Strategic Alliances, Venture Capital, and the Going Public Decision *

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Abstract

We study the tradeoffs that young, private biotechnology firms face in the private equity market when they choose between raising capital from VCs or raising capital from strategic alliance partners. Increased alliance activity makes future alliances more likely, but future VC activity less likely. In contrast, VC activity makes both future alliance and future VC activity more likely. Both types of private capital raise the hazard of going public, and indeed alliances often play a larger role than VC activity in the IPO process. Acquisition as an alternative to IPO is made more likely by increased VC activity, but the link between acquisition probabilities and alliance activity is less clear cut. These results highlight both the importance of alliance partners in resolving asymmetric information problems in the capital acquisition process, as well as the potential conflict of interest between different sources of private equity.

Why do firms go public? Although there is relatively little empirical work examining the motives behind private firms' decisions to IPO, there is a broad consensus among finance scholars and practitioners that one key driver is the need to access large amounts

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of capital, amounts often in excess of what private equity markets can provide. Indeed, in a recent survey Brau and Fawcett (2006) find that 2/3 of all CFOs list the need to grow as the main reason behind the timing of their IPO.

Given that hunger for financial resources is a major factor in the going public decision for many firms, this paper focuses on a natural question: What role do private equity markets play in the going public decision?

To explore this question, we focus on a sample of private firms in the biotechnology sector. Because biotechnology firms frequently access different types of private capital, this sector provides an ideal setting for studying the interaction of public and private capital markets. While venture capital is very active in the biotechnology sector, biotechnology firms at the same time often rely on inter-firm commercialization agreements (strategic alliances) to provide funding. Both types of funding are important sources of private capital for biotechnology firms (Lerner and Merges, 1998).

A major hurdle to empirical work in this area is the dearth of data on private firms. In this paper we develop a novel panel containing over 1900 privately held biotechnology firms that both received venture funding and participated in alliance activity, but to varying degrees. The data begin at a firm's birth, and record the funding histories of the firms in question, as well as prevailing market conditions, both at the time the firm receives its initial funding as well as the time of the focal funding event. This allows us to estimate the effect that strategic alliance activity and venture funding activity have on the hazard of going public: that is, the probability that a firm goes public at a particular point in time as a function of the time since its last funding event.

Our results demonstrate not only the interplay between the two types of private equity capital, but also their joint impact on the going-public decision and alternative exit strategies for private investors. First we explore the interaction of venture and alliance funding in the private equity market. Here we observe an asymmetry. Obtaining more funding through strategic alliances lowers the probability that a firm receives another round of venture financing, but raises the probability that it engages in subsequent alliance activity. In contrast, more venture activity increases both the hazard of future venture activity and the future of additional alliance activity.

Next we explore the role that alliances and venture capital play on the going public decision. It comes as no surprise that firms with more venture funding are at greater risk of going public. What is surprising, however, is the fact that strategic alliance activity has an equal, if not greater, impact on the hazard of going public. An additional alliance raises the hazard of going public by about twenty percent, which is roughly the same as the effect of an additional round of VC funding. Alternatively, raising the log of non-equity alliance funding by one million dollars increases the hazard of going public also by about twenty percent.

Because acquisitions by other biopharmaceutical companies provide an alternative exit mechanism to IPO, we also examine how strategic alliance funding and VC funding affect acquisition outcomes. Increased VC activity unambiguously raises the hazard of being acquired. In contrast, the effect of increased alliance activity is less clear cut. On the one hand, holding constant other factors, an increase in the number of past strategic alliances lowers the hazard of an acquisition. On the other hand, an increase in the amount of alliance funding raises the hazard of being acquired. One explanation for this effect is that being linked tightly to one alliance partner, which is evidenced by increased alliance funding, raises the hazard of being acquired because that firm becomes a potential acquirer through the alliance process. Another explanation is that the presence of past alliance funding indicates that the firm in question is more likely to have intellectual capital valued by an acquisition partner. To contrast these explanations, we replace our project-level measure of alliance funding with equity funding, and find the opposite result: more alliance equity dramatically lowers the hazard of acquisition.

More generally, these findings reflect two competing forces at work. First, the typical alliance contract in this setting affords project-level decision rights and monitoring provisions to the alliance partner (Robinson and Stuart, 2007). This creates potential for conflicts of interest with venture capitalists, whose firm-level investments create exit motives that may be at odds with the intentions of the alliance partner, and whose firm-level control and cash flow rights may be at odds with the decision rights of the alliance partner. The opposing force is the role that VCs and alliance partners play in resolving the asymmetric problems that firms face when they go public. Our results indicate that strategic alliance partners play a critical role in resolving asymmetric information in public capital markets, perhaps a more important role than that played by the venture capitalist, in spite of the fact that their presence may create contractual impediments that crowd out VC funding.

Of course, any attempt to establish a causal link between private capital market behavior and the going public decision must deal with a variety of endogeneity concerns. Because our models relate the stock of past behavior to the hazard of future behavior, reverse causality in the narrow sense is less of an issue here than it often is in cross-sectional regressions. Nevertheless, any link between past behavior and the going public decision may reflect unobserved heterogeneity in firm characteristics that drives preferential selection into the private capital market. To control for this, we allow for unobserved firm-level heterogeneity in our hazard rate estimation. This guards against the possibility that time-invariant, unobserved quality differences across firms simultaneously make them attractive private equity recipients as well as IPO candidates. Likewise, because our sample selection strategy identifies only the firms that receive VC funding, we overlook firms who were unable to attract private funding. Thus, it is unlikely that the variation in the data that allows us to identify these effects is driven by quality differences that would have resulted in these firms being screened from the capital market.

Our paper is related to a number of papers that explore determinants of the going public decision. Pagano, Panetta, and Zingales (1998) explore this question in a sample of private Italian firms. They find that larger, more profitable firms go public. In recent work, Chemmanur, He and Nandy (2006) find a similar relation between profitability, performance and going public in US Census of Manufactures data, and also show that IPOs are more likely among market leaders in more concentrated, and less opaque, industries. Our work compliments these findings by focusing on performance in private capital markets, rather than product market performance, as drivers of the going public decision. In that regard, our paper builds on Lerner (1994), which also examines the going public decision among biotech startups, but focuses on the role of the VC in timing access to the public capital market. The recent paper by Hsu (2006) is also closely related. He uses a small sample of technology firms funded under the SBIR program to explore the role that venture capital plays in the commercialization strategies of small, private companies. His analysis also explores the link between venture capital and the firm's going public decision.

Our analysis is distinct from his in a number of ways. On a methodological level, we study a much larger sample, albeit one that is focused on a narrower range of business activities, and we employ statistical models that explicitly account for the effect of the passage of time between funding events. On a conceptual level, however, our main question concerns the degree to which strategic alliances and venture capital are substitutes or complements for one another in the lead-up to the firm's IPO, and how this spills over into the firm's going public decision. Hsu (2006) is primarily concerned with the role that the venture capitalist plays in facilitating subsequent alliance activity. The VCs role as facilitator may stem from professionalizing the startup firm (Hellmann and Puri, 2002), from providing access to other portfolio companies with complementary assets (Lindsey, 2002), or from screening. By focusing on the feedback between these alternative forms of funding, and on their dual role in the going public decision, our analysis is distinct from Hsu (2006) but complements his work.

Our findings also relate to recent work linking price effects in public and private capital markets to the presence of alliance partners. Nicholson, Danzon and McCullough (2005) find that strategic alliances create larger step-ups in funding in the private equity market, and that this more than compensates for the apparent discounts that firms receive in early alliance deals. Stuart, Huang and Hybels (1999) show how alliance partners play a certification role for young biotech firms, drawing on evidence from IPO markets. In contrast, Gulati and Higgins (2003) find little evidence that alliance partners impact capital raised in an IPO.

Our analysis is also related to numerous studies exploring the role of strategic alliance partners as sources of capital for nascent firms. Most notably, Lerner, Shane and Tsai (2003) show how strategic alliances are relied upon more often during cold IPO markets. This paper's subject is closely related; however, instead of using the substitution of public markets and alliance capital as an identification strategy for measuring differences in control rights across financing regimes, we instead measure the change in the probability of a future IPO as a function of current and past alliance activity.

In that regard, our estimation strategy is related to recent work in the capital structure and investment literature. Our empirical approach is similar to Leary and Roberts (2005), who use duration analysis to study firms' capital structure rebalancing decisions. Whited (2006) uses a similar estimation strategy to measure the role of external financing constraints on the timing of investment decisions. Both these papers implement semi-parametric hazard estimation techniques developed in Meyer (1990).

The remainder of the paper is organized as follows. First, we discuss the relevant theory and offer a series of empirical predictions to guide our analysis. This is contained in Section 1. In Sections 2 and 3 we describe our data and discuss key features of our estimation strategy. Section 4 contains our results exploring how funding opportunities in the private capital market evolve, while Sections 5 and 6 explore exit outcomes. Section 7 concludes.

1 Predictions

In this section we draw on past work to develop a series of predictions about the role of venture capital and strategic alliance funding on the probability of going public. We start with predictions surrounding VC funding, since these are fairly unambiguous. Then we proceed to competing hypotheses surrounding the role of strategic alliance funding.

1.1 Venture Capital

The predictions for venture capital and going public are straightforward. We predict that increasing the venture capital funding that a private biotechnology firm receives should increase the probability that it goes public.

This prediction builds directly on the expressed motives of venture capital investors. A VC investor provides capital to a startup with a view to a later exit opportunity, either in the form of an IPO or a sale to another firm. Therefore, any given VC investor who has already invested in a biotechnology company is likely to press for a favorable exit. Moreover, the selection process that precedes the VC's investment decision is likely to favor biotechnology firm that have a higher probability of a favorable exit. Finally, the role that VCs play in the professionalization of startup firms implies that greater VC contact is likely to predict a higher likelihood of the biotechnology firm reaching the point at which it can successfully IPO.

The predictions for venture capital on subsequent alliance activity are less clear cut. A number of papers suggest that increased venture funding should lead to a greater chance of future alliance activity. Hellmann and Puri (2002) emphasize the role of venture capitalists in professionalizing start-up businesses. Since having a more professionally managed firm likely raises a firm's attractiveness as an alliance partner, this suggests that increased venture activity should increase the hazard of subsequent alliance activity. Likewise, Lindsey (2003) shows that venture capitalists facilitate alliance activities among portfolio companies. In addition, Hochberg, Ljunqvist and Lu (2005) find that better networked VCs are more successful, arguing that this owes to their more extensive business connections that can be brought to the aid of portfolio companies. These arguments also predict that increased VC activity should increase the hazard of alliance activity, since the VC may play an active role in helping the firm forge new alliances.

On the other hand, as we discuss in detail below, the incentives of VCs and alliance partners may differ, and contractual rights that are conferred to the VC in a standard term sheet (see Kaplan and Strömberg (2004) or Sahlman (1990)) may deter subsequent alliance activity. In light of the substantial evidence indicating that strategic alliances facilitate knowledge flows between firms, VCs may be reluctant to have a portfolio company enter into a relationship with another firm when that relationship could dilute the value of the portfolio company's intellectual property. These arguments predict that venture capital should lower the hazard of subsequent alliance activity.

1.2 Strategic Alliances as Substitutes to Venture Capital

The potential for strategic alliances to act as a substitute for venture capital stems from several factors. First, as Robinson and Stuart (2007) note, venture capitalists fund *firms*, not *projects*. In contrast, strategic alliance partners generally sponsor research activity on at most a small subset of projects that the biotechnology firm is operating.

The fact that venture capital and strategic alliance capital have different implications for project-level management inside the firm is borne out by the features of real-world financial contracts. Strategic alliance contracts typically stipulate project-level oversight that is conducted by a team composed of members from both the biotechnology firm and the alliance partner. These contracts also frequently require that certain resources (typically man-hours of research personnel, or else named researchers at the biotechnology firm) be devoted to the project in question. Contracts typically state that the failure to perform along these dimensions constitutes breach, and triggers termination rights. While the alliance partner has broad project-level oversight and monitoring rights, it seldom has firm-level oversight provisions, such as board seats.[1]

In contrast, Kaplan and Stromberg (2003) find that venture capital contracts typically allocate a majority of board seats to the VC firm. Even when the VC does not receive an outright majority, it receives at least some board representation almost without exception. VC investors typically lack the technical expertise to participate in the day-to-day management of biotechnology research projects.

The organizational differences contemplated and installed through these contracts create the potential for conflict of interest between these funding sources. When scarce resources must be allocated across projects, the alliance partner may press the biotechnology firm to divert resources away from other internal projects, towards projects that center around alliance activity. Any such resource diversions that are overall value-destroying, even if they strictly benefit one project, should in principle be frowned upon from the point of view of the VC, since they stand to undermine the value of the VCs exit opportunity. Thus, one reason why strategic alliances may substitute for venture capital is that the potential incentive conflicts between these sources of funding may drive away potential VC investors who fear partial holdup at the hands of the strategic alliance partner.

There are other reasons why alliance partners might substitute for venture capital. Alliance partners may simply crowd out venture capital by lowering a biotechnology firms' funding requirements and hence increasing its bargaining position. Or the provisions in alliance contracts that place limitations on a change in the biotechnology firms' control may make an investment in such a firm less desirable, since VCs may antici-

[1]This description is taken from Robinson and Stuart (2007).

pate having future strategic exit options foreclosed through the presence of the alliance investor.

These arguments all suggest that increased strategic alliance activity may diminish the incentives for VC investors to participate, and may also lower the firm's probability of going public.

1.3 Strategic Alliances as Complements to Venture Capital

The preceding arguments overlook the screening role that strategic alliance partners play in biotechnology. By collaborating with a startup biotechnology firm, an alliance partner sends a powerful signal to outside observers that the biotechnology has valuable ideas and resources (Stuart, Hoang, and Hybels, 1999). This screening role can be substantial, especially given the high degree of uncertainty surrounding technical developments in biotechnology.

Thus, a screening or certification argument would predict that increased strategic alliance activity would increase the probability that a firm goes public. This can occur through two distinct channels. The direct channel is through the certification that the alliance partner provides to participants in the public capital markets: underwriters, investment bankers and future investors are likely to look more favorably upon a firm that has received stronger certification from industry insiders. But there is also an indirect channel. Increased alliance activity may attract greater amounts of venture investment into the company, since the alliance partner's certification also serves to inform participants in the private equity market. Even if alliance activity has no direct certification role for public capital markets, increased alliance activity can still increase the hazard of going public through this indirect channel.

2 Data Description

2.1 Data Sources

To test these predictions, we analyze a large sample of venture capital-backed biotechnology firms. We begin with all available records for VC-backed companies in the biotechnology sector from Thomson Financials VentureXpert database. These data consist of 1903 firms that were founded between the years 1980 and 2004. This is not a random sample of firms; all companies in the data received one or more rounds of funding from venture investors. From VentureXpert, we assembled the financing histories of the firms in the sample. These record include the date of founding of the company, the dates of all private equity financing rounds, the identities of the investors in each round, and when one took place, the time at which firms went public.

The focus of our empirical analysis is on the relationships between venture capital, alliance partnerships, and the public equity markets as potential sources of financing for early stage life sciences companies. We use Recombinant Capitals (ReCap) rDNA database to track the alliance activity of the firms in the ventureXpert sample. ReCap scours the newswire, company websites, securities filings, industry news sources, etc. to identify information on strategic alliances in the biomedical arena. The alliance data, which now list more than 20,000 transactions, date back to the early years of the biotech industry. In addition to the month and year in which each transaction was established, the database contains basic information about the terms of the agreement.

Table 1 records the time series of firm births in our sample, and provides information about how these firms exit our sample. Although the absolute number of firm births, and hence IPOs, is higher in the later portion of the sample, the relative frequency of going public is much higher in the beginning of the sample. This, of course, owes in part to the fact that firms born early in the sample have longer to exit the private capital market. The final two columns report the mean year in which a firm born in year t exits the sample through IPO or acquisition. Throughout the 1980s and most of the 1990s, the typical acquisition takes place several years after the mean IPO.

2.2 Independent Variables

Broadly, our independent variables fall into four categories: VC characteristics, alliance histories, innovation histories, and market characteristics.

2.2.1 VC characteristics

For each firm i in month t, we include the number of distinct financing rounds the firm has experienced prior to month t. One drawback with the VentureXpert data is that it does not contain reliable information on either the size of the financing round or the implied valuation of the firm. Nevertheless, this provides us with valuable information about the reputation of the VC firms involved in the biotechnology company.

There are a number of possible measures of the quality of a venture investor. First, we can tally the previous investment experience of each VC. Presumably, venture investors with extensive track records have repeatedly proven able to raise new investment capital from limited partners, and thus they have probably posted above average returns. Another measure is the network centrality of the VC in question. We focus on the latter approach.

There is one complication with specifying the influence of VC firm quality on the outcomes experience by individual portfolio companies. In most cases, there is a non-unique mapping of VC firms to biotechnology startups. This occurs because venture-backed companies are commonly financed by syndicates of investors. As a result, the typical firm in the data is financed by multiple venture investors. We control for this in two ways. First, we simply measure the centrality of most central VC in the prior financing round. This variable is called Max VC Centrality, last round. We also compute a proportional measure: for each firm-round, compute the fraction of total investor-rounds in which the VC participated. This provides a set of weights that sum to 1. We then use these weights to augment VC quality. We call this variable "VC Centrality, weighted."

2.2.2 Alliance characteristics

We measure three attributes of biotech firms strategic alliance histories. First, we include a time-changing count of the number of alliances the firm has entered. Ceteris paribus, since firms in this industry often require compelling technology to attract alliance partners, firms with greater numbers of alliances are more likely to be operating along in-demand technological trajectories. Second, we include a cumulating sum of the total amount of funding that biotech firms in the sample have raised from strategic partners. Controlling for the number of alliances, this variable offers a potential window into the fact that funding raised from an alliance partner may substitute for capital raised on the public equity market.

In some cases the alliances in our sample involve the sale of equity stakes to the alliance partner. Because some of these may be part of corporate venture programs, we exclude equity stakes from our calculation of funds raised through alliance activity. Thus, our measure of alliance funding tracks the project-level funding that the firm receives through milestone payments, R&D payments, and upfront payments. The results that we demonstrate on alliance funding are generally stronger when we include alliance equity, but concerns about miscounting corporate venture programs lead us to exclude them.

2.2.3 Innovation histories

We also incorporate the evolving stock of intellectual property rights held by each firm. For patents issued pre-1999, we utilize the NBER patent database. For post-1999 patents, we conducted automated searches of the USPTO's searchable patent database. We record the date of the patent application, and accumulate the total number of patent applications in the five years prior to the event in question.

2.2.4 Market Conditions

We also track data on market conditions. These data vary monthly. In addition, we record the historical market conditions that prevailed at the time the firm first received a round of funding, or undertook its initial alliance.

First, we track the intensity of IPO activity. This variable is based on the fact, as Gompers, Lerner, Kovner, and Scharfstein (2005) have shown, that IPO activity spurs VC activity. We keep a count of the number of IPOs that have occurred over the last three months, scaled by the number of firms at risk of IPO over the same period. This variable is updated monthly; in addition, the value of this variable at the time of first VC funding and at the time of first alliance activity are also recorded to study how initial conditions affect funding outcomes.

We also track the number of patents at the time of first funding/alliance, as well as the centrality of VCs funding the initial round. At the same time, we are also interested in broader measures of VC centrality, so we track the average centrality of all VCs active in the bio-pharmaceutical sphere at the time the firm received its initial funding. This global measure of centrality at a point in time captures how much attention VCs are paying to the biopharmaceutical sector.

As a final measure of overall market conditions in the private equity market, we track the aggregate number of funded strategic alliances at a point in time. Like our other measures, this is intended to capture how much money is flowing to young biotech firms from strategic alliance partners over time in the aggregate.

Most theories of capital allocation based on diminishing marginal quality of new firms as more firms enter the market would predict that these aggregate measures should correlate with lower success rates for firms in our sample. On the other hand, resource-based theories predict that access to more resources would strengthen any one firm's chances of survival and success. These measures are included to shed light on these theories. Preliminary results on this issue are presented in Table 10.

2.3 Summary Statistics

Table 2 reports summary statistics for the independent variables based on whether the firm in question remained private throughout the sample or else went public at some point in its life. We report summary statistics at three points in a firm's life: at one year, two years, and three years of age.

The table clearly illustrates the fact that firms that ultimately go public evolve along different financing trajectories than firms which ultimately remain private. At twelve months of age, firms that will eventually go public have received about twice as many VC funding rounds, and are roughly eight times more likely to have had a strategic alliance. These firms have received both more overall alliance funding, and more alliance equity than firms that do not go public in our sample. The VC partners who fund them are more central members of the VC network. The only dimension along which we see no difference is in the stock of patents filed.

By the time firms are 24 months old, their patent histories have begun to diverge in the same way that other variables had already diverged at age 12 months. This difference is marginally statistically significant at 24 months of age, and is highly statistically significant by the time the firm is 36 months old.

Table 2 also reports differences in initial conditions—that is, differences in firm characteristics at the time the firm received a first round of funding. The evidence here suggests that firms that receive initial funding when conditions are favorable are more likely to go public. For example, firms that receive an initial VC round or initiate their first alliance at a time when the IPO market is hot are more likely to go public.

The VC centrality at initial VC round or alliance tracks the average centrality of VCs investing in the biotech sector at these two points in time. As such, these are indications of whether well-networked VCs were active in biotech at a point in time. The results here show that firms that eventually go public received their initial funding at times in which the biotech sector received more attention from VCs. These results taken together offer some preliminary evidence in favor of the idea that firms born in favorable market conditions are more likely to succeed. We take this issue up in greater detail below.

Table 3 reports mean values of firm characteristics based on whether the firm ever receives a funded alliance. The table shows that firms who receive alliance funding are much more likely to both go public or be acquired—that is, they are less likely to be censored. Along every dimension, firms who receive alliance funding outperform those who do not. Of course, this could simply reflect alliance partners' ability to identify successful firms, or it could reflect the fact that the alliance partners provide resources that enable the firm to succeed. To control for this possibility, we implement an estimation strategy that allows us to account for unobserved heterogeneity in funding outcomes.

3 Data Structure and Estimation Strategy

The skeleton of the dataset we analyze is an unbalanced panel of over 150,000 firm-month observations, representing data from approximately 1900 distinct firms. Each firm enters the data at its founding date (as reported by VentureExpert) and exits the sample in one of three ways. First, a firm can exit our sample by experiencing one of the exit events we are interested in studying (an IPO or an acquisition). Such an outcome is typically called a *failure* in duration analysis (although the companies in question no doubt see it differently). A company can also drop out of the sample at some point before the end of our sample (*censoring*). Finally, a company can still be private at the end of our sample period (*right-censoring*). A right-censored observation is presumably still at risk of experiencing a failure, but that failure occurs outside our sample period, if at all.

Table 4 provides a more detailed analysis of censoring and failure. It reports a total of 353 IPOs and 150 acquisitions. All firm-month observations that do not conclude in one of the events we analyze are treated as being censored. This dataset structure allows us to update dependent variables on a monthly basis to reflect changes in the firms financing, alliance, or innovation history, as well as the current state of the equity markets in the biotechnology sector.

3.1 Outcome variables

3.1.1 Time-to-funding

First, we explore the waiting time until a firm experiences a subsequent capital raising event. Because we have a particular interest in the interplay between project-level (alliance) and firm-level (VC) financing, we analyze the likelihood of occurrence of these two types of financing events via separate estimation of distinct hazard rates. That is, first we estimate models of the time to next VC round, then we estimate models of time to next alliance. By estimating separate models, we allow both the baseline hazards to vary as well as the parameter estimates on firm- and market-level covariates to vary. In these regressions, we treat transitions to the terminal states in our data, acquisitions or going public, as censored spells.

3.1.2 Time-to-exit

The private, VC-supported firms in the sample experience three types of exit events (in addition to the continuation of the firm as a private entity at the close of our observation window, which is treated as a censored event): IPO, acquisition, or they cease to exist.[2] In the second set of regressions, we estimate the competing risks of going public, getting acquired, and failing.

3.2 Analysis Time

Since we are interested in modeling the probability of a funding event at a point in time as a function of the time since last funding event, we must specify analysis time in a manner that both satisfies the underlying econometric assumptions of proportional hazard models and yields coefficients that have sensible economic interpretations. The identifying assumption is that controlling for the right-hand side variables, two firms observed at the same point in analysis time have the same hazard of experiencing an event. Therefore, calendar time would not be an appropriate choice for analysis time, even if we accounted for the staggered entry of firms into our sample, because this parametric choice would require all private firms in the data in month t to be at identical risk of IPO or other funding event.

[2]Unfortunately, ventureXpert almost certainly underreports the incidence of firm failure. In many instances, the outcome experienced by the firm is indeterminate, as a public record of a terminal event may not exist and a member of the firm does not respond to a survey questionnaire. In these instances, we censor the final record of the firm.

Instead, we use the firm's age as the main unit of analysis time throughout our analysis. Since our data are monthly, we track the firm's age in months, but for the purposes of reporting estimated coefficients, we track analysis time in quarters of a year (3 month blocks). The choice of time scale has no impact on our analysis except to affect the interpretation of the coefficients.

3.3 Survival and Attrition

A useful way to understand how attrition over time, either through an exit or a firm death, affects our sample is by analyzing an estimate of the survival function for the data. Figure 1 plots the Kaplan-Meier survival estimate. Formally, for all $t_i < t$, the survival function at time t is a step function defined in analysis time given by the following formula:

$$\hat{S}(t) = \prod_{t_i < t} \left[1 - \frac{d_i}{Y_i} \right] \tag{1}$$

where d_i is the number of observations experiencing IPO at t_i and Y_i is the number of firms at risk of IPO at time i; the fraction $\frac{d_i}{Y_i}$ is a measure of the conditional probability of failure at time i. Intuitively, $\hat{S}_t$ simply measures the fraction of the sample that is at risk at time t or greater. It illustrates that about 50% of the firms in our sample have yet to exit (either by IPO or by attrition) at 60 quarters of age.

Although we model a variety of funding decisions and exit events for investors, at the heart of our analysis is estimating a firm's hazard of an event occurring as a function of time. That is, we are interested in the probability of a funding event occurring during a small interval of time t to $t + \Delta t$ as a function of time and other firm and market characteristics. Formally, the hazard function for firm i at time t can be expressed as

$$h_i(t) = \frac{f_i(t)}{1 - F_i(t)} \tag{2}$$

where $f(t)$ is the density function associated with the event at time t and $F(t)$ is the cumulative distribution function associated with the event at time t. Writing the survivor function, 1-F(t), as S(t), this can be expressed as

$$h_i(t) = -dln(S_i(t)). \tag{3}$$

Following standard practice, we assume a proportional hazard specification which allows us to write the hazard of firm i at time t as

$$h_i(t) = \omega_i h(0) e^{x'\beta} \tag{4}$$

where $h(0)$ is the baseline hazard, x is a vector of covariates, β is a coefficient vector, and ω_i is a term that captures unobserved firm-level heterogeneity (known as frailty in the parlance of duration model estimation). To estimate the hazard function, we follow techniques described in Leary and Roberts (2005) and create dummy variables corresponding to the deciles of firm age. Within each age decile, an exponential hazard function is estimated.

Figure 3 plots a kernel density estimate of the empirical hazard of IPO as a function of the firm's age. The graph is truncated to include only those firms who are less than 200 months old to account for 'living dead' effects. Similarly, Figure 4 plots the empirical hazard of being acquired. Also, note that while the hazard of acquisition rises with the hazard of IPO in the early life of a firm, the former stays elevated after five years of age, while the hazard of IPO drops off dramatically after 5 years of age.

4 The Evolution of Funding in the Private Market

We begin by estimating the hazard of a subsequent private equity funding event as a function of past funding history and other firm characteristics. First we investigate how past funding and firm characteristics impact the hazard of receiving an additional round of venture funding. Then we turn to the hazard of entering into a strategic alliance. Finally we turn from financial outcomes to real outcomes, and explore how these same characteristics impact the hazard of filing a patent.

4.1 Time to Next VC Round

Table 5 presents estimates of the hazard of a VC funding round as a function of firm characteristics. A general result from the table is that a firm with more prior rounds of VC funding is at an increased hazard of receiving a future round of funding.

The effect of an additional alliance on a firm's hazard of VC funding is less clear cut. In column (2), which does not control for past VC activity, total alliance activity has a positive impact on the hazard of subsequent funding. This no doubt occurs through a signaling or certification effect, by which higher quality firms are at greater risk of both greater VC funding and more alliance activity. Indeed, when we include the patent count for the firm, we see that it impacts the hazard of VC funding positively, although this effect is insignificant.

Once we control for past VC activity, however, this effect reverses, revealing the fact that increased alliance activity reduces the hazard of future VC activity. This can be seen in two ways. First, in models (3)-(6), the hazard rate associated with an additional alliance is below one, meaning that it lowers the hazard of a subsequent round of VC funding. The effect of additional funding through alliances is even stronger. In models (5)-(6), the hazard associated with the natural log of total alliance equity is about 0.97, which is significantly different than one at the five percent level in model (6). This alliance funding variable captures only the alliance funding coming through non-equity related investments; if we include alliance-related equity stakes (results not shown) the reduction in the hazard is even stronger.

Table 5 also sheds light on the role of VC characteristics and market conditions on VC funding. The intensity of IPO activity has a positive impact on the hazard of subsequent VC funding. This is in line with Gompers, Kovner, Lerner and Scharfstein (2005) who find that IPO intensity spurs VC activity. Likewise, firms that have had prior investments from more reputable VCs have a higher hazard of subsequent VC funding. This effect is highly statistically significant.

The $\ln(\theta)$ parameter tests the significance of the ω_i parameter, which captures firm-level heterogeneity. The significance of this parameter indicates that the firm-level heterogeneity parameter is significantly different than 1, which is to say that unobserved firm-level heterogeneity is important in our analysis.

4.2 Time to Next Alliance

Table 6 turns from VC funding to estimates of the hazard of entering into an alliance as a function. The picture that emerges from this analysis is quite different than that presented in Table 5.

As we see with VC activity in Table 5, increased alliance activity raises the hazard of subsequent alliance activity. This can be seen throughout columns (2)-(6) in the hazard rate associated with Total Alliance Activity, last 5 yrs. In columns (2)-(3), which do not control for the size of past alliance funding, this hazard rate is between 1.35 and 1.4, while in (4) and (5), with controls for past alliance funding, it drops considerably but is still statistically significant.

Likewise, increasing the amount of past alliance funding dramatically raises the hazard of future alliance activity. An increase in the log of alliance funding of \$1 million effectively doubles the hazard of subsequent alliance activity. This effect is highly statistically significant. Therefore combining the results of Tables 5 and 6 we see evidence of path dependence in alliance activity, whereby past alliance activity steers firms away from future VC activity towards future alliance activity.

The asymmetry between alliance and VC partnerships becomes evidence when we examine the effect of past VC activity on subsequent alliance activity. Instead of lowering the hazard of an alliance, increased prior VC funding raises the hazard of a subsequent alliance. The order of magnitude of this effect is comparable to the increase in the hazard associated with prior alliance activity. In general, all the VC variables (prior activity as well as both measures of VC quality) work to increase the hazard of alliance activity.

This asymmetry is consistent with alternative contracting arrangements creating a conflict of interests between VCs and alliance partners. When alliance partners provide funding, they crowd out future VC funding. But when VCs move first, they promote subsequent alliance activity, presumably because they can contractually preclude future alliance partners from contracting in ways that create conflicts of interest.

4.3 The Real Effects of Private Capital Market Activity

In Tables 5 and 6, patent activity has only a modest effect on funding outcomes. Patent filings increase the hazard of subsequent VC funding, but lower the hazard of subsequent alliance activity. In this subsection, we turn the tables and examine how past funding activity affects the hazard of subsequent patent filings.

This is reported in Table 7. Both past VC activity and past alliance activity raise the hazard of patent filing. For alliances, we see that both raw alliance counts as well as alliance funding raise the hazard of patent filing. Note that this holds even when we hold constant the stock of past patent filings; this helps to guard against the possibility that we are simple uncovering a firm quality effect. Nevertheless, we do find that the quality of the firms' VCs has a strong effect on the hazard of filing. This could be simply a firm quality effect, but in light of the fact that we are controlling for unobserved firm-level heterogeneity, this could also picking up effects similar to those documented in

Hochberg, Ljundqvist and Lu (2005).

Interestingly, patent filings rise in times when IPO intensity is high. This suggests that IPO waves in this sector correspond at least in part to spikes in productive activity in the sector, not just to investment fads.

5 The Road to Going Public

Table 8 analyzes the hazard of going public as a function of a firm's past actions and its age. It illustrates that both types of past activity in the private capital market—strategic alliances and venture capital funding—raise the hazard of going public. Note, too, that the effect of additional alliance funding is also positive. Thus, while alliance equity crowds out venture capital, it still has a dramatic effect on the hazard of going public.

Not surprisingly, the intensity of the IPO activity has a dramatic impact on the hazard of going public. Raising IPO intensity by one unit increases four-fold the hazard of going public. What is perhaps more interesting is that our point estimates on alliance and VC hazard rates continue to be highly significant in the presence of controls for variation in market conditions.

Table 8 also illustrates the importance of VC reputation for the going public decision. A one unit increase in weighted VC centrality of the prior participants has a seven-fold increase in the hazard of going public. This finding corresponds to the finding of Hochberg, Ljunqvist, and Lu (2005) who show that better networked VCs have better success. Our analysis shows that an important component of the increased success experienced by better-networked VCs stems from the fact that they take firms public more frequently than other VCs.

6 Exiting through Acquisition

Table 9 analyzes the hazard of being acquired as a function of a firm's past actions and its age. We employ the same set of independent variables as in Table 8 so that we can compare magnitudes in a straightforward manner.

Whereas alliance activity and VC funding work in tandem to raise the hazard of IPO, they work differently on the hazard of acquisition. Additional rounds of VC funding raise the hazard of acquisition, just as they raise the hazard of IPO. When we look at the point estimates associated with alliance funding as reported in Table 9, we see that additional alliance funding raises the hazard of acquisition. One explanation for this effect is that having a strong alliance partner raises the chances that that partner becomes an acquisition partner if the firm needs to exit through acquisition.

To test this explanation, in unreported tables we replace the alliance funding variable with a straight measure of alliance equity. In other words, instead of measuring the dollar value of pledged funds to the biotech firm, we measure the dollar value of equity stakes taken by alliance partners. When measured this way, additional alliance activity dramatically lowers the probability of acquisition. Instead of finding that increased funding doubles the hazard of acquisition, these point estimates are in the range of 0.5-0.6, indicating that additional alliance equity cuts the probability of acquisition by one-half.

Thus, instead of alliance funding representing the presence of a strong potential acquisition partner, the effect of alliance funding on acquisition outcomes probably reflects the fact that firms with greater past alliance funding have more intellectual assets in place of value in an acquisition. In contrast, the presence of a pre-existing alliance partner on the capitalization table of the biotechnology firm may present an impediment to acquisition. Indeed, many alliance contracts explicitly contemplate change of control and list it as an event which triggers the right to terminate the agreement (Robinson and

Stuart, 2007). Perhaps the role that alliance partners play in constraining exit options is a force in lowering the hazard of subsequent VC funding that we see in Table 5.

7 Conclusion

The paper is one of the first to analyze how the interplay between alternative funding sources in the private capital market affect a firm's decision to IPO. Strategic alliances and venture capital funding both raise the hazard that a firm goes public. Past VC funding also raises the hazard of a firm being acquired, while past strategic alliance activity does exactly the opposite.

The results surrounding the effect of VC funding on firm exit are unsurprising. After all, VC funds invest in portfolio companies hoping to book a return through a favorable exit. The findings here bear out this simple intuition, and illustrate the importance of the VC network in bringing about this outcome. Biotechnology companies that have VC investments from better networked VCs are at substantially greater hazard of going public.

What is perhaps more surprising is the role of alliances in the going public decision. The results presented here indicate that alliance activity has roughly the same impact on the hazard of going public as venture funding. Tentative results from semi-parametric frailty models suggest that the results for alliances are actually *stronger* than that of prior VC funding. This illustrates the importance of strategic alliance activity in the going public decision of private high-tech firms.

Our findings raise a number of interesting questions for future research. Our analysis ends where most analyses begin: at the date a firm becomes a public corporation. Linking our findings to the short-term and long-term performance of IPOs is a fruitful avenue for exploring the role of alliances in greater detail. We leave this for future work.

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Kaplan-Meier Survival Estimates

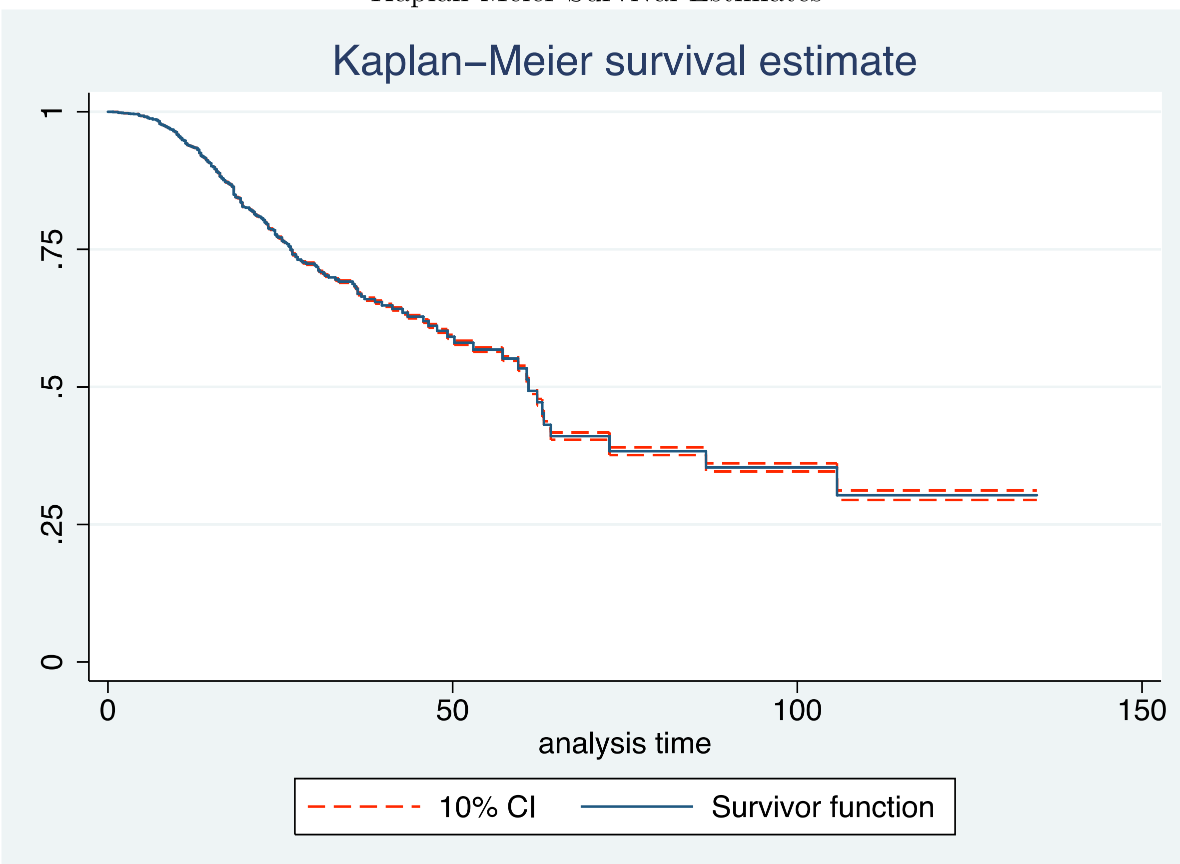

Figure 1: This graph plots the product-limit estimate of the survival function for our sample (the Kaplan-Meier survival estimate). The black line plots $\hat{S}(t) = \prod_{t_i<t} \left[1 - \frac{d_i}{Y_i}\right]$, where d_i is the number of events occurring at time t_i and Y_i is the number of firms at risk at time t_i. The red lines surrounding it are 10% confidence bands around the estimate.

The Distribution of Firm Age at IPO

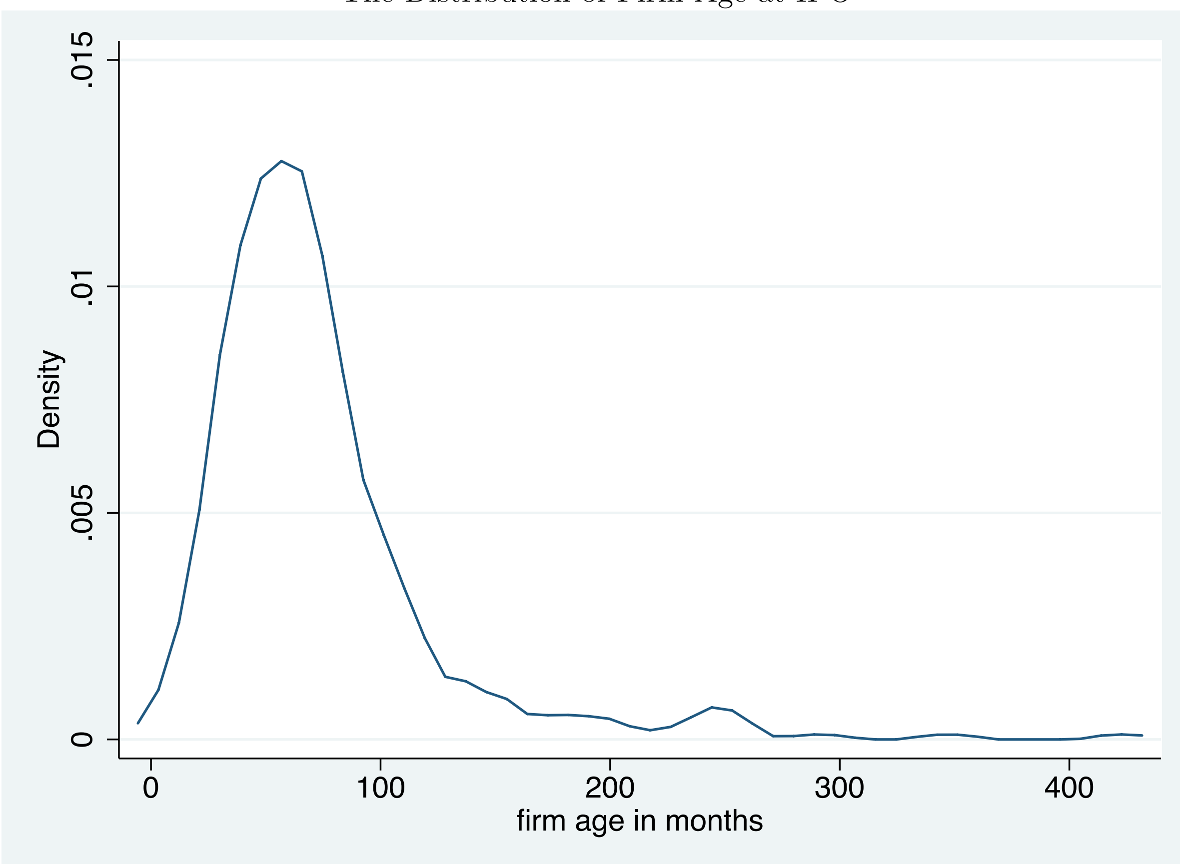

Figure 2: This graph plots the distribution of firms' age at the time of the going public decision.

The Hazard of Going Public

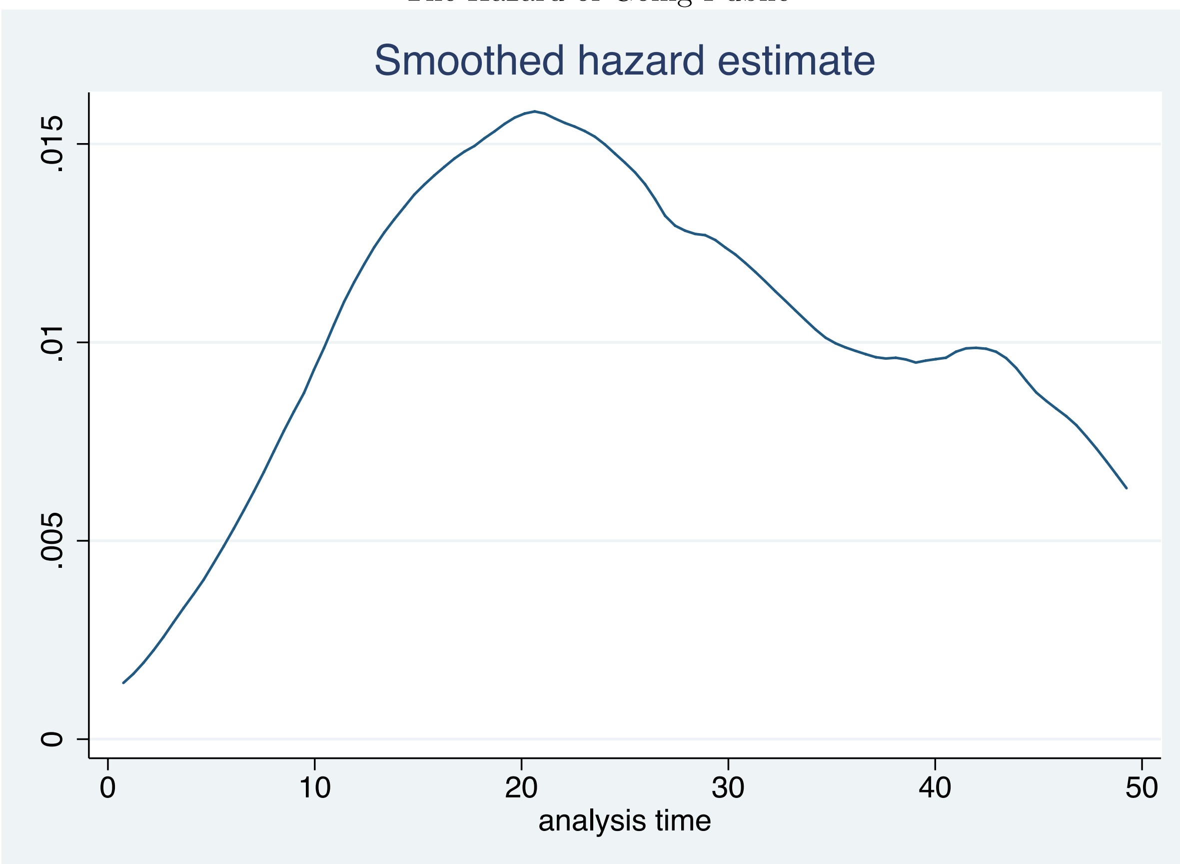

Figure 3: This graph plots the hazard of IPO as a function of the firm's age, measured in quarters.

The Hazard of Being Acquired

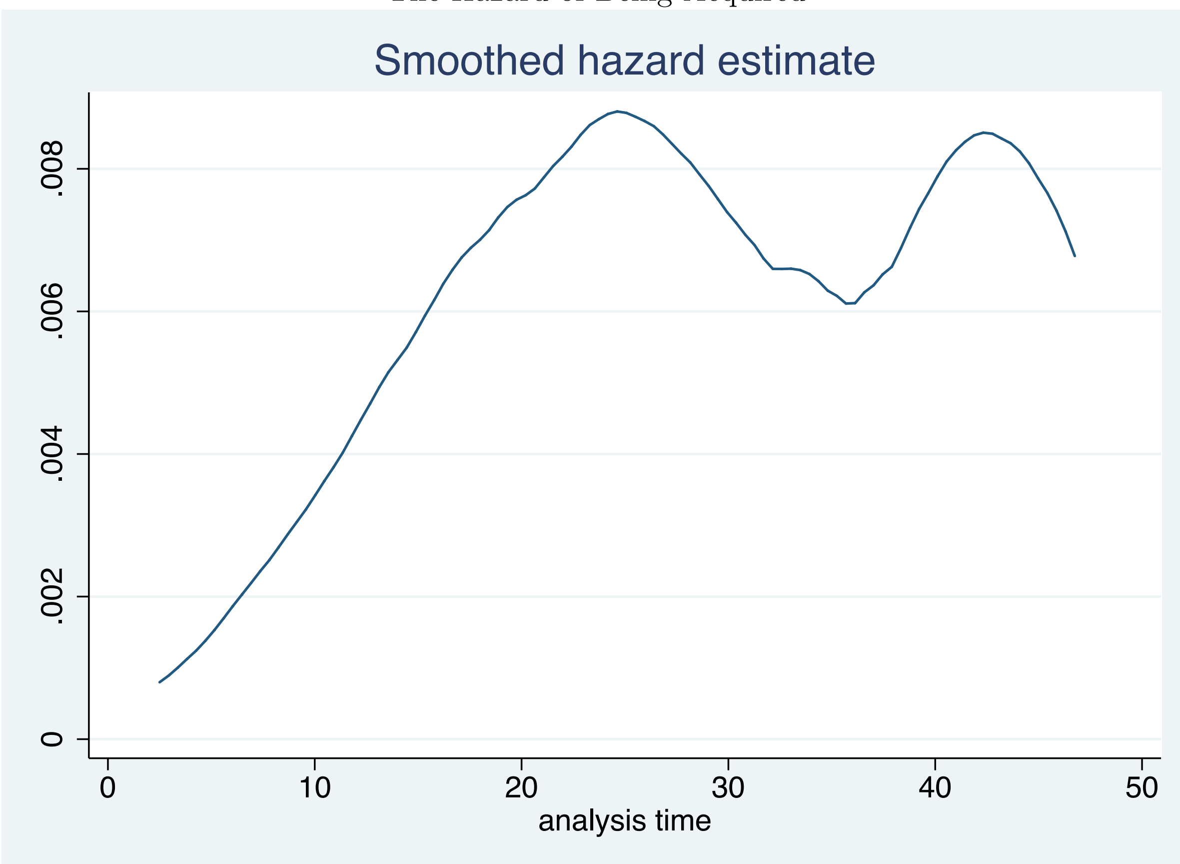

Figure 4: This graph plots the hazard of being acquired as a function of the firm's age, measured in quarters.

Table 1: The Time-Series of Firm Births

This table lists the number of firm births per year, along with the outcomes associated with them. The first column is the year of the cohort's birth. The second column is the size of the cohort. The third column lists the number of firms from that cohort that eventually go public; the fourth column, those that eventually are acquired. The fifth and sixth columns report the mean year in which the firm went public or was acquired.

Year	Firm Births	% Go Public	% Acquired	Mean IPO Year	Mean Acquisition Year
1980	20	12	4	1986	1986
1981	40	25	4	1987	1988
1982	25	11	5	1987	1989
1983	29	11	4	1989	1992
1984	24	10	4	1992	1997
1985	34	10	3	1992	1990
1986	44	20	0	1992	
1987	64	27	6	1993	1997
1988	45	19	5	1994	1996
1989	48	16	7	1993	1998
1990	45	12	7	1997	1995
1991	30	12	4	1995	1998
1992	77	26	11	1997	1999
1993	81	26	11	1998	1999
1994	79	17	12	1999	2000
1995	78	20	6	1999	2001
1996	92	13	15	2001	2001
1997	176	13	15	2001	2002
1998	183	10	5	2002	2003
1999	130	8	5	2003	2002
2000	253	6	8	2002	2003
2001	148	4	6	2004	2003
2002	64	1	0	2004	
2003	29	0	1		2004
2004	13	0	0		
Total	1851	329	148	-	-

Table 2: Summary Statistics at 12, 24, and 36 months of age

This table reports summary statistics for the firms in our sample at three points in their life: age 12 months, age 24 months, and age 36 months. The column labeled 'Overall' reports the grand mean across all observations in the data. For each age category, Priv. denotes firms that never went public, while Pub. denotes firms that IPO at some later point. The column labeled 't(diff)' reports the t-statistic associated with the test that the means across the two groups at that point in time are equal.

		Age = 12 mos			Age = 24 mos			Age = 36 mos		
Variable	Overall	Priv.	Pub.	t(diff)	Priv.	Pub.	t(diff)	Priv.	Pub.	t(diff)
Total Rounds of VC Funding	1.53	0.39	0.72	-5.69	0.71	1.42	-8.56	1.29	2.00	-7.10
Total Patents over last 5 yrs.	1.01	0.14	0.14	0.16	0.32	0.50	-1.99	0.56	1.30	-2.63
Total Alliances over last 5 yrs.	0.48	0.04	0.31	-7.47	0.13	0.83	-8.18	0.26	1.47	-8.04
ln(Alliance Project Funding) over last 5 yrs.	0.19	0.00	0.16	-4.65	0.02	0.33	-6.12	0.05	0.59	-7.04
ln(Alliance Equity) over last 5 yrs.	0.07	0.00	0.05	-2.85	0.01	0.14	-4.54	0.02	0.36	-7.01
Time Since last VC Round	27.81	9.85	8.50	4.99	17.49	12.21	9.38	14.09	14.99	-1.05
Time Since last Alliance	36.47	10.86	9.85	5.74	21.83	18.84	6.20	30.60	25.79	5.37
VC Centrality, weighted	0.03	0.02	0.07	-7.28	0.02	0.09	-9.37	0.03	0.09	-7.98
Max VC Centrality in last round	0.04	0.01	0.09	-6.62	0.02	0.13	-8.12	0.03	0.15	-8.43
Conditions at firm's founding:										
Total Patents at Initial VC Round	0.55	0.41	0.39	0.13	0.41	0.39	0.24	0.43	0.39	0.35
IPO Intensity at Initial VC Round	0.24	0.21	0.36	-5.98	0.21	0.36	-5.84	0.22	0.37	-5.61
Max VC Centrality at Initial Round	0.04	0.02	0.12	-6.96	0.02	0.12	-6.80	0.03	0.11	-6.28
Total Patents at Initial Alliance	0.38	0.15	1.00	-5.25	0.17	1.04	-5.19	0.17	1.15	-5.26
IPO Intensity at Initial Alliance	0.05	0.02	0.16	-9.61	0.02	0.17	-9.46	0.02	0.17	-9.25
VC Centrality at Initial Alliance	0.01	0.01	0.05	-8.45	0.01	0.05	-8.42	0.01	0.05	-8.22

Table 3: Firm Performance and Funded Alliance Activity

This table reports mean firm characteristics based on whether or not the firm in question received alliance funding. The sample is 1903 firms. The final column reports t-statistics of the test that funded and never-funded firms are equal.

Variable	Overall	No Alliance Funding	Alliance Funding	t(diff)
Percent that Exit Sample by Going Public	0.18	0.10	0.56	-16.24
Percent that Exit Sample by Acquisition	0.08	0.06	0.17	-5.14
Total VC Rounds	2.88	2.56	4.35	-10.60
VC Rounds per year	0.50	0.46	0.70	-6.95
Total Patents	1.99	1.27	5.35	-7.65
Patents per year	0.29	0.19	0.76	-8.42
VC Centrality, weighted	0.03	0.02	0.07	-10.62
Max VC Centrality in Initial VC Round	0.04	0.02	0.11	-7.34
IPO Intensity in Initial VC Round	0.23	0.21	0.34	-6.32
Patent Count in Initial VC Round	0.40	0.34	0.70	-2.65

Table 4: Summary Statistics for Funding Spells and Final Outcomes

This table provides summary statistics for various funding events and final outcomes.

		Firm-level values:			
Variable	total	mean	min	median	max
Number of subjects	1903				
Number of records	156442	82.21	3	72	539
Exit time, in quarters		20.55	.75	18	134.75
Funding Events					
VC Financing rounds	5252	2.76	0	2	17
Strategic Alliances (funded)	758	0.399	0	0	14
Final Outcomes:					
IPOs	353	.19	0	0	1
Acquisitions	150	0.079	0	0	1

Table 5: Piecewise Exponential Hazard Estimates of VC Activity

	(1)	(2)	(3)	(4)	(5)	(6)
Total Rounds of VC Funding	1.401**		1.420**	1.418**	1.422**	1.400**
	(0.010)		(0.012)	(0.012)	(0.012)	(0.012)
Total Alliances over last 5 yrs.		1.058**	0.982*	0.978*	0.991	0.989
		(0.010)	(0.009)	(0.009)	(0.011)	(0.011)
Total Patents over last 5 yrs.				1.007	1.008	1.006
				(0.004)	(0.004)	(0.004)
ln(Alliance Size) over last 5 yrs.					0.976	0.971*
					(0.013)	(0.013)
IPO Intensity, last 3 mos.					1.129*	1.054
					(0.057)	(0.054)
VC Centrality, weighted						8.583**
						(1.123)
$\ln(\theta)$	0.026**	0.299**	0.024**	0.022**	0.023**	0.015**
	(0.007)	(0.023)	(0.007)	(0.007)	(0.008)	(0.008)
Observations	152380	132927	132927	132927	132927	129757
Firms	1899	1886	1886	1886	1886	1886
$\chi^2(\theta)$	2891	358.0	2509	2512	2521	2690
χ^2	19.20	385.6	13.32	11.33	12.25	4.804

Table 6: Piecewise Exponential Hazard Estimates of Next Alliance

	(1)	(2)	(3)	(4)	(5)	(6)
Total Rounds of VC Funding	1.406**		1.273**	1.274**	1.075**	1.060*
	(0.040)		(0.032)	(0.032)	(0.025)	(0.025)
Total Alliances over last 5 yrs.		1.399**	1.348**	1.350**	1.049**	1.047**
		(0.024)	(0.023)	(0.023)	(0.016)	(0.017)
Total Patents over last 5 yrs.				0.995	0.979**	0.978**
				(0.008)	(0.008)	(0.008)
ln(Alliance Size) over last 5 yrs.					2.085**	2.070**
					(0.053)	(0.053)
IPO Intensity, last 3 mos.					1.394**	1.343*
					(0.168)	(0.164)
VC Centrality, weighted						8.222**
						(3.420)
$\ln(\theta)$	5.614**	2.168**	1.831**	1.849**	0.458**	0.470**
	(0.516)	(0.269)	(0.233)	(0.237)	(0.083)	(0.082)
Observations	152380	132927	132927	132927	132927	129757
Firms	1899	1886	1886	1886	1886	1886
$\chi^2(\theta)$	254.1	495.7	589.6	590.0	1686	1690
χ^2	916.5	690.9	552.4	526.0	85.80	91.11

Table 7: Piecewise Exponential Estimates of Next Patent

	(1)	(2)	(3)	(4)	(5)	(6)
Total Rounds of VC Funding	1.055**		1.051**	1.055**	1.051**	1.044**
	(0.015)		(0.016)	(0.016)	(0.016)	(0.016)
Total Alliances over last 5 yrs.		1.104**	1.094**	1.069**	1.045**	1.043**
		(0.012)	(0.012)	(0.012)	(0.014)	(0.014)
Total Patents over last 5 yrs.				1.023**	1.024**	1.026**
				(0.0022)	(0.0022)	(0.0022)
ln(Alliance Size) over last 5 yrs.					1.045**	1.045**
					(0.014)	(0.014)
IPO Intensity, last 3 mos.					1.160*	1.156*
					(0.068)	(0.068)
VC Centrality, weighted						6.079**
						(1.58)
Observations	152380	132927	132927	132927	132927	129757
Firms	1899	1886	1886	1886	1886	1847
$\ln(\theta)$	4.160**	3.584**	3.505**	3.137**	3.079**	2.863**
	(0.22)	(0.20)	(0.19)	(0.18)	(0.18)	(0.17)
$\chi^2(\theta)$	6104	5457	5205	3537	3298	3066
χ^2	368.7	610.4	621.4	750.5	768.2	835.5

Table 8: Piecewise Exponential Hazard Estimates of IPO Activity

	(1)	(2)	(3)	(4)	(5)	(6)
Total Rounds of VC Funding	1.451**	1.436**	1.309**	1.216**	1.207**	1.172**
	(0.062)	(0.062)	(0.047)	(0.048)	(0.047)	(0.047)
Total Alliances over last 5 yrs.	1.485**	1.453**	1.230**	1.220**	1.216**	1.200**
	(0.055)	(0.054)	(0.039)	(0.037)	(0.036)	(0.036)
Total Patents over last 5 yrs.		1.056**	1.034**	1.031**	1.031**	1.025*
		(0.019)	(0.012)	(0.011)	(0.011)	(0.011)
ln(Alliance Size) over last 5 yrs.			1.234**	1.226**	1.216**	1.234**
			(0.042)	(0.040)	(0.040)	(0.045)
IPO Intensity, last 3 mos.			4.178**	4.287**	4.218**	4.917**
			(0.510)	(0.516)	(0.511)	(0.691)
Time Since last VC Round				0.988*	0.990	0.971**
				(0.005)	(0.006)	(0.006)
Time squared				1.016	1.000	1.049
				(0.019)	(0.030)	(0.030)
VC Centrality, weighted					7.045**	7.725**
					(4.362)	(5.587)
Max VC Centrality at Initial Round						1.625
						(0.758)
IPO Intensity at Initial VC Round						1.568*
						(0.356)
Total Patents at Initial VC Round						0.927
						(0.048)
$\ln(\theta)$	2.589**	2.655**	1.202	1.006	0.956	0.810
	(0.494)	(0.530)	(0.325)	(0.304)	(0.293)	(0.281)

Table 9: Piecewise Exponential Estimates of Time to Acquisition

	(1)	(2)	(3)	(4)	(5)	(6)
Total Rounds of VC Funding	1.633**	1.813**	1.772**	1.778**	1.734**	1.691**
	(0.201)	(0.220)	(0.175)	(0.218)	(0.210)	(0.224)
Total Alliances over last 5 yrs.	1.228	1.346*	0.949	0.947	0.938	0.962
	(0.134)	(0.162)	(0.082)	(0.084)	(0.082)	(0.091)
Total Patents over last 5 yrs.		0.816**	0.782**	0.772**	0.770**	0.773**
		(0.058)	(0.053)	(0.054)	(0.054)	(0.058)
ln(Alliance Size) over last 5 yrs.			2.017**	2.023**	2.026**	2.055**
			(0.153)	(0.156)	(0.157)	(0.166)
IPO Intensity, last 3 mos.			0.778	0.891	0.845	1.040
			(0.315)	(0.359)	(0.349)	(0.446)
Time Since last VC Round				1.094**	1.089**	1.073*
				(0.030)	(0.030)	(0.031)
Time squared				0.173**	0.188**	0.237*
				(0.097)	(0.105)	(0.134)
VC Centrality, weighted					1.227	1.375
					(1.936)	(2.349)
Max VC Centrality at Initial Round						0.616
						(0.776)
IPO Intensity at Initial VC Round						1.295
						(0.927)
Total Patents at Initial VC Round						1.067
						(0.161)
$\ln(\theta)$	11.10**	13.75**	14.87**	15.60**	15.03**	15.01**
	(5.713)	(5.219)	(3.197)	(3.535)	(3.468)	(3.663)

Table 10: Initial Conditions and Exit Outcomes

	Time to IPO		Time to Acquisition	
	(1)	(2)	(3)	(4)
Initial conditions:				
IPO Intensity at Initial VC Round	1.292	1.492*	1.115	1.148
	(0.22)	(0.26)	(0.28)	(0.32)
Max VC Centrality at Initial Round	4.672**	1.993*	3.494*	2.174
	(1.26)	(0.67)	(1.73)	(1.35)
Global Average Centrality at Initial VC Round	1149**	124.3*	8.825	1.797
	(2387)	(271)	(31.2)	(7.08)
Total Global Funded VC Rounds at Initial VC Round	0.907**	0.926**	0.956**	0.978
	(0.011)	(0.015)	(0.015)	(0.018)
Global Funded Alliance Activity at Initial VC Round	1.232*	1.169	1.221*	1.212
	(0.10)	(0.13)	(0.11)	(0.13)
Time-varying conditions:				
IPO Intensity, last 3 mos.	3.085**	4.375**	0.537*	0.639
	(0.39)	(0.66)	(0.17)	(0.21)
VC Centrality, weighted		6.524**		6.931*
		(3.45)		(6.52)
Total Patent Applications		1.007		0.962*
		(0.0052)		(0.019)
Total Alliances over last 5 yrs.		1.164**		1.090**
		(0.028)		(0.028)
Total Rounds of VC Funding		1.255**		1.209**
		(0.034)		(0.040)
Observations	138372	120181	138372	120181