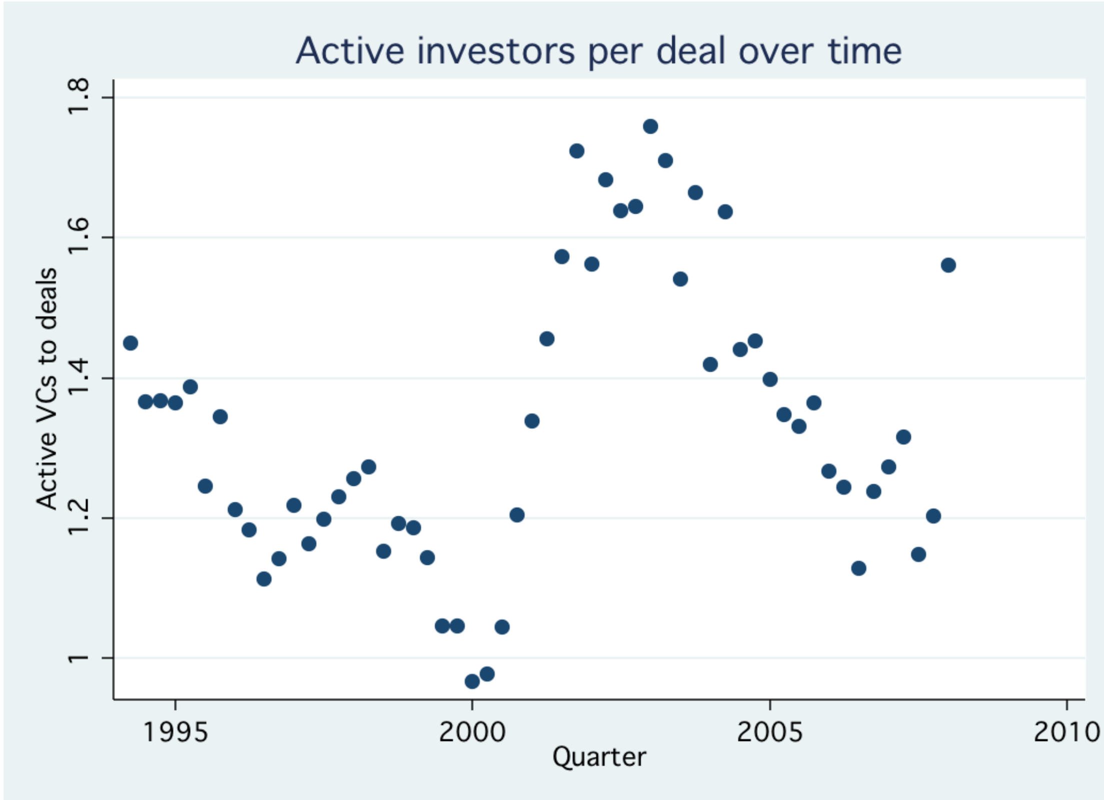

Figure 2.5: Competition measure

there is no clear bias in this choice. If it makes the pre-spinoff parent better than the post-spinoff parent, one must assume that spinoff founders leave above-average investments. There is no reason to think they would behave this way. Second, it is difficult to accurately date non-exits and bankruptcies. If I use the investment date as the cutoff and use end-of-sample knowledge to define outcomes, I don't require perfect information about the actual exit date.

3 Entrepreneurial Spawning and the Transfer of Social Networks

Abstract

The source of the competitive advantage of employee spinoff firms and their formation's negative impact on parent firms is often attributed to a transfer of knowledge from parent firm to spinoff. This paper studies one potential asset transfer in the venture capital industry that can explain both patterns: social networks. Results comparing the social network evolution of venture capital spinoffs and other new firms shows that the former have more central network positions and gain those positions more quickly. Non-spinoffs are more likely to join smaller, more isolated cliques in the network. Spinoffs also have higher survival rates, co-invest with more experienced investors and produce more positive exit outcomes for their investments. The results suggest that parent and employee relative network status in other human capital-intensive industries predicts spinoff formation. The conclusions also extend the Ljungqvist et al. (forthcoming) study of entry costs and social networks in the venture capital industry by detailing the differences in social network evolution of new entrants.

3.1 Introduction

Startups founded by former employees at incumbent firms – spinoffs – are a significant source of new firms in many industries. These new firms alter the competitive landscape and may shift resources and information from firm to firm. Several studies show that the exit of employees to these spinoff firms can harm the parent firm. Little is known, however, about the source of such impacts. Spinoff founders can steal clients, intellectual property or exploit tested processes from their parent firm. In human capital industries, a different transfer of assets from parent to spinoff is likely: social networks. An understanding of if and how social networks can move from firm to firm reveals possible avenues for competitive changes in the industry and the source of the negative impact of spinoff formation. Moreover, Ljungqvist et al. (forthcoming) find a strong relationship between new venture capital firms' entry costs and existing social networks. Thus, spinoff formation and new firm development should be closely related to the industry's social network. Finally, few social network studies analyze the time series evolution of actors' positions. A large panel database of new venture capital firms is excellent means of furthering the research on how actors become networked.

Founders of VC spinoffs are typically the best partners at their parent firm (Ewens (2010a)). When these partners start their own firm, what assets if any do they exploit from their past employer? By construction, spinoffs have one feature missing from other startups: connections to other active VC firms. These connections formed when the spinoff founder made investments as a partner at her parent firm. This paper uses this unique separation to study how the social network of spinoff firms differ in both their level and growth relative to denovo entrants. If spinoff founders use their past connections, their new firm's network position should differ from those of other startups. Next, the paper addresses other forms of heterogeneity between the two types of new firms. If new firm networks diverge, Hochberg, Ljungqvist and Lu (2007b) illustrate other investor features will differ. A cross-sectional analysis compares spinoff and de novo survival rates, size and investment performance to reveal how social network differences manifest themselves.

Spinoff VC firms have both a more central network position and grow their social networks more quickly than denovo firms. Compared to denovo entrants, spinoff firms have more network connections to highly-connected investors and attain more central network position two years after founding. Spinoffs are more likely to act as information brokers and be connected to authorities in the network. In contrast, denovo entrants join the network in smaller cliques and rarely attain the same central network position as spinoffs. These differences are robust when controlling for investment activity, year effects and location. The conclusions expand on the Ljungqvist et al. (forthcoming) study of entry costs by illustrating the network growth consequences of lacking previous connections. Moreover, the stark advantage in network position presents strong evidence that spinoff founders exploit the social networks formed at their parent firms.

Next, the differences in social networks coincide with other important sources of heterogeneity. Hochberg et. al. (2007) show that a central network position results in better VC investment outcomes. This study reinforces these conclusions by finding higher spinoff survival rates. All else equal, spinoff firms fail 30% less often than denovo firms by three years after founding. If social networks help spinoffs survive, then it follows that any transfer of networks from parent to spinoff explains some of the negative impacts of the latter's formation.

The more central network positions correlate with better investment outcomes for a specific set of entrepreneurial exits. Investments with only a spinoff firm as an investors (i.e. no denovo firm) have the same likelihood of an IPO event, but significantly larger chance of being acquired. As acquisition outcomes themselves can be facilitated by connections to non-VC firms, it appears that spinoffs' competitive advantage expands outside the VC market.

Finally, the paper documents differences in spinoff and denovo asset size and investment syndicate composition. Spinoff firms raise and invest 28% more capital denovo firms. When co-investing with other venture capitalists and forming network links, spinoffs are in smaller groups with more experienced partners. For similar financings, spinoff firms invest with other investors that take relatively larger equity stakes. This difference combined with the larger number of network connections for spinoff firms show that they invest in higher quality deals. Overall, spinoff firms have several distinguishing characteristics linked to the social networks built during their past employment.

This study complements results in the literature on spinoffs and venture capital firms. In a study on entry in the venture capital industry, Ljungqvist et al. (forthcoming) show that a firm's previous connections to existing investors in a new market (i.e. industry and location) facilitates entry. This paper's examination of post-entry network development of new VC firms illustrates how these constraints manifest in new firm development. This study also contributes to the rich empirical and theoretical literature on spinoff formation. A few studies of spinoff formation isolate the transfer of knowledge, clients or social capital from parent to spinoffs. Phillips (2002) argues that above-average performance of spinoff law firms stems from a "transfer of routines" from the parent firm, but his data cannot identify such transfers. Next, Agarwal, Echambadi, Franco and Sarkar (2004) show some transfer of technological knowledge to spinoffs in the hard drive industry. This study of venture capital spinoffs expands on their work by tracking an observable feature of new firms that could be transferred from parent to spinoff.

The paper proceeds as follows. Section 2 details the literature on spinoffs and venture capital networks. Next, Sections 3 and 4 describes the data and the spinoff construction. Section 5 follows with the basic hypotheses of the paper. A discussion of social networks and centrality measures is found in Section 6 along with the results of the network comparison regressions. Further differences in spinoff and denovo characteristics follow in Section 7. The paper concludes with a discussion of further research in Section 8.

3.2 Previous literature

Klepper (2009) reviews of the literature on spinoff formation, impacts and patterns across a wide range of industries and companies. Several authors investigate the performance of spinoff firms and hypothesize where the differences arise. Agarwal et al. (2004) study the disk drive industry and find that spinoffs have better performance than denovo entrants. The authors argue that differences stem from a transfer of knowledge about technology and processes from parent firm to spinoff. Elfenbein et al. (2009) show that smaller firms have higher spinoff rates and argue it follows from the more entrepreneurial nature of workers at such firms. Studies also show that spinoff firms survive longer, while their performance depends on parent type. These results have been found for US automobile manufacturers (Cabral and Wang (2009)) and the Brazilian economy (Hirakawa et al. (2010)). Overall, spinoff firms have unique features relative to denovo entrants that give them performance advantages. Identifying the source of these advantages is an unanswered question.

Although we understand when spinoffs occur (e.g. Cabral and Wang (2009)) and their potential impacts on parent firms (Phillips (2002)), Klepper (2009) points out that we do not yet know what kind of knowledge spinoffs exploit from their parent firms. In technological industries, spinoff founders often learn the processes of production at their parent firms such as in the laser industry (Klepper and Sleeper (2005)). Agarwal et al. (2004) argue that the knowledge gained from spinoff founders parent firms present a competitive advantage. Similarly, spinoffs founders could pursue ideas closely related to their parent's business line, but too far for its internal implementation. A spinoff firm represents an opportunity to exploit this tangential knowledge as modeled by Hellmann (2007) and Cassiman and Ueda (2006). Rauch and Watson (2010) present a model of "client entrepreneurship" where spinoff firms exploit the parent firm's client network. One possible transfer from parent to spinoff yet to be analyzed applies to most human capital-intensive industries: social networks. Hochberg et al. (2007a) show that a VC firm's social network centrality explains much of the observed cross-sectional performance differences. Social networks also influence the cost of entry in the VC industry. Ljungqvist et al. (forthcoming) conclude that connections to incumbent firms facilitates entry for VC firms into new locations and industries. Motivated by these results and the relatively easy transfer of social networks, this paper takes the first look at the differences in social networks between spinoffs and denovo entrants.

3.3 Data

The paper uses the VentureOne database provided by the Dow Jones subsidiary VentureSource. The sample covers the venture capital market from 1987 to 2007 and tracks investments of $361 billion in 55,457 rounds and 16,849 companies. VentureOne collects their data on venture-capital backed companies with surveys of venture capitalists and entrepreneurial firms. The data lacks financings where corporations or institutions are the only investors in a particular company. For all financings that involve a venture capitalist, VentureOne claims near perfect coverage of 1992 – present. Smaller (in total assets) venture capitalists that invest alone in an entrepreneurial firm are less likely to be observed than the average size venture capitalist. However, if the small investor co-invests with larger venture capitalists already in the dataset, VentureOne starts to actively track the former's financings. For this study, I focus on the rich data available on the investors in a venture capital financings along with the database of spinoffs constructed in Ewens (2010a).

3.4 Spinoffs

A new VC firm is a spinoff if it has at least one founder that previously worked at an incumbent VC firm. The list begins with all new firms founded from 1992 - 2007 not including hedge funds, investment banks and other non-standard investors. A new firm is observed after it makes its first investment and receives a board seat. This requirement limits the set of new firms slightly because not all venture capital investors receive board seats when they invest. Second, board seat activity identifies all those employees that sat on a entrepreneurial board within a year of the firm's founding and the set of possible spinoff founders.

The condition that the potential founders sit on a board seat excludes individuals who start new firms and simply act as a CEO or manager. Also, many firms founded during the dot-com boom simply supplied capital to cash-hungry entrepreneurial firms. Without board seats, many of these VC firms will not be counted. With this list of original employees, online biographies identify firm founders.

Last, a spinoff founder must have past employment at another VC firm. These spinoff founders could be past associates, partners or managing partners at their previous job. From this set I eliminate serial founders and label all firms as spinoffs or non-spinoffs and all active partners (i.e. those that sit on entrepreneurial boards) as spinoff-founder or non-spinoff-founder. Figure 3.1 presents the number of new firms and new spinoffs by year. On average, 15% of all new firms are spinoffs each year, while the sharp increase in both firm types follows the increase in dollars invested during the boom era of 1998 - 2000. Ewens (2010a) has details about the timing of spinoffs and characteristics of their founders.

3.5 Hypotheses

Ewens (2010a) shows that the exit of a VC partner from a firm to start a spinoff has a detrimental impact on the parent firm's performance. Similar results have been found for law firms (Phillips (2002)) and the laser industry (Klepper and Sleeper (2005)). An unanswered question about these impacts concerns what the spinoff founders take with them when they start the new firm. I hypothesize that one of the possible assets taken with these founders is some of the social capital of the parent firm. In particular, spinoff founders take with them the network of connections formed through investment syndication. Any existing networks at firm formation would separate the growth of social network connections between spinoff firms and de novo entrants.

De novo entrants are defined by their lack of previous direct connections to incumbent firms. This lack of connections should result in a less dense, less central network position relative to spinoff firms. For example, if spinoff firms have access to past connections formed at their parent firms, they will find it relatively easier to form new links and form links with more connected individuals. I posit that due to their past experience in the social network, spinoff firms will grow their network more quickly than denovo entrants (all else equal):

H1: A spinoff firms degree should be larger than de novo entrants

Next, the access to experienced VCs from their past employment at the parent firm should give spinoff firms relatively better access to central investors in the VC network. Thus:

H2: Over time, spinoff firms should have higher centrality measures than de novo entrants.

3.6 Spinoff and denovo networks

3.6.1 Preliminaries

Why networks matter

Differences in social networks between venture capital firms explain much of the cross-sectional differences in fund performance and is thus could be a crucial competitive advantage for spinoff firms. Networks map to the coveted "deal flow" shown by Sorensen (2007) to explain a significant proportion of performance heterogeneity. A central network position with connections to other highly connected VC firms also increases the chances of finding sufficient capital to complete syndicates and take entrepreneurial firms to exit. Hochberg et al. (2007a) show that network connections change the cost of entry for venture capital firms entering new location-industry markets. Thus, spinoff firms should find deals and investment partners more easily than de novo firms.[1] If network growth has momentum, one should also observe changes in the growth of spinoff and de novo network positions over time.

Definitions

A social network contains links and nodes. The venture capital firm comprises the nodes of the network. A link forms when two different VC invest in the same financing event, for which there can by many for the same entrepreneurial firm.[2] The VC capital market has significant exit and entry. Some VC firms fail, while links formed years in the past have less value over time. I capture the first issue by constructing the network at any time t for all active investors as of time t. So if a VC firm fails at time t, all networks for $s > t$ will exclude their links. The link definition captures the idea of declining link value by only considering links formed in a five-year window.[3] This link definition follows that of Hochberg et al. (2007a) .

Network centrality

I follow Hochberg et al. (2007a) and compute three basic network centrality measures which capture the number of connections and the quality of those connections for a VC firm.

[1] Spinoff firms have at least one more network connection to the VC network than denovos: their parent firm.

[2] A link could also form when the two firms invest in the same entrepreneurial company, but not the same financing event.

[3] Results are insensitive to this assumption.

Degree centrality

One way a venture capital firm can achieve a central network status is through co-investing with a large number of other firms. In doing so, the firm increases the set of possible future syndicate members and the information about new deals. *Degree centrality* captures this notion by counting the number of links connecting a VC firm to others in the network. Normalized by $n-1$ – the total number of other active investors – this measure describes the proportion of all investors that a VC firm has interacted with in the past. As the VC network considered here is undirected, the standard in-degree and out-degree measures will be the same.

Betweenness centrality

The shortest path between two actors i and j in a network is the least amount of links required to transverse from i to j. Consider all shortest paths in a network of venture capital firms. A node with high *betweenness centrality* is found along a high proportion of such paths. These VC firms can be thought of as "bridges" in the network that can facilitate communication and information sharing between distant VC firms. The measure is normalized by dividing each firm's betweenness by its theoretical maximum $2(n-1)(n-2)$.

Eigenvector centrality

Eigenvector centrality is a recursive network measure that incorporates the centrality of a node's neighbors. A VC firm with relatively more well-connected neighbors will have a high *eigenvalue centrality*. Thus, it is possible for a firm to have a low degree centrality, but a high eigenvector centrality. Formally, let $\mathbf{A}$ be the adjacency matrix of a network, where the i, j element equals one if there is a connection between firms i and j. The eigenvector centralities result from the following eigenvector equation:

$$\mathbf{A}x = \lambda x$$

where λ is the largest eigenvalue and the $nx1$ vector x contains the centrality measures. The computation normalizes the centrality measure for each week by the largest possible eigenvector centrality. I add a fourth measure that invites analysis of a node's propensity to be in cliques.

Closeness centrality

A VC firm can be very close to a large percentage of the network if the distance between its typical neighbor is short. Similar to betweenness centrality, *closeness centrality* measures the average distance between a VC firm and all of its connections. Formally, let $d(i,j)$ be the number of links between VC firms i and j. Let N_i be all the firms that VC firm i is connected to. Then the firms closeness centrality is:[4]

$$\frac{N_i - 1}{\sum\limits_{j \in N_i} d(i,j)}$$

This measure of centrality can be similar for two VC firms with different network positions. If a firm is located in a closed sub-network with few individuals, its closeness centrality can be high. A firm who is instead connected to the whole network by a moderate distance can have the same closeness centrality. However, combined with the less sensitive betweenness centrality, closeness centrality can reveal a node's propensity to be connected to a small clique within the whole network. If a firm or certain firm type has a low betweenness measure, but relatively higher closeness centrality, the firm is closely connected to a small subset of the network, but distance from the crucial paths in the whole network. These differences allow identification of a node's relative propensity to be in a clique.

3.6.2 Identification

Identifying any differences in the social network evolutions of spinoffs and de novo firms requires calculating the four measures discussed above over time. For each week in the sample period (1987 - 2007), the set of network centrality measures are computed for all active VCs in the previous five years. A VC firm will have a centrality measure for a given week even if it did not have any investment activity. The set of VC firms is then restricted to new firms – spinoffs and de novo entrants – founded post-1992. A simple comparison of these two types of firm's network status requires pooling each by age. Let a denote the age of a firm where $a \in 1,2,3,4,\ldots$ is in years. For each year, let C_{ia} be the last observed network centrality measure for firm i. Figure 3.2 shows the average of the C_{ia} over all a and across new firm types.

On average, spinoff firms have higher network centralities as measured by betweenness, eigenvalue centrality and degree. De novo firms have a unconditionally higher closeness centrality some 3 - 5 years after firm founding. Of course, these differences do not account for unobserved heterogeneity such as year founded and investment preferences. A regression framework identifies any real differences between network centrality. For each age group a I estimate

[4] There is no simple normalization available for closeness.

the following model for each network centrality measure C_{ia}:

$$C_{ia} = \beta_{0a} + \beta_{1a} Spin_i + \beta_{2a} X_{ia} + \beta_{3a} Z_i + \varepsilon_{ia} \tag{3.1}$$

where $Spin_i$ is one if firm i is a spinoff firm, X_{ia} includes control variables for firm i at age a and Z_i contains time-invariant variables for firm i. The main hypothesis concerns the series of coefficients $\{\beta_{11}, \beta_{12}, \ldots, \beta_{1\bar{a}}\}$. For some a, these coefficient are positive if spinoff firms at age a have more central network positions than de novo firms. Equation (3.1) is estimated for each age group a, so it only includes surviving firms.[5] Restricting the sample in this way ensures that the set of firms are comparable. Figure 3.3 shows that spinoffs have a higher survival rate than de novo firms, where some 45% of the latter fail after 2 years versus 20% for spinoffs.

3.6.3 Control variables

The unconditional differences between the network positions of spinoff and denovo firms in Figure 3.2 could stem from differences in investment preferences, year founded, location or capital stock. First, the overall features of the VC market and the VC network differ over time. Firms that entered in 1999 faced a market of abundant investment options and thus opportunities to form links in the network. All regressions include year dummies. Similarly, a VC founded in Silicon Valley or Boston has relatively more investment opportunities than one founded in Nebraska. The control variable Z_i includes dummies for headquarters in California or Massachusetts. Next, an investor's preference for early-stage financings will result in smaller syndicates and thus a lower degree centrality. Finally, the dollars that a VC invests in a given year proxies for the number of deals and therefore the number of interactions with co-investors. A VC could build a relatively more central network position by simply investing a large amount of money in many deals. The control variables Z_{ia} include the sum total of all dollars invested for the age year a. Addressing all these forms of heterogeneity should help identify the unique benefit of spinoff firms for network formation. Table 3.1 details the characteristics of the control variables and the dependent variables, while Tables 3.2 - 3.4 present correlations for ages 1,3 and 5.

3.6.4 Results

Table 3.5 presents the coefficient estimates for the β_{1a} for $a \in \{1, 2, \ldots, 6\}$. The sample of spinoffs for ages greater than six is less than 90, so they are excluded. Each row holds the

[5] A more efficient estimator would pool all the firms across all ages and include a series of age dummies plus interactions. For ease of interpretation, I settle on individual regressions conditional on survival.

estimates for the network centrality measures. Row 1 shows that spinoff firms have a larger degree centrality from 1 year after birth and on. The betweenness centrality of spinoffs and de novo firms differs for ages greater than three, while eigenvalue centrality is larger for spinoffs for ages greater than one. The results confirm the basic picture in Figure 3.2 and indicate that spinoff firms attain a more central network position than denovo firms and maintain that position over time. Figures 3.4 through 3.7 show the predicted network centralities with confidence intervals implied by the regression estimates. The only indistinguishable network centrality measure is closeness.

Spinoffs have a larger centrality after 2 years and a lower measure for firms that survive at least five years. The lack of a strong pattern suggests that there is no systematic difference between the closeness centralities of spinoffs and denovo firms. Combined with the stronger betweenness centrality of spinoffs and the ambiguity in the closeness computation shows that denovo firms are more likely networked in sub-networks or cliques. Given this, it is not surprising that the patterns in Figure 3.2 do not show centrality convergences. Denovo VC firms enter the market and interact with a smaller subset of the network that itself is weakly connected to the whole.

The propensity of denovo firms to enter or form cliques confirms the conclusions of Ljungqvist et al. (forthcoming). These authors showed that entry of VC firms into new geographic areas and industries was facilitated by past connections to the area. If VC firm j from region A invested with VC firm k in Region B, the probability that firm j subsequently invested in region A increased. Denovo firms are extreme versions of outsiders as they are defined by the lack of connections through past investments to the VC network. It is thus not surprising that if they enter the whole market, they do so on the fringe and cannot build a central position as insiders like spinoff firms. The results show that even when the barriers to entry are overcome – a denovo firm is founded – the growth in networks is stymied.

Robustness

The paper's original hypothesis posited that spinoff firms could exploit the connections made at their parent firm to separate themselves from de novo entrants. However, the differences observed in Table 3.5 could stem from other sources. Spinoff firms could simply be more active by investing in more unique entrepreneurial companies. The results thus far only include controls for the total dollars invested for each age year. Investing in more entrepreneurial companies rather than financing rounds in the same company will lead to interaction with more VCs. Replacing the total dollars invested with the log of number of entrepreneurial investments has little impact on results. The differences in betweenness and eigenvector centrality now appear after 3 years, but otherwise the conclusions are the same.

3.7 Further comparisons of spinoff and denovo firms

Spinoff VC firms have an advantage in building their network relative to de novo firms. The advantage appears to stem from their past experience in the VC market and the network built at the parent firm. Studies on VC firm performance show that a more central network position results in better investment performance. Thus, it is likely that spinoff firms are better than denovo firms by several measures. Even without these results, the literature on spinoffs has shown that they have higher survival rates, are larger and perform better than their denovo counterparts.

3.7.1 Survival

For both specific industries and across all sectors, many studies find a higher survival rate of spinoff firms compared to denovo firms. Hirakawa et al. (2010) show that spinoff firms in Brazil outlast other startups, while Klepper and Sleeper (2005) shows spinoffs in the laser industry have lower exit rates than denovo entrants. I address this question with the sample of spinoff and denovo firms in the VC industry. If the higher network centrality found for spinoffs translates to better performance, then one might expect higher spinoff survival rates.

For each new firm in the database, a label for "Inactive" identifies firms that are no longer investing. I add to this list firms that have not invested in a new financing since 2003 (the sample ends in 2007). For each inactive firm, the exit date is set to two years after their last observed financing event or exit of an entrepreneurial firm. Estimates of a Cox proportional hazard for exit times in years are in Table 3.6. Control variables include year dummies, dollars raised in the first two years of founding, industry preference and stage preference.

The coefficient on the spinoff dummy is positive and significant in all specifications. De novo firms fail more often and more quickly than spinoff VC firms. Perhaps spinoff firms higher survival rates are attributable to their more central network position. Columns 3 through 5 includes an additional regressor for the centrality measures. The coefficient on the spinoff dummy is statistically smaller, but still negative. The estimated survivor and hazard functions in Figures 3.8 and 3.9 illustrate the sharp differences in survival rates between spinoffs and de novo.

3.7.2 Size

Raising capital for a new VC firm requires gathering limited partners from pension funds and endowments. Such a process may be facilitated by a spinoff founder's connections formed at their parents firms. The network growth regressions in Table 3.5 controlled for heterogeneity in dollars raised that could generate higher centrality measures. To test for any differences in asset size between the two types of new firms, I compute the total dollars invested in the first two years of the firm's life. Dollars invested during these early years proxy for the full size of the fund and the pace of its investments. Table 3.7 presents the simple OLS estimates of log asset size and a series of control variables.

Spinoff firms invest more dollars in the first two years of their lifetimes, suggesting that they raise more initial capital than de novo firms. The connections to actors outside the VC market (e.g. limited partners) appear to improve the fund-raising ability of spinoff founders and represent another hurdle for denovo entry.

3.7.3 Syndicate size

The size and composition of a financing round's syndicate – the pool of venture capital firms that invest in the entrepreneurial company – can show the role that networks and experience play in new venture capital firm's investments. I study the differences in the number of investors for financing rounds that only have a spinoff firm or a de novo entrant.

Table 3.8 shows the regression results for the number of investors for a financing round. Controls include year dummies, an indicator for stage, and interactions of year and industry. In each specification, financings with spinoff firms have fewer investors than those with de novo entrants. All else equal, if a syndicate has relatively fewer investors it could signal that the financing was not popular (i.e. under-subscribed) or that the investors in the syndicate each contributed more capital due to larger asset bases. The researcher cannot observe the first scenario, while the second can be identified using venture capital firm size or experience proxies. To further investigate the differing syndicate sizes, I look at the characteristics of the syndicate members of spinoff and de novo financings. The average age of the co-investors and the total dollars invested at each financing event may differ between the two new firms types. Table 3.9 shows the basic results.

Rounds with spinoff firms have more experienced and larger co-investors. Given the larger and older VC firms are also more likely to be more successful (i.e. they survived), this additional difference suggests that the smaller number of investors for spinoff rounds stems not from a lack of interest, but from need. The average round with a spinoff firm requires less capital (all else equal) because its syndicate members each contribute relatively more. Such rounds may be more insular because the existing investors do not require outsiders to validate its quality (Lerner (1994)). The higher degree centrality for spinoffs combined with smaller syndicates show that spinoffs invest in more unique firms and more financings over time.

3.7.4 Performance

Many studies of spinoff firms find that they have better performance rates than de novo entrants. The standard measure of performance for VC firms is the proportion of positive exit events. Exits can be IPOs or acquisitions. I analyze the probability of such events for each investment made by a spinoff or de novo firms. The sample contains only those entrepreneurial firms that did not have both a spinoff and de novo investor. Table 3.10 analyzes the exit outcomes of all entrepreneurial firms that were founded prior to 2003. Column 1 considers IPO events, column 2 pools IPO and acquisition events and Column 3 includes only acquisition events. If spinoff firms are either better at nurturing entrepreneurial firms to good exits or simply have better investment opportunities, then the coefficient for "had spin" will be positive. Control variables include location, industry, stage of investment, year dummies and dollars raised at the first investment by the new VC firm.

The coefficient on the "Had Spin" dummy is only significant in the second and third columns. The results show that spinoff firms do not produce more IPOs, but significantly more acquisitions. Although acquisitions are typically a second-best outcome for entrepreneurial investments, the stark differences in their probabilities between spinoffs and de novos indicates that the former have higher returns. Moreover, the difference only in acquisitions outcomes may stem from differences in network status. Entrepreneurial firms are often acquired by previously VC-backed firms, so having connections to these firms could increase the likelihood of an acquisition.

3.7.5 Syndicate composition

The higher probability of acquisitions for spinoff-backed investments could stem from heterogeneity in deal flow quality, the composition of spinoff syndicates or simply the network characteristics of the new firm. The differences in network centrality of spinoffs and denovo firms should translate into observable differences between the co-investors shown in Table 3.9. In particular, spinoffs are connected to more central VC firms (i.e. eigenvector centrality), who themselves may be larger and more experienced than the average VC firm. Table 3.11 repeats the exit outcome regressions with the additional controls for syndicate composition.

The inclusion of the syndicate experience measure does not have a large impact on the estimated difference between spinoff and de novo-backed outcomes. The coefficient on "Had Spinoff" is statistically significant at the 5% value for all but one of the specifications. Even with controls for the spinoffs network status or the quality of its co-investors, these new firms produce more acquisition outcomes. The spinoff founder type – illustrated as predominantly high quality partners in Ewens (2010a) – could explain the differences. Spinoff founders are above-average venture capitalists able to select the right deals or nurture their investments to exit. Overall, the higher acquisition probability for spinoff-backed entrepreneurial firms is robust to differences in syndicate composition.

3.8 Conclusion and Further Work

A key distinguishing feature of spinoff venture capital firms is their network centrality. These firms attain more central network positions than denovo firms and maintain that advantage over many years. These results suggest that one of the more important assets transferred from a parent VC to spinoff is founder's social network. A more central network position comes with several other crucial differences between these new firm types. Spinoffs survive longer, produce more acquisition outcomes, raise more capital and co-invest with larger, more experienced VCs. Simply, denovo VC firms have a lot of disadvantages to starting their firms. Much more can be learned about spinoffs in the venture capital industry and human capital-intensive industries in general. A comparison of the social networks of the parents post-spinoff and that of spinoffs will demonstrate any "stealing" or overlap of social connections. The stark differences in acquisition outcomes suggests that another network beyond that built from syndication functions in the background: that of potential acquiring firms. Finally, the impacts of spinoffs in Ewens (2010a) and other industries where social connections are an important competitive advantage may result from the transfer of networks from parent to spinoff.

3.9 Tables and Figures

Table 3.1: Summary of control and dependent variables

	mean	sd	min	max
Prop. IT	.136199	.2226611	0	1
Prop. Health	.1823475	.3286183	0	1
Prop. Early	.5784577	.4108161	0	1
CA	.2739405	.4460115	0	1
MA	.0859364	.2802906	0	1
Log Total inv.	2.744524	1.45494	-3.717894	7.775697
Degree	.0102086	.0127997	.0003254	.1067762
Between	.0003958	.0008604	0	.0103897
Closeness	.035324	.0180677	.0003254	.1377535
Observations	6819			

All variables summarized across all VC age up to year 6.

Includes all new VC firms founded after 1991.

Table 3.2: Correlation matrix: age = 1

	(1)								
	Prop. IT	Prop. Health	Prop. Early	CA	MA	Log Total inv.	Degree	Between	Closeness
Prop. IT	1								
Prop. Health	-0.188***	1							
Prop. Early	0.0623*	-0.0556*	1						
CA	0.0242	-0.0485	0.0247	1					
MA	-0.0502	0.0278	-0.0157	-0.171***	1				
Log Total inv.	0.152***	0.0731**	-0.340***	0.114***	-0.00467	1			
Degree	0.0883**	0.0709**	-0.259***	0.194***	-0.00565	0.627***	1		
Between	0.0829**	-0.00819	-0.0333	0.0679*	-0.0400	0.247***	0.463***	1	
Closeness	-0.103***	0.143***	-0.156***	0.0191	0.0198	0.0216	0.154***	0.00537	1

Correlation of dependent and independent variables for all one year old new firms. “CA” and “MA” are dummies for office state locations.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 3.3: Correlation matrix: age = 3

	(1)								
	Prop. IT	Prop. Health	Prop. Early	CA	MA	Log Total inv.	Degree	Between	Closeness
Prop. IT	1								
Prop. Health	-0.270***	1							
Prop. Early	0.00576	-0.0333	1						
CA	0.0153	-0.0772*	0.00185	1					
MA	0.00493	0.0180	0.00244	-0.194***	1				
Log Total inv.	0.0542	0.0452	-0.307***	0.138***	0.0286	1			
Degree	0.0577	0.0121	-0.183***	0.256***	0.00441	0.587***	1		
Between	0.0730*	-0.0255	-0.0249	0.0908**	-0.0323	0.368***	0.684***	1	
Closeness	-0.0569	0.0320	-0.153***	0.00467	0.0753*	-0.0715*	-0.0267	-0.0591	1

Correlation of dependent and independent variables for all three year old new firms. “CA” and “MA” are dummies for office state locations.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 3.4: Correlation matrix: age = 5

	(1)								
	Prop. IT	Prop. Health	Prop. Early	CA	MA	Log Total inv.	Degree	Between	Closeness
Prop. IT	1								
Prop. Health	-0.339***	1							
Prop. Early	-0.0818*	-0.0360	1						
CA	0.0415	-0.110**	-0.00125	1					
MA	-0.0432	0.0386	0.0134	-0.218***	1				
Log Total inv.	0.0530	0.0543	-0.294***	0.0892*	0.0729	1			
Degree	0.0899*	-0.0308	-0.142***	0.223***	0.0597	0.535***	1		
Between	0.0729	-0.0270	-0.0252	0.0654	0.0537	0.376***	0.769***	1	
Closeness	-0.0146	-0.0198	-0.0667	0.0826*	-0.0261	-0.0930*	-0.0561	-0.114**	1

Correlation of dependent and independent variables for all five year old new firms. “CA” and “MA” are dummies for office state locations.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 3.5: Spinoffs vs. denovo network status: coefficient of spinoff dummy

	Age = 1	Age = 2	Age = 3	Age = 4	Age = 5	Age = 6
Degree centrality	0.000953**	0.00240**	0.00449**	0.00583**	0.00805**	0.00739**
	(0.000400)	(0.000668)	(0.000880)	(0.00110)	(0.00150)	(0.00168)
Betweenness centrality	-0.0000194	0.0000766	0.000237**	0.000290**	0.000428**	0.000472**
	(0.0000339)	(0.0000561)	(0.0000735)	(0.0000962)	(0.000112)	(0.000137)
Closeness centrality	0.00150**	0.000171	-0.000985	-0.00201**	-0.000884	-0.00256**
	(0.000737)	(0.000733)	(0.000734)	(0.000950)	(0.000976)	(0.00108)
Eigenvector centrality	0.00437*	0.00954**	0.0215**	0.0309**	0.0458**	0.0491**
	(0.00253)	(0.00400)	(0.00539)	(0.00675)	(0.00890)	(0.00980)
Observations	1351	1145	962	805	670	566

Standard errors in parentheses

Notes: Coefficients on the “spinoff” variable from equation 3.1. Tobit regressions used in all specifications. Each sample includes only firms that survived. Year dummies included but not shown. For each year after firm birth, the network statistics is calculated as of end of year.

* $p < 0.10$, ** $p < 0.05$

Table 3.6: Survival of spinoffs and denovo firms

	1	2	3	4	5
Spinoff	-1.311**	-0.673**	-0.441**	-0.452**	-0.492**
	(-6.88)	(-3.42)	(-2.23)	(-2.30)	(-2.50)
Dollars2		-0.288**	-0.144**	-0.136**	-0.206**
		(-10.46)	(-4.43)	(-4.19)	(-7.06)
Prop. early stage		-1.599**	-1.461**	-1.516**	-1.435**
		(-11.37)	(-10.61)	(-11.09)	(-10.38)
Prop. Healthcare		-0.244	-0.309	-0.372*	-0.224
		(-1.11)	(-1.45)	(-1.72)	(-1.06)
Prop. IT		-1.653**	-1.314**	-1.272**	-1.438**
		(-7.37)	(-5.83)	(-5.57)	(-6.60)
Degree			-59.55**		
			(-7.88)		
eig				-9.743**	
				(-8.33)	
Betweenness					-829.6**
					(-7.53)
Observations	1480	1464	1464	1464	1464

t statistics in parentheses

Cox proportional hazard estimates, exponentiated coefficients.

is the log of the real dollars invested in the first two years.

is the proportion of portfolio in industry or stage.

* $p < 0.10$, ** $p < 0.05$

Table 3.7: Spinoff and denovo asset size

	Total invested2	Log total invested2
Spinoff	0.920**	0.289**
	(0.0849)	(0.0262)
Early stage pref.	-1.443**	-0.435**
	(0.110)	(0.0400)
IT preference	0.00837	-0.0207
	(0.146)	(0.0542)
Healthcare preference	-0.0687	-0.0299
	(0.105)	(0.0432)
California	0.362**	0.0887**
	(0.0796)	(0.0346)
Massach.	0.0163	0.0272
	(0.129)	(0.0436)
Observations	1379	1364
Adjusted R^2	0.278	0.170

Standard errors in parentheses
Dependent variable is the sum total real dollars invested in the first two years of a VC's life. Regressions include year founded dummies.
Preference variables measure the proportion of investments by stage and industry.
* $p < 0.10$, ** $p < 0.05$

Table 3.8: Difference is syndicate size

	Tobit	OLS log size
Has Spinoff	-0.327**	-0.0695**
	(0.0598)	(0.0214)
Real dollars raised (m)	0.0333**	0.00724**
	(0.00632)	(0.00146)
Observations	9959	9959
Adjusted R^2		0.318

Standard errors in parentheses
Column 1 is tobit on the total number of investors.
Column 2 is OLS of the log of the number of syndicate members.
is the total dollars raised in the financing.
Regressions include stage, industry and year dummies with full interactions
* $p < 0.10$, ** $p < 0.05$

Table 3.9: Differences in syndicate composition

	Mean syndicate age	Total past dollars
Has Spinoff	0.424**	0.915**
	(0.0516)	(0.150)
Real dollars raised (m)	0.0121**	0.0500**
	(0.00256)	(0.0106)
Observations	9959	9959
Pseudo R^2	0.050	0.046

Standard errors in parentheses
Tobit regression of mean age in years of syndicate and experience
proxied by sum of past dollars raised.
Difference in syndicate composition
is the average age of all other non-new firm investors.
is the total dollars invested in the past by all other non-new syndicate members.
Regressions include year and industry dummies and their interactions (not shown).
If an investor invested alone, value set to 0.
* $p < 0.10$, ** $p < 0.05$

Table 3.10: Spinoff and denovo investment performance

	IPO Exit	IPO or Acq. exit	Acquisition exit
Spinoff	0.00940	0.110**	0.104**
	(0.0748)	(0.0467)	(0.0467)
Early stage	-0.656**	-0.373**	-0.104**
	(0.0546)	(0.0393)	(0.0397)
California	0.0993*	0.0881**	0.0540
	(0.0573)	(0.0373)	(0.0376)
Massach.	-0.0671	0.118*	0.159**
	(0.101)	(0.0611)	(0.0607)
Total dollars raised	0.000556	0.000590*	-0.0000126
	(0.000339)	(0.000357)	(0.000186)
Observations	5976	5976	5976
Pseudo R^2	0.213	0.075	0.022

Standard errors in parentheses
Includes all investments with only a spinoff or only a denovo investor before 2003.
Probit regressions with year and industry dummies.
All independent variables measured at the first investment date and dollars are in millions.
* $p < 0.10$, ** $p < 0.05$

Table 3.11: Spinoff and denovo performance: syndicate controls

	Acq.?	Acq.?	Acq.?	Acq.?	Acq.?	Acq.?	Acq.?
Spinoff	0.104**				0.0899*	0.0998**	0.0841*
	(0.0467)				(0.0471)	(0.0469)	(0.0473)
Early stage	-0.104**	-0.0894**	-0.0830**	-0.0744*	-0.0937**	-0.0883**	-0.0794*
	(0.0397)	(0.0399)	(0.0413)	(0.0408)	(0.0400)	(0.0414)	(0.0409)
California	0.0540	0.0342	0.0563	0.0282	0.0280	0.0474	0.0228
	(0.0376)	(0.0389)	(0.0377)	(0.0391)	(0.0391)	(0.0380)	(0.0393)
Massach.	0.159**	0.162**	0.176**	0.156**	0.145**	0.155**	0.140**
	(0.0607)	(0.0599)	(0.0596)	(0.0600)	(0.0610)	(0.0608)	(0.0610)
Total dollars raised	-0.0000126	-0.0000459	-0.0000520	-0.0000646	-0.0000319	-0.0000359	-0.0000504
	(0.000186)	(0.000201)	(0.000201)	(0.000207)	(0.000196)	(0.000195)	(0.000202)
Eigen. centrality		0.398**		0.355**	0.365**		0.327**
		(0.144)		(0.146)	(0.145)		(0.147)
Log Syndicate dollars inv.			0.00466			0.00422	
			(0.00312)			(0.00313)	
Mean log syndicate age				0.0275*			0.0255*
				(0.0152)			(0.0152)
Observations	5976	5976	5976	5976	5976	5976	5976
Pseudo R^2	0.022	0.022	0.021	0.022	0.022	0.022	0.023

Standard errors in parentheses

Dependent variable is whether investment had acquisition. Includes all investments with only a spinoff or a denovo investor before 2003.

Probit regressions with year and industry dummies.

All independent variables measured at the first investment date.

* $p < 0.10$, ** $p < 0.05$

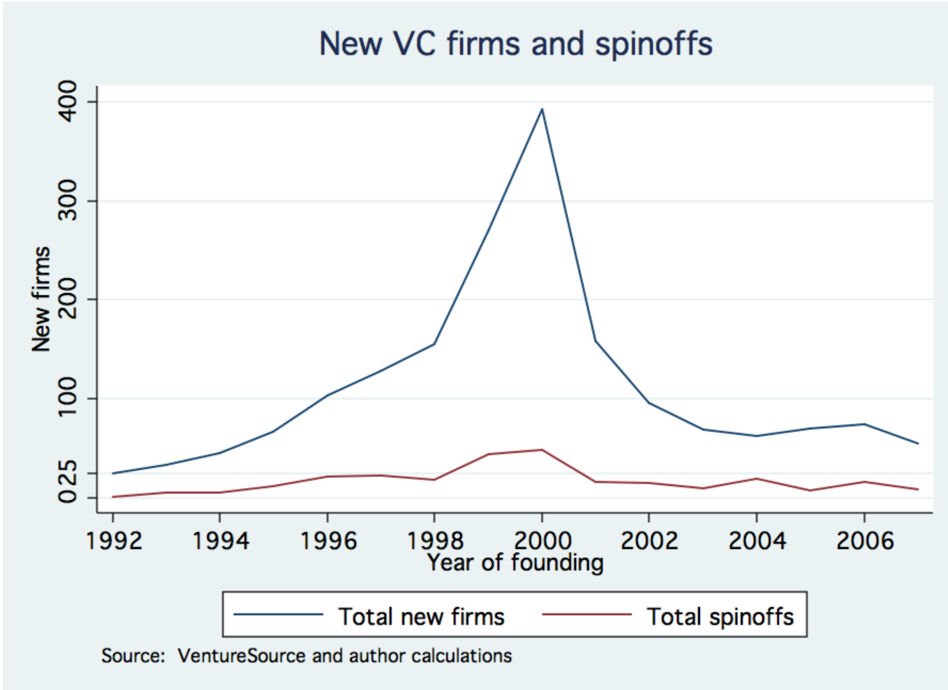

Figure 3.1: New firms and spinoffs over time

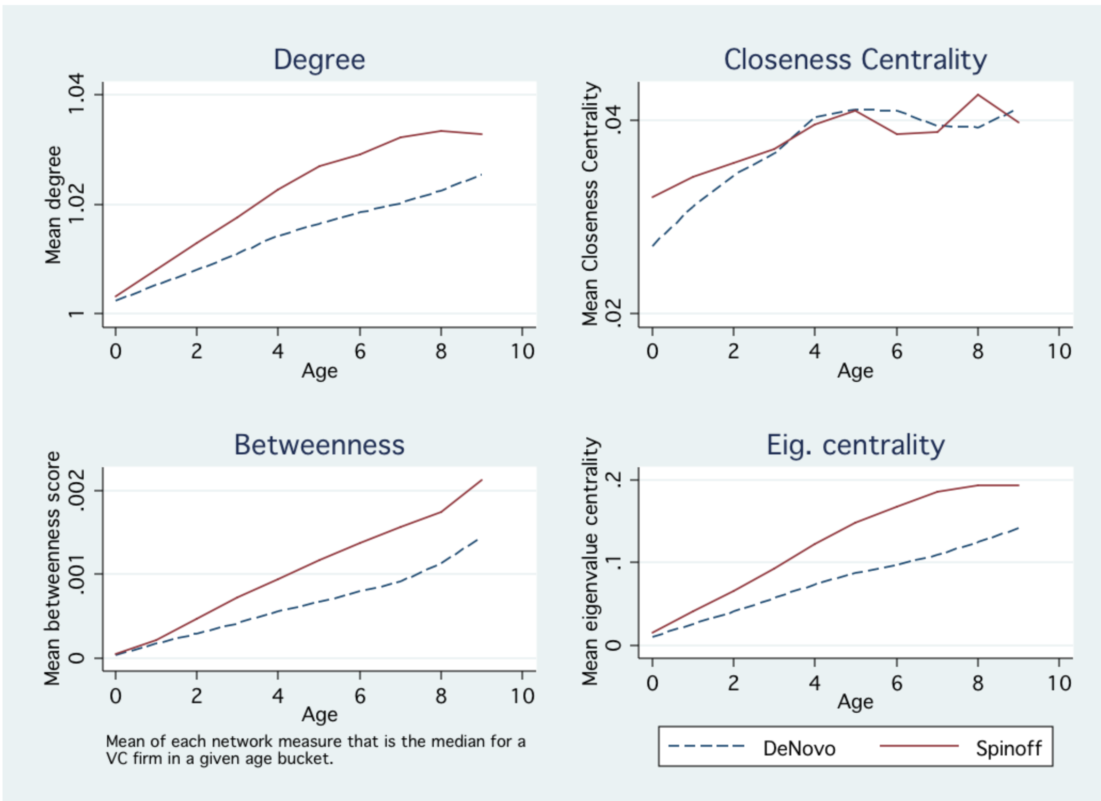

Figure 3.2: Spinoffs and denovo network centralities

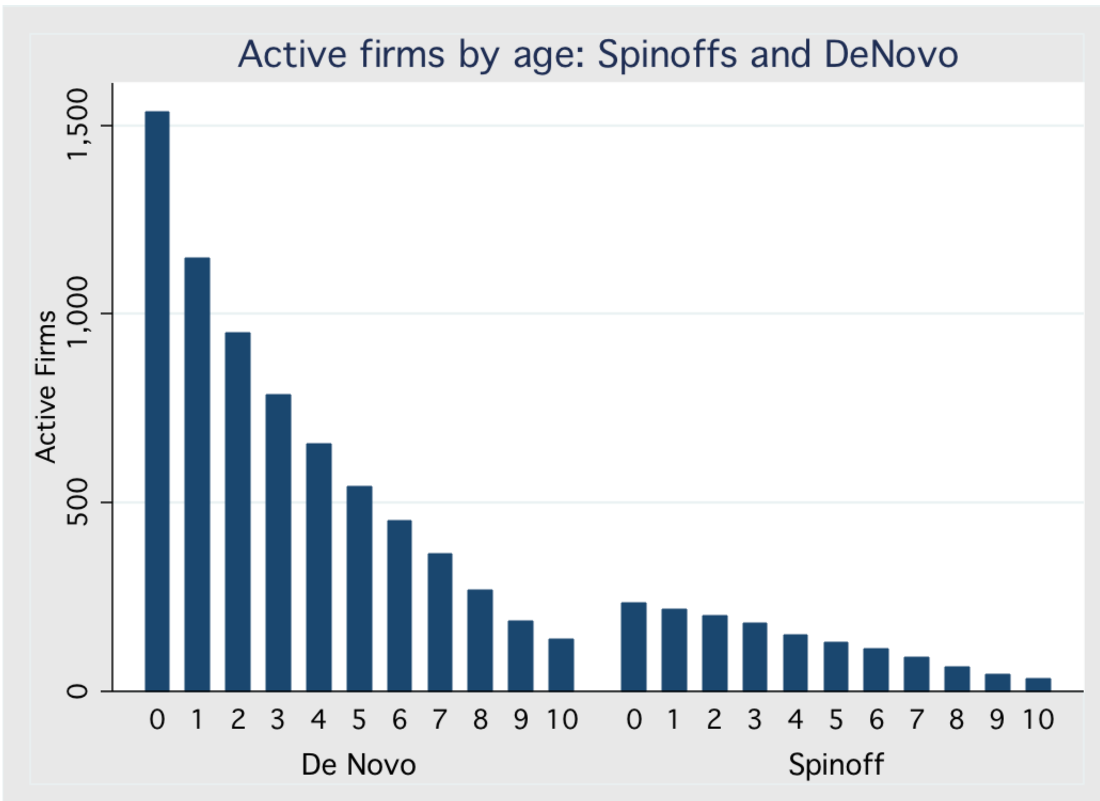

Figure 3.3: Spinoffs and denovo survival

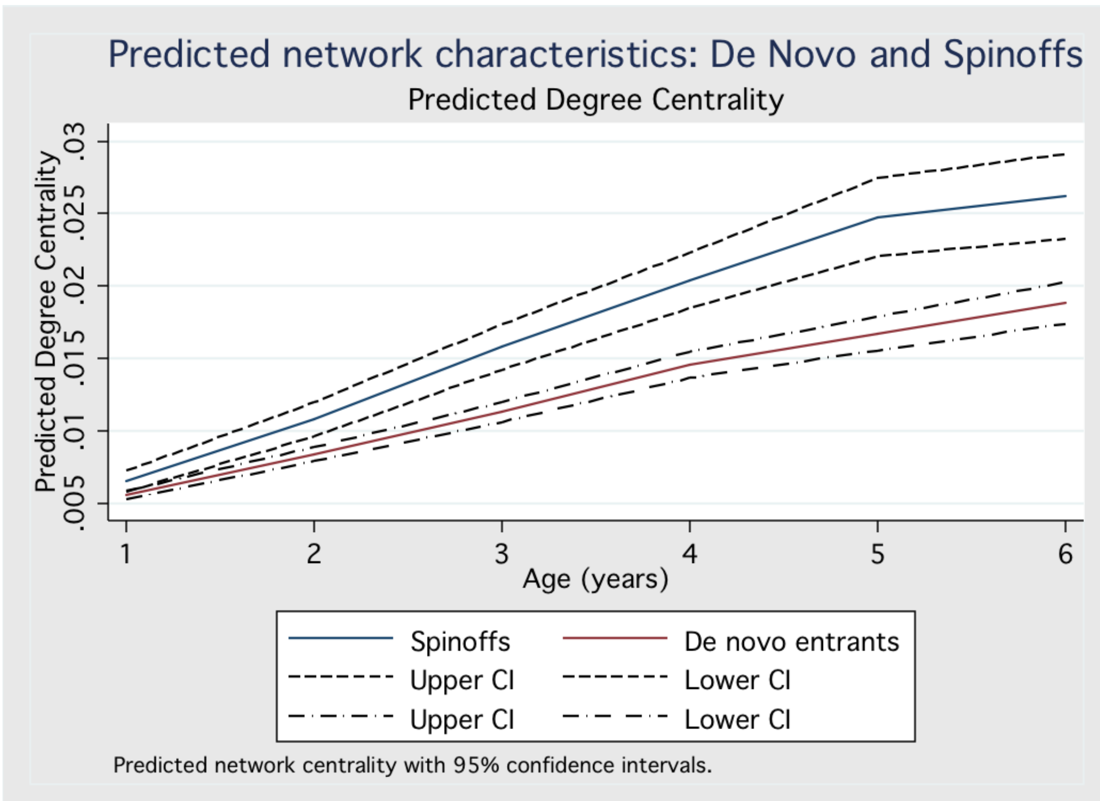

Figure 3.4: Predicted spinoffs and denovo network centralities: degree

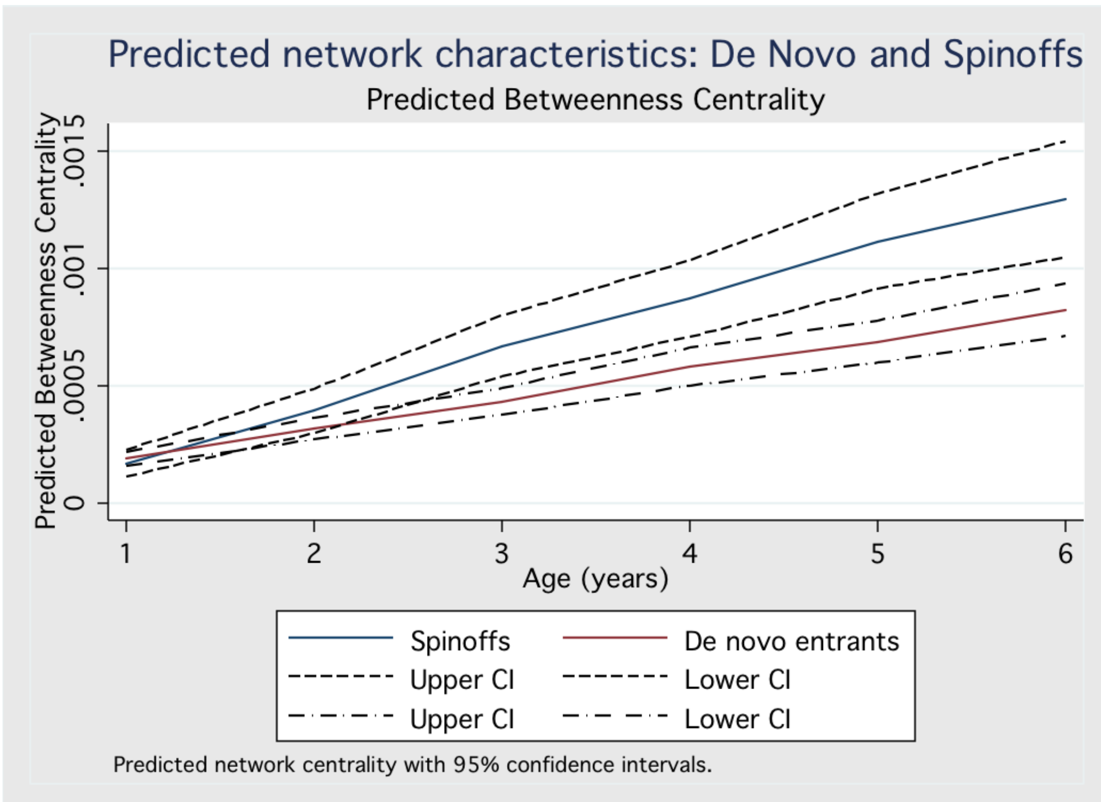

Figure 3.5: Predicted spinoffs and denovo network centralities: betweenness

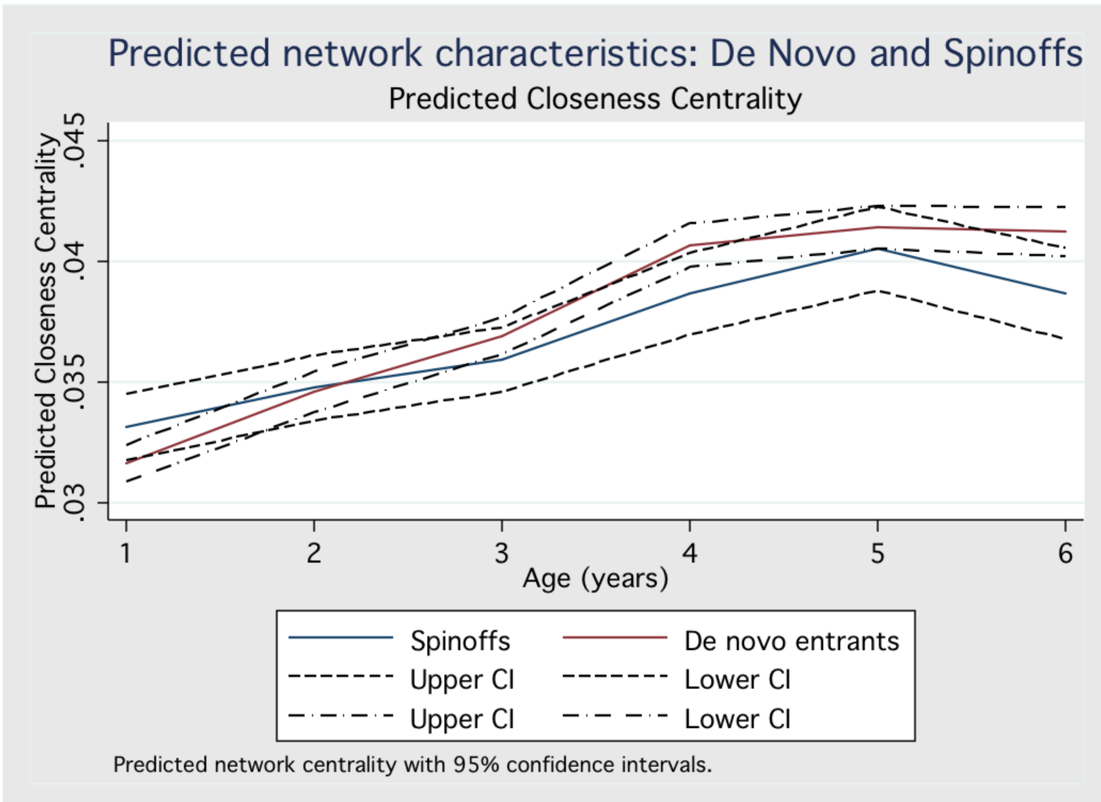

Figure 3.6: Predicted spinoffs and denovo network centralities: closeness

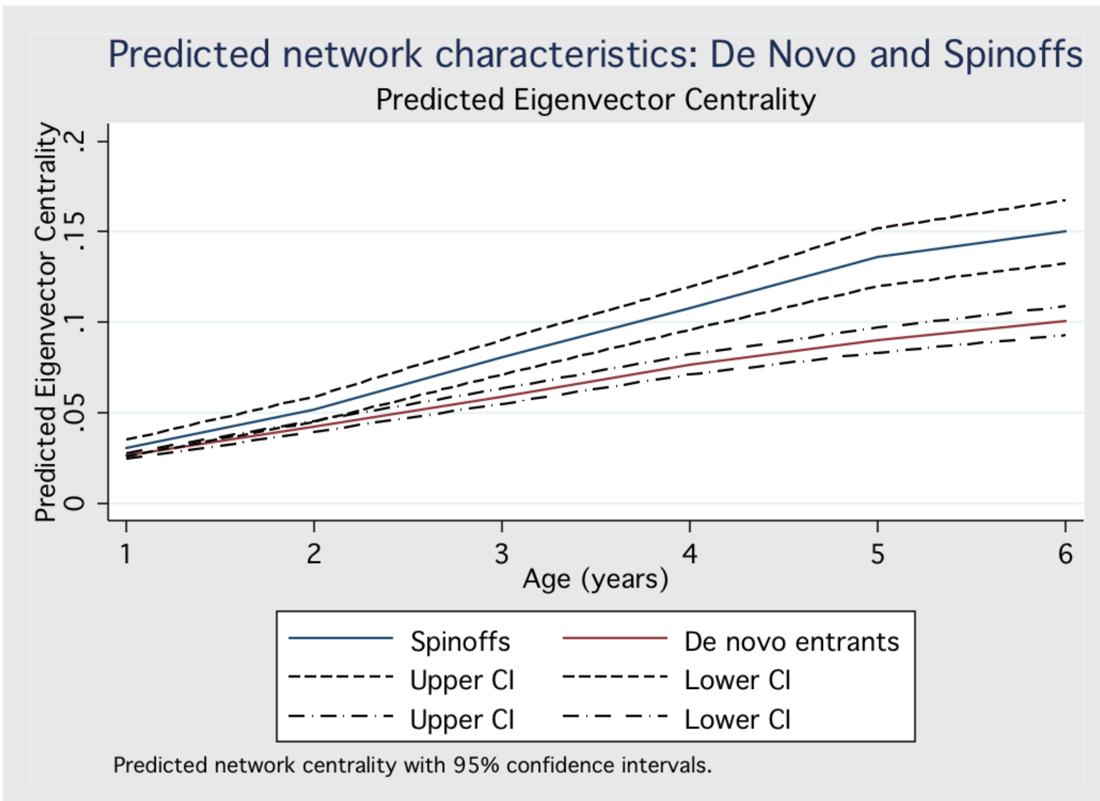

Figure 3.7: Predicted spinoffs and denovo network centralities: eigenvector

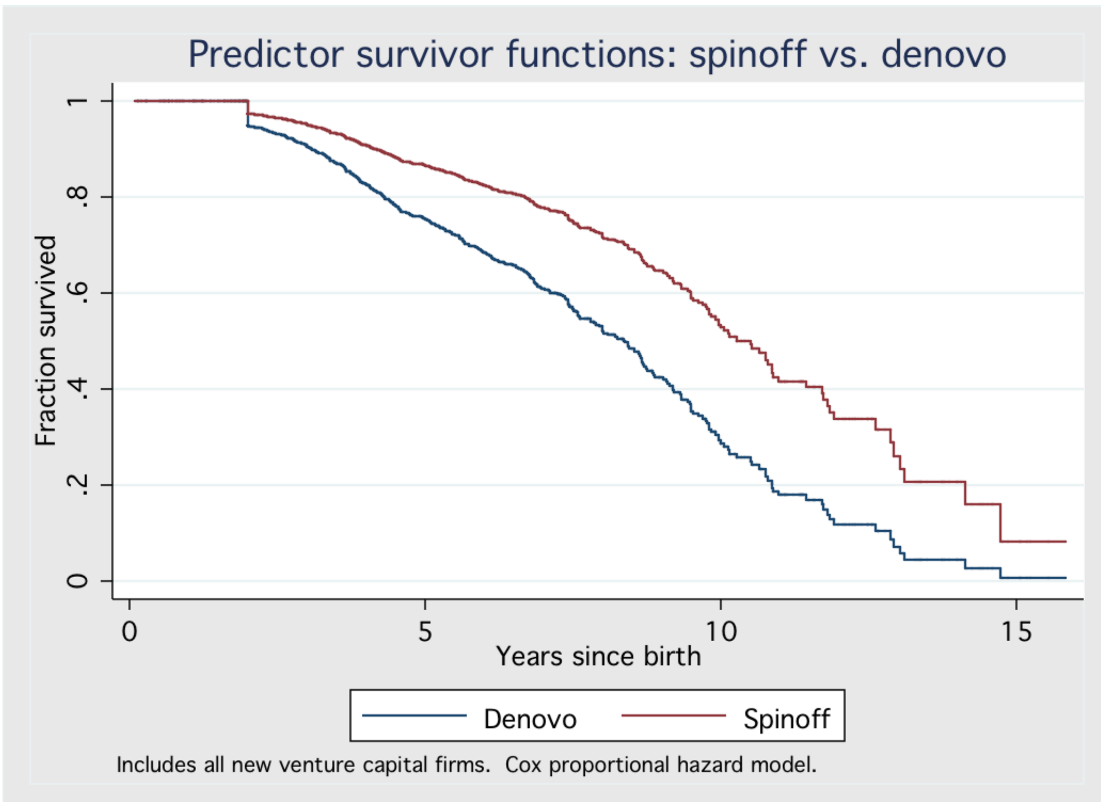

Figure 3.8: Estimated survivor function for spinoffs and denovo

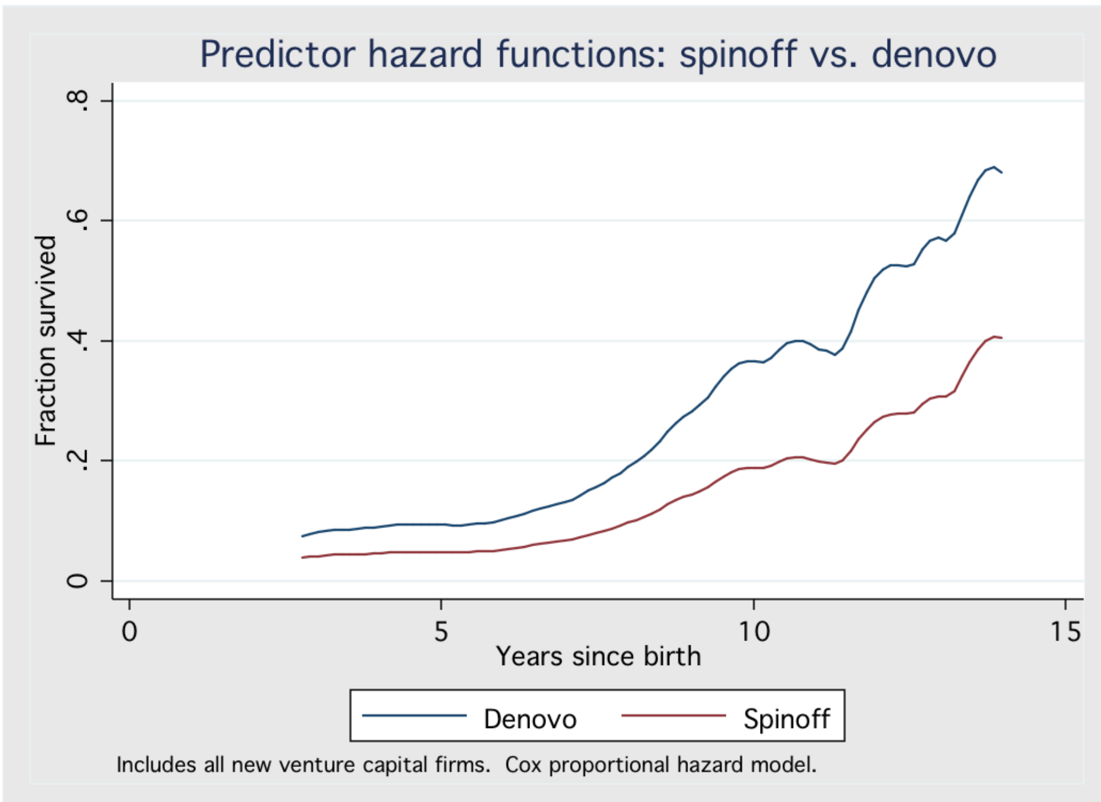

Figure 3.9: Estimated hazard of exit for spinoffs and denovo

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