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Strategic alliances, venture capital, and exit decisions in early stage high-tech firms ☆

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ABSTRACT

We study the trade-offs that biotech start-ups face in the private equity market when they choose between raising firm-level capital from venture capitalists or project-level capital from strategic alliance partners. Increased alliance activity makes future alliances more likely, but future VC activity less likely. In contrast, venture capital (VC) activity makes both future alliance and future VC activity more likely. Both types of private capital raise the hazard of going public. Acquisition as an alternative to initial public offering 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 and the potential conflict of interest between different sources of private equity.

1. Introduction

Early-stage fund-raising decisions are critical to the growth and survival of nascent companies. This is especially true in high-technology sectors. Start-up companies in these sectors not only require large capital injections but also face a number of strategically distinct alternative sources of capital in private capital markets. In particular, while venture capital (VC) is very active throughout the sector, many high-tech companies at the same time rely heavily on inter-firm commercialization agreements (strategic alliances) for funding. Both types of funding are especially important sources of private capital for biotechnology firms (Lerner and Merges, 1998, and Stuart, Hoang, and Hybels, 1999).

In this paper, we explore how these alternative funding sources in the private capital market interact with one another. We first ask how venture capital and strategic alliance funding complement or substitute for one another in the private capital market. Then we ask how these funding sources affect exit outcomes. Because acquisition activity is common in this sector, we ask how choices in the private capital market affect the going public decision as well as how they affect the possibility that a start-up company is acquired.

A major hurdle to empirical work in this area is the dearth of data on private firms. Here, we develop a novel panel containing 1,899 privately held biotechnology

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start-up companies that both received venture funding and participated in alliance activity, but to varying degrees. The data begin at a company's birth, and record the funding histories of the firms in question, as well as prevailing market conditions, at the time the firm receives its initial funding and at the time of the focal funding event. This allows us to estimate the effect that strategic alliance and venture funding activity have on the probability that a firm goes public or is acquired at a particular time as a function of the time since its last funding event and other factors.

Our results demonstrate the interplay between the two types of private equity capital and their joint impact on exit decisions. 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 start-up company 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.

More generally, these findings reflect two competing forces at work. The typical alliance contract in this setting affords project-level decision rights and monitoring provisions to the alliance partner (Robinson and Stuart, 2007a). This creates potential for conflicts of interest with venture capitalists (VCs), whose company-level investments create exit motives that could be at odds with the intentions of the alliance partner, and whose company-level control and cash flow rights could be at odds with the (typically project-level) decision rights of the alliance partner. The opposing force is the complementary 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 spite of the fact that alliance contracts often include terms that diminish the attractiveness of a potential investment to VC funders.

Next we explore the role that alliances and venture capital play on the decision to go public or be acquired. It is well established that firms with more venture funding are at greater risk of going public. What is surprising, however, is the fact that strategic alliance activity also has a high, if not greater, impact on the hazard of going public.

Increased VC activity unambiguously raises the hazard of being acquired. Alliances also play an important role in shaping acquisition outcomes. An increase in the number of a start-up company's previous alliances raises the hazard of being acquired. One explanation for this effect is that being linked tightly to an alliance partner can raise the hazard of being acquired because that company becomes a potential acquirer through the alliance process. Another explanation is that an active alliance history indicates that the focal start-up company is more likely to have intellectual capital that is valued by acquirers.

Any attempt to establish a causal link between private capital market behavior and the later-stage exit decisions must deal with a variety of endogeneity concerns. First, a link between past behavior and exit outcomes could reflect unobserved heterogeneity in a start-up's characteristics that drives preferential selection into the private capital market. To partially control for this, we allow for unobserved company-level heterogeneity by including frailty parameters in the hazard rate estimation. (This is discussed in detail in Section 3.) Frailty parameters guard against the possibility that time-invariant differences across start-ups drive their attractive as private equity recipients or candidates for exit events.

It is important to acknowledge, however, that frailty parameters in hazard models, which are effectively firm-level random effects, cannot absorb time-varying firm-level heterogeneity. We take additional steps to control for time-varying differences across firms by collecting data that allow us to measure whether the start-up company has products in clinical trial stages with the Food and Drug Administration (FDA) at the time of the funding event. We also control for the start-up's previous patenting activity. These time-varying measures allow us to partially control for the factors such as the quality of the company's scientists or the state of its research portfolio, which would be known to funders but difficult for the econometrician to observe. Nevertheless, in the absence of an instrumental variables specification or a natural experiment, we must caution against attaching causal interpretations to our findings given the possible unobserved heterogeneity that could remain.

Our paper is related to a number of works that explore the determinants of the going public decision. Pagano, Panetta, and Zingales (1998) examine this question in a sample of private Italian firms. They find that larger, more profitable companies go public. In recent work, Chemmanur, He, and Nandy (2010) find a similar relation between profitability, performance, and going public in US Census of Manufactures data, and they 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, instead of 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 start-ups, but focuses on the role of the venture capitalist in timing access to the public capital market. The venture capitalist's role as facilitator could stem from professionalizing the start-up firm (Hellmann and Puri, 2002), from providing access to financial capital (Gompers and Lerner, 1999) and other portfolio companies with complementary assets (Lindsey, 2008), or from certifying the quality of the start-up (Carter and Manaster, 1990; Hsu, 2004; Megginson and Weiss, 1991). Recent work by Hsu (2006) uses a small sample of private technology start-ups receiving funding from the Small Business Innovation Research program and shows that the start-ups receiving funding from VC firms are more prone to engage in commercialization strategies. These studies show that VCs add value to start-ups in various ways as well as certifying the quality of start-ups and, consequently, increase the quality and future prospects of the start-ups. Because such start-ups are more likely to do an IPO, VC funding should increase the likelihood of an IPO.

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 companies receive in early alliance deals. Stuart, Hoang, and Hybels (1999) show how alliance partners play a certification role for young biotech start-up companies, drawing on evidence from IPO markets.

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 (1998) 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 measure the change in the probability of various exit decisions as a function of current and past alliance activity.

Our estimation strategy is related to recent work in the capital structure and investment literature. Our empirical strategy is similar to that of 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.

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 2. In Section 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, and Sections 5 and 6 explore exit outcomes. Section 7 considers robustness issues, while 8 concludes.

2. 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, because these are fairly unambiguous. Then we proceed to competing hypotheses surrounding the role of strategic alliance funding.

2.1. Venture capital

The predictions for venture capital and going public are straightforward. We predict that increasing the VC 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 start-up with a view to a later exit opportunity, either in the form of an IPO or a sale to another firm (Gompers and Lerner, 1999). Therefore, any given VC investor who has already invested in a biotechnology company is likely to press for an attractive exit. Moreover, the selection process that precedes the venture capitalist's investment decision favors biotechnology companies that have a higher estimated probability of a successful exit. Finally, the role that VCs play in the professionalization of start-up companies implies that greater VC contact is likely to predict a higher likelihood of an exit (Hellmann and Puri, 2000, 2002).

We also predict that biotech start-up companies that attract funding from VCs with central positions in the VC syndicate network are more likely to undergo an IPO or a sale to another company. Central, hence more connected, VCs have better access to extensive information channels and typically will have earned reputations as successful investors (Sorensen and Stuart, 2000; Podolny, 2001, Hochberg, Ljungqvist, and Yu, 2007). As a result, receiving funding from central VCs is a form of certification of a start-up company's quality (Stuart, Hoang, and Hybels, 1999). In addition, because they are better able to access private information in a timely manner, central VCs may be more adept at pooling information collected by other market participants before committing to invest in an early stage venture (Hochberg, Ljungqvist, and Yu, 2007).

It is important to acknowledge, however, that associations between VC funding and exit outcomes are likely to arise from omitted variables. If some company attribute, such as scientific quality, attracts VC interest and alliance activity, as well as elevates the likelihood of a successful exit, then VC and alliances may signal underlying firm quality to an econometrician who does not observe it. This is one reason that it is so critical to our empirical strategy that we employ a statistical technique that controls for unobserved, time-invariant, firm-level heterogeneity, as well as include variables that allow us to measure time-varying firm quality.

The literature is clear on the expected association between VC and exit events, but research is mixed on how VC funding affects the likelihood that the start-up subsequently contracts with alliance partners. At a practical level, much of the financing raised in venture rounds is invested in the development of scientific programs that generate intellectual property, which potentially forms the basis for future alliance contracts. In addition, the value-adding functions of the VC described in Hellmann and Puri (2000, 2002) and others are likely to elevate the attractiveness of portfolio companies as prospective alliance partners. Likewise, Lindsey (2008) shows that VCs facilitate alliance activities among portfolio companies. In addition, Hochberg, Ljunqvist, and Lu (2007) find that better networked VCs have more successful portfolio companies in part because their more extensive business connections can be brought to the aid of portfolio companies.

However, the incentives of VCs and alliance partners may depart in a few primary ways, both of which stem from the fact that alliance contract terms are project level and VC investments are at the firm level. First, the two levels of ownership may create incentives for managers to shift resources across projects, within firms. Specifically, managers at young companies often have the incentive to shift resource from alliance-based projects to others within the firm, because profits from any products that are developed under an alliance contract are shared with

the partner. Second, the contractual cash flow rights that are granted to alliance partners often place a de facto cap on the upside of the equity value of the portfolio company. This occurs because an alliance contract often grants half or more of the revenues or profits of a start-ups development project to the alliance partner. In addition, portfolio companies that have successfully raised many rounds of VC may have little need for additional capital from alliance partners. For these reasons, VC activity may deter subsequent alliance formation.

2.2. Strategic alliances as substitutes to venture capital

The potential for strategic alliances to act as a substitute for VC stems from several factors. As Robinson and Stuart (2007a) note, VCs fund companies, not projects. In contrast, strategic alliance partners generally sponsor research activity on a subset of projects that the biotechnology company is operating.

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

In contrast, Kaplan and Strömberg (2003) show that VC contracts typically allocate a majority of board seats to the VC firm. Even when the venture capitalist does not gain a majority of board seats, it receives at least some board representation, almost without exception. VC investors often 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 could press the biotechnology company to divert resources away from other internal projects, toward projects that fall under the scope of the alliance contract. Conversely, the biotech firm often faces the incentive to shift resources away from projects that are under contract to partners because the firm retains the full cash flows rights from solo projects. Any such resource diversions that are overall value-destroying, even if they strictly benefit one project, should in principle be frowned upon by the venture capitalist, because they stand to undermine the value of the venture capitalist's exit opportunity. Thus, one reason that strategic alliances could substitute for venture capital is that the potential incentive conflicts between these sources of funding could drive away potential VC investors who fear partial holdup at the hands of the strategic alliance partner.

There are other reasons that alliance partners might substitute for venture capital. Alliance partners may crowd out venture capital by lowering a biotechnology start-up company's funding requirements and, hence, increasing its bargaining position. In addition, the provisions in alliance contracts that place limitations on a change in control may deter investment because VCs could anticipate the foreclosure of future exit options because of the presence of the alliance investor. Lastly, the cash flow right accorded to alliance partners may diminish the upside of the start-up company's equity value, which will decrease the likelihood of investment.

These arguments all suggest that increased strategic alliance activity could diminish the incentives for VC investors to participate and could also lower the start-up's probability of going public.

2.3. Strategic alliances as complements to venture capital

The preceding arguments overlook the screening role that strategic alliance partners play in the biotechnology industry. By collaborating with a start-up in this sector, an alliance partner sends a quality signal to outside observers (Stuart, Hoang, and Hybels, 1999). This certification role can be substantial, especially given the high degree of uncertainty surrounding the promise of novel technological approaches in the industry. Future investors, underwriters, and the public markets are more likely to look more favorably upon a start-up that has received certification from experienced industry insiders. As a result, certification mitigates uncertainty and other market participants' cost of assessing the actual quality of a start-up (Stuart, Hoang, and Hybels, 1999), which increases a start-up's chances of future funding events and successful exit.

Finally, just as VCs add value to start-ups, alliance partners may improve their quality in several ways. Most important, start-ups with more alliances may be in a position to access some of the complementary assets of their partners, which can range from access to compound libraries and screening technologies, to the partner's expertise in managing the FDA clinical trials process, to access to the partner's sales and marketing resources (Mitchell and Singh, 1996; Pisano, 1994; Shan, Walker, and Kogut, 1994; Singh and Mitchell, 2005; and Stuart, 2000). Through access to these types of resources, alliance activity can enhance the quality of the start-up, which may improve the start-up's prospects for future VC funding and its chances of a successful exit.

3. Data description and estimation strategy

In this section we describe our data sources, estimation strategy, variables, and summary statistics.

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

3.1. Data sources and outcomes of interest

To test these predictions, we analyze a large sample of venture capital–backed private biotechnology companies. We begin with all available records for VC-backed companies in the biotechnology sector from Thomson Financial's VentureXpert database. These data consist of 1,899 companies that were founded before 2004. This is not a random sample. All companies in the data received one or more rounds of funding from VC investors. We then augment these data with data from Recombinant Capital's Strategic Alliance database, SDC's Mergers and Acquisitions database, and IMS Health's R&D Focus database.

Our sampling strategy – conditioning on the presence of VC funding – is designed in part to minimize the scope for heterogeneity in firm quality to drive the estimates. Because we are effectively sampling only firms that are of sufficient quality to attract at least one round of venture funding, we purge our sample from extreme variation in quality by removing the lowest quality firms. This means that we do not have observations from firms that pursue the strategy of forming alliances and forgoing all venture capital funding. However, this most likely means that our point estimates understate the degree of substitutability between the two types of funding. Many of the alliance transactions listed on the Recombinant Capital website are culled from Securities and Exchange Commission (SEC) filings, and the firms in question often take a conservative approach to the relevant materiality thresholds (Lerner and Merges, 1998; Lerner, Shane, and Tsai, 1998). Thus, conditioning on VC activity helps weed out firms that would appear on Recombinant Capital but exist only to license existing technologies, etc., making our study comparable to prior work in this area.

The firms in our data potentially experience four outcomes of interest. They receive a round of VC funding, they form a strategic alliance, they are acquired by another firm, or they go public. We use the VentureXpert data to assemble the VC funding histories of these firms, including the date of founding of the company, the dates of all private equity financing rounds, and the identities of the investors in each round. We use the Deloitte Recap LLC (previously Recombinant Capital or ReCap) rDNA database to track the alliance activity of the companies in the data. ReCap scours the newswire, company websites, securities filings, and industry news sources to identify information on strategic alliances in the biopharmaceutical 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.

For IPOs, we begin with VentureExpert data, which gives us good coverage of biotech IPOs. As the bottom portion of Table 1 indicates, a total of 353 IPOs are in our sample. Most of these cluster among firms that were born before the mid-1990s, and most of the IPOs themselves occurred in the mid 1990s.

To track acquisition outcomes, we augment VentureExpert with data from the SDC's Mergers and Acquisitions database to make up for the former's sparse coverage of M&A. We manually match the names of all VC-backed biotech companies (as reported by VentureXpert) with the universe of all targets in SDC's Mergers and Acquisitions database, not just those flagged as biotech companies. Through this process, we identified 230 acquisitions of privately held biotech companies. For the most part, firms that are acquired are older at the time of acquisition than are firms from the same birth cohort that go public. For example, in 1987 there were 59 firm births in our data. Of these, 23 result in IPOs, with an average year of IPO of 1992 (i.e., at age five years) while the 12 firms that were acquired had a mean age at acquisition of ten years.

In addition to these exit events, our data contain 5,203 strategic alliance transactions and 7,148 venture capital financing rounds.

3.2. Estimation strategy

Our objective empirically is to connect these outcomes of interest to variables that measure the firm's quality and evolving sequence of prior outcomes. At the heart of this exercise is the company's hazard of one of the four events occurring as a function of analysis 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. Because we are interested in modeling the probability of a funding event at a particular time as a function of the time since the 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 account for the staggered entry of companies into our sample, because this parametric choice would require all private companies in the data in month t to be at identical risk of an IPO or other funding event. Instead, we use the start-up company's age (in months) as the unit of analysis time.

Formally, the hazard function for firm i at time t can be expressed as

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

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

$$h_i(t) = -d\ ln(S_i(t)). \tag{2}$$

Following Leary and Roberts (2005), we write the hazard of firm i at time t as

$$h_i(t|\omega_i) = \omega_i h(0) e^{x'\beta}, \tag{3}$$

where $h(0)$ is the baseline hazard, x is a vector of covariates, and β is a coefficient vector. To estimate the hazard function, we follow techniques described in Leary and Roberts (2005) and create dummy variables corresponding

Table 1
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 lists the number of firms born in that year. 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. (For the two firms that were acquired from the 1986 cohort, one was acquired in 1993 and one in 2004.) Then, in the remaining columns, we list the number of strategic alliances, venture funding rounds, patents, and fraction of life spent with drugs in Food and Drug Administration (FDA) trials. Our data end in 2004, so these are reported as average total amounts per birth cohort through 2004. Columns 7 and 8 list total number of alliances and venture rounds, respectively, through 2004. Columns 9 and 10 list the fraction of time in FDA trials (the number of months for which the FDA clinical trial dummy is one divided by the total number of months) and the number of patents for firms in each birth cohort that later go public. The final two columns list the same information for members of the birth cohort that did not go public on or before 2004.

						Average total (through 2004) Number of					
Birth	Firm	That exit via		Mean year of		Strategic	VC	If later IPO		If never IPO	
year	births	IPO	Acquired	IPO	Acquired	alliances	rounds	FDA	Patents	FDA	Patents
<1980	62	29	6	1988	1988	147	228	0.1	4	0	3.5
1980	21	13	5	1987	1987	56	96	0.2	3.7	0	0.4
1981	42	28	4	1987	1989	120	188	0.2	8.1	0.1	4.1
1982	24	9	7	1988	1988	38	89	0.1	6.6	0	1.6
1983	33	14	6	1990	1992	83	158	0.1	5	0	2.3
1984	23	9	5	1987	1996	62	91	0	5.7	0	1.9
1985	38	11	5	1993	1990	99	204	0.3	4.8	0.1	1.9
1986	45	21	2	1992	–	132	173	0.1	4.7	0	2.1
1987	59	23	12	1992	1997	180	254	0.2	3.4	0.1	3.8
1988	49	23	6	1994	1996	152	236	0.3	3.1	0.1	2.2
1989	47	13	10	1995	1997	105	203	0.2	3.9	0	2.0
1990	47	10	12	1996	1995	131	210	0.4	8.5	0.1	1.3
1991	35	16	6	1996	1998	125	145	0.2	6.6	0.2	1.5
1992	81	27	15	1998	1999	321	377	0.5	5.6	0.2	4.1
1993	74	23	18	1998	1999	246	313	0.4	5	0.2	2.9
1994	79	19	16	1998	2000	277	355	0.4	3.4	0.1	2.7
1995	75	18	13	1999	2001	279	317	0.5	3.8	0.1	1.7
1996	102	15	26	2001	2001	314	389	0.4	1.5	0.2	1.0
1997	175	9	25	2000	2002	524	641	0.5	1.6	0.2	1.6
1998	179	6	9	2000	2002	484	616	0.5	5.8	0.2	1.0
1999	127	6	8	2003	2002	312	399	0.6	1.2	0.1	0.9
2000	251	6	10	2001	2003	556	769	0.3	0.3	0.2	0.3
2001	139	4	4	2004	2004	291	422	0.3	0	0.2	0.3
2002	59	1	0	–	–	119	190	1	0	0.1	0.1
2003	25	0	0	–	–	50	61	0	0	0.1	0.0
2004	12	0	0	–	–	0	24	0	0	0.3	0.0
Total	1,903	353	230			5,203	7,148	0.3	4.5	0.2	1.4

to the deciles of firm age. Within each age decile, an exponential hazard function is estimated. This is akin to a spline specification of the baseline hazard rate, in which the rate is assumed to be constant within each piece, but is allowed to vary freely between them.

The ω_i parameter in Eq. (3) is known as a frailty parameter. It captures time-invariant, unmeasured, firm-level heterogeneity. As in Whited (2006) and Leary and Roberts (2005), we assume this parameter follows a gamma distribution. Because it is essentially a firm-level random effect, it only can absorb variation across firms, not variation within firms over time. This is why it is so critical to our analysis that we include information such as the stock of patents at a particular time, or whether a firm has drugs in clinical trials at a specific time, because this allows us to hold constant within-firm variation over time that would otherwise pollute our inferences of the link between early-stage and later-stage funding decisions.

All spells in the data that do not conclude in one of the events we analyze are treated as being censored. This data structure allows us to update independent variables on a monthly basis to reflect changes in companies' financing, alliance, or innovation histories, as well as the current state of the equity markets in the biotechnology sector and overall market conditions.

3.3. Independent variables

Broadly, our independent variables fall into four categories: venture capitalist characteristics, alliance histories, market characteristics, and company attributes such as their stage in the FDA clinical trials process.

3.3.1. 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. We call this measure "accumulated funding rounds."

We measure the access to information channels and reputation of the venture capitalist using its centrality in the VC syndication network. Following prior studies (e.g., Hochberg, Ljungqvist, and Yu, 2007; Robinson and Stuart, 2007a,b; Sorensen and Stuart, 2000; Podolny, 2001), we

use the formula developed in Bonacich (1987), which is

$$C_{i,t} = \sum_{j=1}^{N_t} (\alpha_t + \delta_t C_{j,t}) R_{i,j,t}, \quad (4)$$

where $C_{j,t}$ is the centrality of the VC firm j at year t, and $R_{i,j,t}$ is the relation matrix that shows the number of co-investments between VC firms i and j for the time period between $t-5$ and t. The variable N_t is the total number of VC firms that were active at any time between t and $t-5$. δ_t is the weighting coefficient set equal to 0.75 of the reciprocal of the largest eigenvalue of R (Podolny, 1993, 2001). We set α so that the maximum centrality for each year is equal to one.

One complication with specifying the influence of VC firm centrality on the outcomes experienced by individual portfolio companies arises because venture-backed companies are commonly financed by syndicates of investors. As a result, the typical start-up company in our data is financed by multiple VC firms. We account for this in a few ways. First, we compute a proportional measure: For each start-up company-round, we compute the fraction of total VC firm-rounds in which a particular VC firm has participated as of time t. This provides a set of weights reflecting each venture capitalist's participation in funding a particular start-up company as of time t, and these weights sum to one across VCs. We then use these weights to augment overall VC centrality. We call this variable "VC centrality, weighted." As a second measure of VC centrality, we simply measure the centrality of most central venture capitalist among the VCs invested in the start-up as of time t. Finally, we calculated the mean VC centrality by taking the mean of the centralities of the VCs that have invested in a start-up as of time t.

3.3.2. Alliance characteristics

We measure three attributes of biotech start-up companies' strategic alliance histories. We include a time-varying count of the number of alliances the company has entered during the past five years. We choose a five-year sliding window because this has been the convention in the alliance literature to account for the fact that most alliance contracts will terminate within that period of time. Ceteris paribus, because companies in the biotechnology industry often require compelling technology to attract alliance partners, companies with greater numbers of recent alliances are more likely to be operating along in-demand technological trajectories (Powell, Koput, and Smith-Doerr, 1996; Stuart, 1998, Stuart, 2000; Singh and Mitchell, 2005).

In some cases the deals in our sample involve the sale of partial equity stakes to the alliance partner. Therefore, we also control for the amount of equity stakes sold to the start-up's previous partners. Likewise, many of the deals in the data include provisions for substantial, nonequity investments by the alliance partner, typically in the form of research and development funding for the biotech. We also control for the cumulative research and development funding and pledged milestone payments from a start-up's past alliances because this conveys additional information about the intensity of a start-up's alliance activity and perhaps, its level of funding need.

3.3.3. Time-varying measures of firm quality

To mitigate the aforementioned concern about time-varying, company-level, unobserved heterogeneity, we incorporate two time-varying measures of firm quality. First, we include the evolving stock of patents based (e.g., Hagedoorn and Schakenraad, 1994; Shan, Walker, and Kogut, 1994; and Stuart, 2000). Following prior studies, we record the date of the patent application, and accumulate the total number of patent applications during the past five years (e.g., Sorensen and Stuart, 2000).

Second, we incorporate a measure of whether a firm has compounds in FDA clinical trials. Our data source for information on drug projects in development comes from IMS Health's R&D Focus database. An observation in this database is a drug in development at a particular time.[2] To use this information, we hand-match our data to the IMS data using FKA (formerly known as) company names as often as possible, and we create a dummy variable for whether a start-up company is listed in the IMS dataset at a particular time. For example, if Biotech ABC was born in 1990, had a drug in clinical trials from 1992 to 1995, and again from 1998 to 2001, then the dummy would be set to zero for 1990–1992, one for the 1992–1995 range, zero for 1995–1998, one for 1998–2001, and zero thereafter. The idea behind coding the variable this way is that it provides the most parsimonious way of capturing the fact that the firm's expected future value could be varying over time according to whether or not there is a viable drug candidate in its pipeline.

These variables are summarized in Table 1. The four right-most columns present average total patents as well as the average fraction of a firm's life (while private) that is spent with a compound in clinical trials. To provide a sense of how the trajectories of IPO and non-IPO firms diverge, we split each birth cohort according to whether it later goes public or not. Firms that later go public spend on average about 30% of their time with a compound in clinical trials, while firms that never go public do so only about 20% of the time. Firms that later go public generate 4.5 patents, roughly three times the number of those that do not go public.

3.3.4. Market conditions

We also include biotech IPO market conditions. For this purpose, we measure the "intensity of IPO activity" in the biotech industry. This variable is based on the fact, as Gompers, Kovner, Lerner, and Scharfstein (2008) show, 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 venture-backed biotech companies at risk of an IPO during the same period. This ratio is updated monthly. In addition to biotech IPO market conditions, we control for overall equity market conditions using the Nasdaq composite monthly index

[2] More information can be found at www.ovid.com/site/catalog/DataBase/1244.jsp.

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 firm-months in the data. (There are 1,903 firms and 156,433 firm-months.) For each age category, "Private" denotes firms that never went public, and "Public" denotes firms that had an initial public offering (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 time are equal. VC=venture capital.

		Age=12 months			Age=24 months			Age=36 months		
Variable	Overall	Private	Public	*t* (diff)	Private	Public	*t* (diff)	Private	Public	*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, last five years	1.01	0.14	0.14	0.16	0.32	0.50	−1.99	0.56	1.30	−2.63
Total alliances, last five years	0.48	0.04	0.31	−7.47	0.13	0.83	−8.18	0.26	1.47	−8.04
ln(Alliance Funding), last five years	0.19	0.00	0.16	−4.65	0.02	0.33	−6.12	0.05	0.59	−7.04
ln(Alliance Equity), last five years	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
Maximum VC centrality	0.04	0.01	0.09	−6.62	0.02	0.13	−8.12	0.03	0.15	−8.43

return. In unreported robustness analyses, we use alternative index return measures, in which we replace Nasdaq return with Standard & Poor's 500 value-weighted and equal-weighted monthly index returns both with and without dividends.

3.4. Summary statistics

Table 2 reports summary statistics for the independent variables based on whether the start-up company in question remained private throughout the sample or else went public at some point in its life. We report summary statistics for firms at one, two, and three years of age.

The table clearly illustrates that start-ups that ultimately go public evolve along very different financing trajectories than start-ups that ultimately remain private. At 12 months of age, start-ups that go public have received about twice as many VC funding rounds and are roughly eight times more likely to have had a strategic alliance, relative to those that remain private throughout the duration of our dataset. These start-ups have received both more overall alliance funding and more alliance equity than firms that do not go public in our sample. The VC firms that fund companies that go public are more central members of the VC network. The only dimension along which we see no difference is in the stock of patents filed. However, by the time start-ups are 24 months old, their patent histories also have begun to diverge in the same way that other variables had already departed at age 12 months. This difference is marginally statistically significant at 24 months of age and is highly statistically significant by the time firms reach 36 months old.

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. We investigate how past funding and start-up company's characteristics impact the hazard of receiving an additional round of venture funding. Then we turn to the hazard of entering into a strategic alliance. Because we have a particular interest in the interplay between project-level (forming alliance) and company-level (receiving VC funding) financing, we analyze the likelihood of occurrence of these two types of financing events via separate estimation of distinct hazard rates. That is, we estimate models of the time to the next VC round, then we estimate models of time to the next alliance. By estimating separate models, we allow both the baseline hazards and the parameter estimates on company and market-level covariates to vary. We discuss robustness issues associated with this approach in Section 7.

4.1. Time to the next VC round

Table 3 presents estimates of the hazard of a VC funding round as a function of start-up company's characteristics. A general result from the table is that a start-up with more prior rounds of VC funding is at an increased hazard of receiving a future round of funding. Furthermore, start-ups with more central VCs funding them have higher hazard of getting one more VC funding round.

The effect of an additional alliance on a start-up's hazard of VC funding is less clear-cut. In Column 1, where we control only the FDA clinical trial dummy, alliance count has a positive impact on the hazard of subsequent funding. Once we control for the accumulated number of funding rounds, however, this effect reverses, revealing the fact that increased alliance activity reduces the hazard of future VC activity (Columns 3–9). Alliance count continues to have negative and significant point estimates when we use alternative measures of VC centrality (Columns 10–11), and is robust to alternative measures of market index returns (results available upon request). Furthermore, the magnitudes of the point estimates are similar across different models. However, neither the size of start-up's alliances during the past five years nor the amount of equity sold to alliance partners seem to have an impact on the hazard of a new funding round. These findings are in line with the possible conflict of interests between VC investors and alliance partners.

Table 3
Piecewise exponential hazard estimates of venture capital (VC) activity.

This table reports piecewise exponential hazard estimates of VC activity. A unit of observation is a particular firm in a given month. The dependent variable is the time since the last VC funding event that the firm experienced. "Total VC rounds" is the number of rounds of VC funding the firm has received prior to each date. "Total alliances, last five years" is the total number of strategic alliance partnerships that the firm has entered into over the last five years. (A rolling sum over the last five years is used because alliances are usually not open-ended.) "Total patents, last five years" measures the number of patent applications filed by the firm over the last five years prior to each date. The variable labeled "ln(Alliance Size), last five years" measures the natural log of the amount of nonequity funding that the firm has received through strategic alliance partnerships over the last five years. "IPO intensity". takes on the same value for each firm at a given time and is the ratio of the number of initial public offerings that have occurred over the last three months prior to each date to the number of private biotech companies. "VC centrality" is a measure of the reputational quality of members of all the venture capitalists that have invested in the firm up to that date. "VC centrality (weighted)" averages the Bonacich centrality for each VC firm in the most recent round in which it participated, weighting by the recency of the round. "VC centrality (mean)" is the simple average across all venture capitalists that have participated. "VC centrality (maximum)" is the maximum centrality of any venture capitalist that has invested. The hazard rate analysis is performed using a piecewise exponential specification for the baseline hazard function. In addition, firm-level frailty effects are measured. The variable $\ln(\theta)$ measures the significance of the firm-level frailty. Standard errors appear in parentheses below point estimates, which are expressed as hazard impact factors.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Total VC rounds	1.342**		1.349**	1.350**	1.351**	1.351**	1.351**	1.337**	1.337**	1.327**	1.315**
	(0.008)		(0.008)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
Total alliances, last five years		1.043**	0.973**	0.973**	0.979*	0.983	0.984	0.979*	0.979*	0.978*	0.970**
		(0.009)	(0.008)	(0.008)	(0.009)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
FDA clinical trial dummy	1.188**	1.346**	1.224**	1.224**	1.224**	1.226**	1.234**	1.232**	1.232**	1.236**	1.234**
	(0.041)	(0.058)	(0.043)	(0.044)	(0.044)	(0.044)	(0.044)	(0.044)	(0.044)	(0.044)	(0.044)
Total patents, last five years				0.998	0.999	0.999	0.999	0.997	0.997	0.996	0.994
				(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
ln(Alliance Equity), last five years					0.930	0.958	0.955	0.968	0.968	0.959	0.954
					(0.041)	(0.048)	(0.048)	(0.048)	(0.048)	(0.048)	(0.047)
ln(Alliance Size), last five years						0.968	0.967	0.959	0.959	0.959	0.968
						(0.025)	(0.025)	(0.025)	(0.025)	(0.025)	(0.025)
IPO intensity							1.018**	1.009	1.008	1.008	1.011*
							(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
VC centrality (weighted)								8.189**	8.208**		
								(1.066)	(1.069)		
Nasdaq return									0.906	0.906	0.947
									(0.164)	(0.164)	(0.170)
VC centrality (mean)										4.366**	
										(0.385)	
VC centrality (maximum)											1.914**
											(0.084)
$\ln(\theta)$	0.018**	0.263**	0.020**	0.021**	0.021**	0.021**	0.021**	0.019**	0.019**	0.018**	0.016**
	(0.006)	(0.020)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.007)	(0.007)	(0.007)	(0.007)
Number of observations	159,131	159,131	159,131	151,837	151,837	151,837	151,837	148,344	148,344	148,344	148,344
Number of firms	1,899	1,899	1,899	1,899	1,899	1,899	1,899	1,860	1,860	1,860	1,860
χ^2	2343	127.5	2355	2318	2321	2323	2336	2508	2508	2527	2497
χ^2 frailty	11.14	405.6	13.73	13.93	13.85	14.15	14.22	10.21	10.21	9.091	7.718

*, **, and *** denote statistical significance at the 10, 5 and 1 percent level, respectively.

Table 3 also sheds light on the role of VC characteristics and market conditions on VC funding. Start-ups that have successfully completed more VC funding rounds have higher hazard of receiving further VC funding. As the start-up receives a new funding round, its hazard of new VC funding round increases by more than 30%. Similarly, start-ups that have had prior investments from more central VCs have a higher hazard of subsequent VC funding. A 1 standard deviation increase in VC centrality increases the hazard of new funding round by 18%. This is consistent with the view that central VCs either add more value through their connections or provide stronger signals of start-up quality, which attracts subsequent investment.

The dummy for having drugs in FDA clinical trials has a positive and highly significant impact on the hazard of a subsequent funding round. This presumably reflects both supply and demand effects that push the firm toward more capital. Companies whose products have reached the clinical trial stage would be expected to have more promising future prospects, making these start-up companies more attractive investments for VC (the supply channel). At the same time, taking drugs through the clinical trials process is an expensive endeavor, and firms with drugs in clinical trials probably also have greater demand for venture capital than other firms.

In Columns 8–11, we have done robustness analyses using alternative measures of VC centrality along with the Nasdaq index return.[3] The impact of the accumulated funding rounds, VC centrality, and alliance activity is similar across these models.

[3] In untabulated robustness tests, we also replace the Nasdaq market return with other indexes. The loadings on alternative index specifications are very similar to the reported coefficients, both quantitatively and qualitatively. Results are available upon request.

The ln(θ) parameter tests the significance of the ω_i parameter in Eq. (3), which captures time-invariant firm-level heterogeneity. The significance of this parameter indicates that the company-level heterogeneity is important in our analysis, as we can reject the null of no firm-level heterogeneity.

4.2. Time to the next alliance

Table 4 turns from VC funding to estimates of the hazard of entering into an alliance. The picture that emerges from this analysis is different from that presented in Table 3.

Increased alliance activity raises the hazard of subsequent alliance activity. This can be seen throughout Columns 2–9 in the hazard rate associated with total alliance activity during the last five years. The total alliance count and the log total amount of capital committed in alliances both have positive and significant effects on the hazard of forming a new alliance ($p < 0.001$). These variables have high economic significance as well: a one-unit increase in a start-up's alliance count increases its estimated hazard of new alliances by 19%. Alternatively, a 1 standard deviation increase in alliance count raises the hazard of subsequent alliance activity by 33%. Therefore, combining the results of Tables 3 and 4, there is suggestive evidence of path dependence in alliance activity, whereby past alliance activity steers firms away from future VC and toward future alliances.

The asymmetry between alliance and VC partnerships becomes evident 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.

Table 4
Piecewise exponential hazard estimates of next alliance.

This table reports piecewise exponential hazard estimates of the next strategic alliance. A unit of observation is a particular firm in a given month. The dependent variable is the time since the last strategic alliance event that the firm experienced. "Total VC rounds" is the number of rounds of venture capital (VC) funding the firm has received prior to each date. "Total alliances, last five years" is the total number of strategic alliance partnerships that the firm has entered into over the last five years. (A rolling sum over the last five years is used because alliances are usually not open-ended.) "Total patents, last five years" measures the number of patent applications filed by the firm over the last five years prior to each date. The variable labeled "ln(Alliance Size), last five years" measures the natural log of the amount of nonequity funding that the firm has received through strategic alliance partnerships over the last five years. "IPO intensity" takes on the same value for each firm at a given time and is the ratio of the number of initial public offerings that have occurred over the last three months prior to each date to the number of private biotech companies. "VC centrality" is a measure of the reputational quality of members of all the venture capitalists that have invested in the firm up to that date. "VC centrality (weighted)" averages the Bonacich centrality for each VC firm in the most recent round in which they participated, weighting by the recency of the round. "VC centrality (mean)" is the simple average across all venture capitalists that have participated. "VC centrality (maximum)" is the maximum centrality of any venture capitalist that has invested. The hazard rate analysis is performed using a piecewise exponential specification for the baseline hazard function. In addition, firm-level frailty effects are measured. The variable ln(θ) measures the significance of the firm-level frailty. Standard errors appear in parentheses below point estimates, which are expressed as hazard impact factors.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Total VC rounds	1.209**		1.117**	1.120**	1.114**	1.110**	1.107**	1.096**	1.097**	1.087**	1.064**
	(0.013)		(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)
Total alliances, last five years		1.245**	1.221**	1.225**	1.211**	1.194**	1.192**	1.191**	1.190**	1.190**	1.180**
		(0.009)	(0.008)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
FDA clinical trial dummy	1.997**	1.666**	1.602**	1.620**	1.605**	1.587**	1.570**	1.560**	1.562**	1.562**	1.573**
	(0.112)	(0.081)	(0.076)	(0.079)	(0.078)	(0.076)	(0.075)	(0.075)	(0.076)	(0.076)	(0.077)
Total patents, last five years				0.996	0.994	0.991*	0.991*	0.990*	0.991*	0.990*	0.987**
				(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
ln(Alliance Equity), last five years					1.223**	1.053	1.075	1.057	1.048	1.034	1.038
					(0.047)	(0.047)	(0.048)	(0.047)	(0.047)	(0.046)	(0.046)
ln(Alliance Size), last five years						1.166**	1.170**	1.168**	1.163**	1.169**	1.169**
						(0.027)	(0.027)	(0.027)	(0.027)	(0.027)	(0.027)
IPO intensity							0.927**	0.921**	0.938**	0.936**	0.939**
							(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
VC centrality (weighted)								8.205**	7.787**		
								(1.648)	(1.573)		
Nasdaq return									31.111**	30.523**	30.972**
									(7.319)	(7.176)	(7.242)
VC centrality (mean)										4.936**	
										(0.667)	
VC centrality (maximum)											2.325**
											(0.154)
ln(θ)	0.707**	0.260**	0.227**	0.230**	0.218**	0.204**	0.200**	0.191**	0.197**	0.201**	0.207**
	(0.042)	(0.026)	(0.025)	(0.026)	(0.025)	(0.024)	(0.024)	(0.023)	(0.024)	(0.024)	(0.024)
Number of observations	159,131	159,131	159,131	151,837	151,837	151,837	151,837	148,344	148,344	148,344	148,344
Number of firms	1,899	1,899	1,899	1,899	1,899	1,899	1,899	1,860	1,860	1,860	1,860
χ^2	729.1	1278	1407	1377	1404	1447	1539	1616	1835	1866	1904
χ^2 frailty	1062	561.8	437.7	430.5	395.4	304.5	296.7	282.5	295.9	305.2	304.8

*, **, and *** denote statistical significance at the 10, 5 and 1 percent level, respectively.

In general, both of the VC measures – accumulated funding rounds and VC centrality – increases the hazard of alliances. A 1 standard deviation increase in centrality of the VC investors increases the hazard of next alliance by 17%, and the addition of a VC funding round elevates the hazard of a subsequent alliance by 10%.

This asymmetry is consistent with alternative contracting arrangements creating a conflict of interest 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 their earlier presence can preclude future alliance partners from contracting in ways that create conflicts of interest.

As with the hazard of new VC funding, the FDA clinical trial dummy continues to have a positive and highly significant impact in determining the hazard of forming new alliances. This suggests that the companies whose products have reached clinical trial stages are expected to have more promising future prospects, making these companies more attractive alliance partners and more attractive investments for VC firms. In contrast, firms with more patents are not necessarily more likely to form more alliances. In Models 4 and 5 there is an insignificant relation, but in Models 6–11 there is a weakly significant negative relation between a firm's stock of patents and its propensity to form alliances.

Market conditions also play an interesting role in alliance formation. When IPO intensity increases, the propensity to engage in alliance activity declines, consistent with arguments in Lerner and Merges (1998). This suggests that as the market for private equities in this sector heat up, other forms of capital become more attractive. In contrast, recent stock market performance has a positive impact on the propensity to form alliances.[4] In view of the large literature in finance that illustrates the role that stock market conditions play on firm investment, one interpretation of these findings is that the (usually larger, publicly traded) alliance partners use the additional liquidity in their stock to increase their investment activity, some of which includes strategic alliances with other firms.

5. The road to going public

Table 5 shows the hazard of going public as a function of a start-up's past VC funding and alliance activity. It illustrates that both types of past activity in the private capital market – strategic alliances and venture capital funding – raise the start-up's hazard of going public. The number of past VC funding rounds raises the hazard of going public significantly ($p < 0.001$). The economic significance of the relation between VC funding rounds and the IPO hazard also is quite high. According to the point estimate in Column 9, each additional venture round a start-up receives raises its hazard of going public by more than 40%.

Column 9 indicates that even after controlling for the various factors affecting the IPO hazard, VC centrality also has significant importance in determining the going public decision. In particular, a 1 standard deviation increase in weighted VC centrality of the VC investors in a company from its mean value is associated with an 18% increase in the hazard of going public. When we use maximum and mean VC centrality, instead of the weighted VC centrality, we obtain similar results.

The effect of additional alliance activity on the IPO likelihood also is positive and highly significant. The number of a start-up's previous alliances has the strongest effect ($p < 0.001$): each additional alliance raises the hazard of going public increases by 25%. The size of a start-up's alliances also has a significant effect on the start-up's hazard of going public. Our findings suggest that while previous alliances crowd out VC investments, the number and size of a start-up's previous alliances still have large effects on the hazard of going public.

Turning to the controls, the FDA clinical trials dummy has a positive and highly statistically significant impact on the hazard of an IPO throughout the various specifications considered in Table 5. Likewise, firms with greater numbers of patents are more likely to go public.

Not surprisingly, the intensity of the biotech IPO activity has a dramatic impact on the hazard of going public. In fact, a 1 standard deviation increase in IPO intensity increases the start-up hazard of going public by almost 70%. This also diminishes the significance of the frailty parameter, which captures unobserved heterogeneity at the firm level, in turn suggesting that much of the heterogeneity in the going public decision that is not captured by past funding decisions is the ease of going public at a particular point in a firm's age. 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. In addition to the intensity of biotech IPO activity, we control for the Nasdaq composite index return, which is insignificant in the presence of the IPO intensity measure. (We obtain similar results in untabulated specifications that replace the Nasdaq return with other market indices.)

6. Exiting through acquisition

Table 6 analyzes the hazard of being acquired as a function of a start-up company's past actions and its age. We employ the same set of independent variables as in Table 5. VC funding rounds, VC centrality, and alliance count all are statistically and economically significant in the regressions. These findings hold up after controlling for whether or not the company has a drug candidate in FDA trials and after adding the other controls in Columns 1–9. The results do not change in robustness tests reported in Columns 10 and 11, where we use alternative measures of VC centrality and market indices.[5] This suggests that the impact of VC and

[4] As in Table 3, we replace the Nasdaq index with other market indices and obtain similar results.

[5] As in Tables 3–5, specifications that replace the Nasdaq index return with alternative indices produce qualitatively similar findings, which are available upon request.

Table 5
Piecewise exponential hazard estimates of initial public offering (IPO) activity.

This table reports piecewise exponential hazard estimates of an IPO. A unit of observation is a particular firm in a given month. The dependent variable takes on the value zero in all months prior to an IPO and takes on the value one in the month of the IPO and in all subsequent months. "Total VC rounds" is the number of rounds of venture capital (VC) funding the firm has received prior to each date. "Total alliances, last five years" is the total number of strategic alliance partnerships that the firm has entered into over the last five years. (A rolling sum over the last five years is used because alliances are usually not open-ended.) "Total patents, last five years" measures the number of patent applications filed by the firm over the last five years prior to each date. The variable labeled "ln(Alliance Size), last five years" measures the natural log of the amount of nonequity funding that the firm has received through strategic alliance partnerships over the last five years. "IPO intensity" takes on the same value for each firm at a given time and is the ratio of the number of IPOs that have occurred over the last three months prior to each date to the number of private biotech companies. "VC centrality" is a measure of the reputational quality of members of all the venture capitalists that have invested in the firm up to that date. "VC centrality (weighted)" averages the Bonacich centrality for each VC firm in the most recent round in which they participated, weighting by the recency of the round. "VC centrality (mean)" is the simple average across all venture capitalists that have participated. "VC centrality (maximum)" is the maximum centrality of any venture capitalist that has invested. The hazard rate analysis is performed using a piecewise exponential specification for the baseline hazard function. In addition, firm-level frailty effects are measured. The variable ln(θ) measures the significance of the firm-level frailty. Standard errors appear in parentheses below point estimates, which are expressed as hazard impact factors.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Total VC rounds	1.847**		1.610**	1.573**	1.523**	1.510**	1.438**	1.411**	1.415**	1.408**	1.402**
	(0.105)		(0.072)	(0.071)	(0.068)	(0.066)	(0.053)	(0.052)	(0.052)	(0.052)	(0.053)
Total alliances, last five years		1.511**	1.435**	1.409**	1.332**	1.294**	1.257**	1.245**	1.246**	1.247**	1.245**
		(0.055)	(0.051)	(0.051)	(0.050)	(0.049)	(0.038)	(0.036)	(0.036)	(0.036)	(0.037)
FDA clinical trial dummy	2.600**	1.755**	1.585*	1.566*	1.552*	1.545*	1.778**	1.799**	1.800**	1.821**	1.831**
	(0.456)	(0.280)	(0.288)	(0.293)	(0.281)	(0.276)	(0.292)	(0.292)	(0.293)	(0.298)	(0.299)
Total patents, last five years				1.092**	1.075**	1.068**	1.046**	1.044**	1.045**	1.044**	1.043**
				(0.024)	(0.023)	(0.023)	(0.016)	(0.015)	(0.015)	(0.015)	(0.016)
ln(Alliance Equity), last five years					1.547**	1.319	1.283	1.251	1.254	1.251	1.260
					(0.214)	(0.209)	(0.180)	(0.171)	(0.172)	(0.173)	(0.175)
ln(Alliance Size), last five years						1.177	1.198*	1.192*	1.192*	1.197*	1.194*
						(0.101)	(0.090)	(0.087)	(0.088)	(0.089)	(0.089)
IPO intensity							1.209**	1.206**	1.204**	1.205**	1.206**
							(0.012)	(0.012)	(0.012)	(0.012)	(0.012)
VC centrality (weighted)								8.387**	8.656**		
								(5.370)	(5.560)		
Nasdaq return									0.308	0.312	0.324
									(0.226)	(0.228)	(0.236)
VC centrality (mean)										3.990**	
										(1.896)	
VC centrality (maximum)											1.560*
											(0.323)
ln(θ)	3.751**	2.098**	3.164**	3.472**	2.983**	2.808**	1.666*	1.491	1.527	1.554*	1.567*
	(0.717)	(0.404)	(0.544)	(0.594)	(0.576)	(0.557)	(0.353)	(0.331)	(0.337)	(0.339)	(0.341)
Number of observations	159,131	159,131	159,131	151,837	151,837	151,837	151,837	148,344	148,344	148,344	148,344
Number of firms	1,899	1,899	1,899	1,899	1,899	1,899	1,899	1,860	1,860	1,860	1,860
χ^2	437.7	408.9	603.9	604.8	614.2	617.8	869.8	872.4	875.0	872.7	869.6
χ^2 frailty	72.96	76.01	104.7	110.1	88.94	86.22	57.27	48.85	49.96	52.72	52.49

*, **, and *** denote statistical significance at the 10, 5 and 1 percent level, respectively.

alliance funding on the start-up's exit outcomes cannot be attributed to observable firm-level differences. These empirical associations indicate the value-adding and certification benefits of VC investors and alliance partners.

Column 9, which represents the full model, indicates that additional VC centrality and additional rounds of VC funding raise the hazard of acquisition, just as they raise the hazard of going public ($p < 0.001$). The point estimates indicate that the hazard rate for accumulated rounds remains at approximately 1.3 as additional variables are introduced in Columns 2 through 11. A 1 standard deviation increase in the weighted centrality of the VCs investing in a start-up elevates the hazard of being acquired by 28%. In Columns 10 and 11, we use mean and maximum VC centrality as alternative measures of VC centrality with similar results.

Regarding the magnitudes associated with alliance activity as reported in Table 6, each additional alliance is estimated to raise the hazard of being acquired by 11%. One explanation for the significant impact of the alliance count is that having more alliances increases the odds that one of the existing partners transitions to become an acquirer (Robinson and Stuart, 2007b). This occurs frequently because alliances provide windows into the start-up's technology and the value of its future prospects, which mitigates information asymmetries between the start-up and would-be acquirers that are also alliance partners.

The size of the equity stakes that previous alliance partners have acquired in a start-up is insignificant in the full model. This may reflect two, offsetting effects. On one hand, if an alliance partner has acquired a large equity position in a focal biotech, it may have done so with an eye to an eventual, outright purchase of the company. On the other hand, if one or more alliance partners possesses a large equity stake in a start-up and they choose not to

Table 6
Piecewise exponential estimates of time to acquisition.

This table reports piecewise exponential hazard estimates of an acquisition. A unit of observation is a particular firm in a given month. The dependent variable takes on the value zero in all months prior to an acquisition, and takes on the value one in the month that an acquisition of a private firm occurs and in all subsequent months. Firms leave the risk set if they go public prior to being acquired, so a firm that is acquired after going public is not recorded here as an acquisition [87 of the 353 initial public offerings (IPOs) were later acquired as of 2004]). "Total VC rounds" is the number of rounds of venture capital (VC) funding the firm has received prior to each date. "Total alliances, last five years" is the total number of strategic alliance partnerships that the firm has entered into over the last five years. (A rolling sum over the last five years is used because alliances are usually not open-ended.) "Total patents, last five years" measures the number of patent applications filed by the firm over the last five years prior to each date. The variable labeled "ln(Alliance Size), last five years" measures the natural log of the amount of nonequity funding that the firm has received through strategic alliance partnerships over the last five years. The variable "ln(Alliance Equity)" is the natural log of the amount of equity stakes sold to the alliance partners in millions of dollars during the last five years. "IPO intensity" takes on the same value for each firm at a given time and is the ratio of the number of IPOs that have occurred over the last three months prior to each date to the number of private biotech companies. "VC centrality" is a measure of the reputational quality of members of all the venture capitalists that have invested in the firm up to that date. "VC centrality (weighted)" averages the Bonacich centrality for each VC firm in the most recent round in which they participated, weighting by the recency of the round. VC centrality (mean)" is the simple average across all venture capitalists that have participated. "VC centrality (maximum)" is the maximum centrality of any venture capitalist that has invested. The hazard rate analysis is performed using a piecewise exponential specification for the baseline hazard function. In addition, firm-level frailty effects are measured. The variable $\ln(\theta)$ measures the significance of the firm-level frailty. Standard errors appear in parentheses below point estimates, which are expressed as hazard impact factors.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Total VC rounds	1.375**		1.338**	1.326**	1.317**	1.316**	1.314**	1.287**	1.287**	1.269**	1.259**
	(0.043)		(0.041)	(0.041)	(0.041)	(0.041)	(0.041)	(0.039)	(0.039)	(0.039)	(0.040)
Total alliances, last five years		1.218**	1.155**	1.153**	1.121**	1.115**	1.116**	1.108**	1.108**	1.108**	1.103**
		(0.034)	(0.031)	(0.032)	(0.033)	(0.036)	(0.036)	(0.034)	(0.034)	(0.034)	(0.035)
FDA clinical trial dummy	1.349	1.167	1.096	1.100	1.064	1.062	1.071	1.059	1.059	1.072	1.075
	(0.228)	(0.204)	(0.193)	(0.194)	(0.188)	(0.188)	(0.189)	(0.185)	(0.185)	(0.187)	(0.188)
Total patents, last five years				0.999	0.996	0.996	0.996	0.994	0.994	0.993	0.993
				(0.013)	(0.013)	(0.014)	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)
ln(Alliance Equity), last five years					1.486**	1.428*	1.409*	1.339	1.340	1.335	1.336
					(0.203)	(0.232)	(0.228)	(0.212)	(0.212)	(0.211)	(0.211)
ln(Alliance Size), last five years						1.041	1.042	1.051	1.052	1.054	1.053
						(0.095)	(0.094)	(0.092)	(0.092)	(0.092)	(0.093)
IPO intensity							1.033	1.023	1.023	1.022	1.028
							(0.021)	(0.021)	(0.021)	(0.021)	(0.021)
VC centrality (weighted)								25.393**	25.523**		
								(14.751)	(14.834)		
Nasdaq return									0.808	0.814	0.884
									(0.651)	(0.652)	(0.703)
VC centrality (mean)										8.617**	
										(3.401)	
VC centrality (maximum)											2.060**
											(0.420)
$\ln(\theta)$	1.791*	1.822*	1.751*	1.711*	1.689*	1.665*	1.622	1.342	1.343	1.283	1.343
	(0.432)	(0.445)	(0.420)	(0.423)	(0.411)	(0.412)	(0.407)	(0.375)	(0.375)	(0.367)	(0.382)
Number of observations	159,131	159,131	159,131	151,837	151,837	151,837	151,837	148,344	148,344	148,344	148,344
Number of firms	1,899	1,899	1,899	1,899	1,899	1,899	1,899	1,860	1,860	1,860	1,860
χ^2	198.2	121.3	225.2	213.1	221.0	221.2	223.6	245.3	245.3	244.4	232.0
χ^2 frailty	37.64	36.68	36.89	34.03	35.09	34.00	32.53	24.36	24.38	22.95	23.56

*, **, and *** denote statistical significance at the 10, 5 and 1 percent level, respectively.

acquire it, the presence of these equity positions likely will interfere with an acquisition by a third party because block equity holders will complicate any transaction that might occur.

The intensity of IPO activity in biotechnology appears to be independent of the likelihood of an acquisition. As shown in Columns 9–11, the Nasdaq composite index return also does not produce significant results, nor do the alternative measures of VC centrality. Likewise, neither of the two time-varying measures of firm quality, the FDA dummy and patent account, affects the hazard of being acquired. The likely explanation for this set of findings is that acquisition is a blended outcome. Based on inspection of the deals in our data, more often than not, acquisitions appear to be successful exits. However, a non-negligible proportion of the transactions in the data are small acquisitions, which may indicate that companies are acquired for assets. Therefore, an acquisition is a noisier indicator of success than is an IPO, making it difficult to have a connection for the FDA clinical trial dummy and the hazard of acquisition. This interpretation is consistent with the evidence in Danzon, Epstein, and Nicholson (2007), who find that acquisitions of smaller firms often are exit strategies for troubled companies.

7. Robustness considerations

Although we have been cautious about attaching a causal interpretation to the findings, it is also important to acknowledge the limitations of our empirical strategy. In particular, our estimations of VC funding include the amount of alliance activity prior to that event, and

Table 7
Interaction effects between alliances and venture capital (VC).

This table explores the interaction effects between previous alliance activity and previous VC funding activity. The key variable of interest is "VC/alliance interaction," which is simply the product of total VC rounds and total alliance count over the last five years. All other variables are described in Table 2. Column 1 estimates the hazard of the next VC funding round (comparable to Table 3). Columns 2–4, respectively, estimate hazards of the next alliance formation (Table 4), going public (Table 5), and being acquired (Table 6). ln(θ) is the frailty parameter estimate, and χ^2 values test the goodness of fit of the model and the frailty distribution. IPO = initial public offering.

	VC round (1)	Alliance funding (2)	IPO (3)	Acquisition (4)
Total VC rounds	1.356**	1.188**	1.437**	1.359**
	(0.009)	(0.014)	(0.053)	(0.045)
Total alliances, last five years	1.047**	1.331**	1.316**	1.270**
	(0.014)	(0.015)	(0.052)	(0.056)
VC/alliance interaction	0.984**	0.965**	0.983*	0.960**
	(0.003)	(0.003)	(0.008)	(0.009)
Nasdaq return	0.909	32.456**	0.319	0.815
	(0.165)	(7.674)	(0.233)	(0.660)
Total patents, last five years	0.997	0.996	1.042**	0.998
	(0.004)	(0.004)	(0.014)	(0.013)
ln(Alliance Equity), last five years	1.006	1.105*	1.276	1.393*
	(0.050)	(0.049)	(0.168)	(0.214)
ln(Alliance Size), last five years	0.976	1.180**	1.194*	1.092
	(0.025)	(0.027)	(0.085)	(0.094)
IPO intensity	1.008	0.936**	1.205**	1.021
	(0.005)	(0.008)	(0.012)	(0.021)
VC centrality (weighted)	7.626**	5.542**	7.737**	20.122**
	(1.001)	(1.166)	(4.946)	(11.859)
FDA clinical trial dummy	1.214**	1.394**	1.732**	0.996
	(0.043)	(0.069)	(0.276)	(0.173)
ln(θ)	0.019**	0.220**	1.331	1.249
	(0.007)	(0.025)	(0.321)	(0.358)
Number of observations	148,344	148,344	148,344	148,344
Number of firms	1,860	1,860	1,860	1,860
χ^2	2547	2017	878.6	265.0
χ^2 frailty	10.56	339.6	40.47	22.69

*, **, and *** denote statistical significance at the 10, 5 and 1 percent level, respectively.

likewise, our estimations of alliance activity include the number of VC rounds prior to that event. These are estimated as independent equations, which allows separate baseline hazard functions to be estimated. However, this does not come without its own set of costs. In particular, an appealing alternative to our strategy would be to posit a bivariate distribution for the joint hazard of the two events (VC funding and alliance formation) and introduce exogenous parameters to each outcome that would allow us to identify the outcomes jointly. Unfortunately, this would require us to write down a structural model of the joint distribution, as well as posit variables that are related to one outcome, but not the other. This is not feasible in the current setting. Nevertheless, as Kalbfleisch and Prentice (2002) point out, with time-varying data, including counts of the competing risks as right-hand side variables is partly a way to address the fact that the risks are not independent (see also Rodriquez, 2012).[6] This is essentially the approach we have taken in this paper.

One feasible alternative to this is to explore interactions between VC and alliance activity more directly. Table 7 presents this analysis. In each column, we repeat the main specification (Column 9) of each duration analysis (Tables 3–6), but introduce a new variable, which is the interaction of the total number of VC rounds with the total number of alliances formed over the last five years.

Each type of funding partnership provides three essential sources of value to the firm. First, it provides direct funding. Second, it provides certification of quality to uninformed outsiders, which in turn impacts the terms under which a company is able to raise funding later (Nicholson, Danzon, and McCullough, 2005). Finally, it helps connect the firm to other firms with resources that help the firm achieve its strategic objectives (Hochberg, Ljundqvist, and Lu, 2007; and Lindsey, 2008). The interaction effects can help to assess the relative importance of these three value sources on net. If introductions are relatively more important, then we would expect the interaction term to be positive, as the presence of one type of funding increased the impact of the other. If the first two factors outweigh the third, then we would expect the interaction term to be negative.

[6] It contains online course material for a biostatistics course that covers the concepts referenced in the paper

The main result from Table 7 is that VC funding and alliance formation are substitutes. This can be seen by the fact that, in each of the four columns, the interaction term has a value that is statistically significantly less than one. This is intuitively clear and speaks to the signaling and certification role of both, as we describe above. If the interaction term were significantly greater than one, it would suggest, for instance, that a key role of VC partnering was to help the firm identify suitable alliance partners, and this effect was stronger than the funding channel.

Because the interaction term is negative, when we include it in the regression specifications, the main effects of VC and alliance funding are larger. For example, comparing the hazard ratios from Column 9 of Table 6 with Column 4 of Table 7, the loading on the VC funding round variable grows from 1.287 to 1.359, and the loading on the total alliance variable goes from 1.108 to 1.27. This is most interesting in Column 1, where we examine the hazard of the next VC funding as a function of VC and alliance activity. In Table 3, the hazard ratio on total alliances is greater than one alone but significantly less than one in specifications that include the prior rounds of VC funding. With the interaction (Column 1 of Table 7), we again find that the main effect of alliances on later VC funding is positive, but previous alliance activity attenuates the effect of prior VC funding rounds to such an extent that the overall effect of strategic alliance activity is negative (as can be seen from the point estimates in Table 3).

It is also important to acknowledge that the exit outcomes that we study are associated with a set of prices at which firms launch an IPO or are acquired, and that these prices are interesting and important in their own right. In untabulated results, we study how our key independent variables affect IPO underpricing, as well as IPO and merger valuations. First, a connection exists between IPO underpricing and the degree of prior VC and alliance activity. Consistent with Megginson and Weiss (1991), Barry, Muscarella, Peavy, and Vetsuypens (1990), Ljungqvist and Wilhelm (2003), and others, we find that increased numbers of VC rounds and increased VC centrality diminish underpricing. Alliance activity, patent activity, and the FDA dummy have no effect on underpricing, which suggests that at least part of the quality signals they provide are incorporated into the offer price. In addition, when we consider merger valuations, we find that increasing previous alliance activity is associated with higher valuations at acquisitions. A full analysis of these findings is beyond the scope of this paper, but these results are available upon request.

8. Conclusion

This paper is one of the first to analyze how the interplay between alternative funding sources in the private capital market affects a start-up company's exit decisions from the private capital market. Strategic alliances and venture capital funding both raise the hazard that a start-up company goes public as well the hazard of being acquired.

The results surrounding the effect of VC funding on firm exit are unsurprising. After all, VC funds invest in portfolio companies hoping to generate a return through a favorable exit. The findings here bear out this simple intuition and illustrate the importance of the VC syndicate network in bringing about this outcome. Furthermore, biotechnology companies that have VC investments from better networked VCs with more central positions in VC syndicate networks are at substantially greater hazard of going public. This finding suggests that central, i.e., better networked, VCs have more extensive information channels, enabling them to add more value to their portfolio companies. Such VCs also certify the quality of their portfolio companies, further increasing the chances of successful exit for start-ups funded by central VCs. In addition, previous alliance activity has a significant role in the going public decision. One reason for this is that alliances represent the start-up's collaborative activity, which leads to the exchange of complimentary knowledge and other resources.

We also find that previous VC and alliance activity both increase the hazard of new alliance formation. They have opposite impacts on the hazard of new VC funding. Even though biotech companies that accumulated more VC funding rounds are more likely to receive new VC funding, previous alliances lower the hazard of new VC funding in the next period. One reason for this is the potential for conflict of interest between VC firms and alliance partners. VC equity stakes are horizontal slices of value across all of a firm's potential product lines, whereas alliance cash flow rights tend to represent narrower, more vertical slices within a particular product line. Given the prevalence of strategic alliances, a deeper understanding of how early-stage firms optimally balance the competing interests of project-level and company-level funding opportunities is an important question for future research.

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