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Blurring Firm Boundaries: The Role of Venture Capital in Strategic Alliances

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ABSTRACT

This study documents a new value-added role of venture capitalists and addresses important questions about how resources are combined to create firms. As part of the nexus of contracts surrounding a firm, strategic alliances can be viewed as relational contracts that blur firm boundaries. This paper provides evidence that alliances are more frequent among companies sharing a common venture capitalist. The effect is concentrated in alliances in which contracting problems are more pronounced, consistent with venture capitalists utilizing informational and other advantages in providing resources to firms. Further, these alliances improve the probability of exit for venture-backed firms.

MODERN CORPORATE FINANCE INCREASINGLY RECOGNIZES the importance of understanding the role of the theory of the firm as it relates to financing decisions. As relational contracts that lie between the boundaries of a single firm and market transactions, strategic alliances are part of the nexus of contracts that surround a firm and can be an important source of value (Jensen and Meckling (1976)). This paper provides evidence that strategic alliances are disproportionately more frequent between companies that share a common venture capital investor and that venture-backed portfolio firms with these strategic alliances are associated with a higher probability of successful exit. The empirical findings in this study document a new type of value-added service provided by venture capitalists (VCs) and address important questions about how resources are combined to create new firms.

Venture capital firms have long stressed their role as value-added investors, claiming to facilitate key contacts for their portfolio firms and to encourage interaction within their networks. For example, Kleiner, Perkins, Caufield, and Byers, a leading Silicon Valley firm, notes in promotional materials,

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"We pioneered the idea 20 years ago of bringing the businesses we work with into an informal network ... Connections made through the [network] have helped facilitate ... strategic alliances and countless business partnerships."[1] Implicit in this statement is the benefit of companies working closely together.

The alliance behavior of venture-financed firms offers a unique laboratory to identify organizational arrangements where, absent a common investor, contracting may be problematic due to high information asymmetries or expropriation risks. For example, R&D alliances may be particularly problematic in an incomplete contracts setting because of difficulties in governing ownership of intangible assets, more uncertainty about project outcomes, and greater information asymmetries at the time of contracting. There is evidence that marketing alliances may also experience similar difficulties (Allen and Phillips (2000)). For alliances between firms competing in the same industry, the risk of stealing trade secrets or proprietary knowledge might preclude some alliances from taking place. Venture capitalists, in their role as monitors, have access to detailed information about a firm's strategy and progress. They can use this knowledge to govern the flow of information and identify profitable collaborations between firms (Aoki (2000)). In addition to having informational advantages that may overcome disclosure problems preventing alliance formation, the venture capitalist can also serve as an enforcement mechanism to punish noncooperative strategies such as direct expropriation. The venture capitalist could withhold future alliance partners from the more mature companies participating in the alliance if they engage in undesirable behavior and directly discipline the management in private companies where VC control rights are still strong. Further, if a VC funds a company knowing that it fits well in a strategic sense with the rest of the portfolio, that selection should be viewed as a value-enhancing activity important for the development of new firms. Consistent with Hellmann (2002), a VC's past portfolio could change the complementary resources available to support the new portfolio company.

This paper first asks whether sharing a common venture investor affects the probability of firms pairing in an alliance. Because the formation of any given alliance may constrain the choice of available partners for subsequent alliances, the strong independence assumptions required for traditional discrete choice models make them unsuitable in this setting. Using a unique empirical approach based on sequential sampling, this study finds evidence of a blurred firm boundary effect, defined as an increased probability that two firms pair in an alliance if they share a common venture capitalist investor.

Moreover, this blurred boundary effect is strongest in areas where contracting problems are likely to be most pronounced and where the VC is still likely to be active as a monitor in the firm. Specifically, the effect is observed only in alliances involving at least one private firm; two public firms who share a common venture capital investor exhibit no such extra propensity to ally. Further, this effect is stronger for companies competing in the same industry

[1] Kleiner, Perkins, Caufield, and Byers Website, http://www.kpub.com (accessed in 2002).

or developing more in-depth alliances, such as R&D and marketing alliances. As a result, these findings inform the literature on incomplete contracting and the theory of the firm. These results suggest that venture capitalist involvement in facilitating alliances has economic meaning and adds financial market value. Indeed, these alliances are shown to create real value for the venture portfolio firms as measured by exiting through a public offering or acquisition, even after controlling for factors that may have influenced the probability of entering such alliances.

There are two main contributions of this study. First, by providing new evidence of how firms and their partnerships are formed, the paper documents the value-added role of venture capitalists in combining resources to form new entities. This paper adds to the literature that explores the value added by venture capitalists through advice, support, or improved governance. Previously documented mechanisms include venture capitalists helping firms to recruit key managers (Gorman and Sahlman (1989), Hellmann and Puri (2002)), monitoring and advising through service on the company's Board of Directors (Lerner (1995), Baker and Gompers (2003)), and implementing other strong governance mechanisms (Hochberg (2004)). Facilitating strategic alliances is an additional channel through which venture capitalists add value. Studies by McConnell and Nantell (1985), Koh and Venkatraman (1991), Chan et al. (1997), and Das, Sen, and Sengupta (1998) find favorable market reactions to the announcement of joint ventures or strategic alliances, particularly for those focused on technical knowledge. Lerner and Merges (1998) and Lerner, Shane, and Tsai (2003) show that alliances can be important sources of financing, even for venture-backed firms. Other studies recognize the value of strategic relationships when combined with block ownership (Allen and Phillips (2000)) or corporate venture capital (Gompers and Lerner (2000)).

A second contribution is in highlighting the types of strategic alliances where, absent a common investor, information and expropriation problems may prevent relational contracting ex ante. Models such as that of Grossman and Hart (1986) or Hart and Moore (1990) focus on contracting problems in the presence of relationship-specific investment, but resolve hold-up and related problems by integrating the activity within a single firm. As early as Coase (1937), however, attempts to develop the theory of the firm have recognized the difficulty in drawing a tight boundary around a firm. As such, strategic alliances have been regarded as lying somewhere in between single-firm activity and spot contracting. (See also Baker, Gibbons, and Murphy (2002) and Garvey (1995)). Recent empirical studies support this view. For example, Gomes-Cesseres, Jaffe, and Hagedoorn (2006) show that strategic alliances are important for knowledge flows between firms. As with the blurred boundary effect documented here, they find knowledge flows are stronger when R&D is involved and when the firms are in the same industry. In the context of venture capital, the relational contracting literature has focused on contracts between the financier and the entrepreneur. (See, e.g., Admati and Pfleiderer (1994), Gompers (1995), and Kaplan and Strömberg (2003, 2004)). Here, venture capitalists are shown to have a role in relational contracting among their portfolio firms.

The ideas in this paper also relate to topics in the management and sociology literature. For example, Gulati (1998), (1999) focuses on social networks in which firms are embedded as important factors in influencing alliance formation. Eisenhardt and Schoonhoven (1996) combine this emphasis on the social position of firms with strategic considerations to argue that alliances arise when firms in vulnerable strategic positions need additional resources. Further, Williamson (1991), Larson (1992), and Robinson and Stuart (2007) consider networks as a possible governance mechanism for activity between firms.

The remainder of the paper is structured as follows. The next section describes the data. Section II presents a simple univariate test of whether alliances within a VC's portfolio are more frequent than alliances across VC portfolios. The multiple variable estimation approach for whether sharing a common VC investor increases the probability of two firms pairing in an alliance is developed in Section III. Section IV presents results and discusses the types of alliances in which the blurred boundary effect is most prominent. Section V documents the value-enhancing role of alliances for portfolio firms. Robustness and alternative explanations are discussed in Section VI. Section VII concludes.

I. Data

The data for strategic alliances are from the Thomson Financial Strategic Alliances and Joint Ventures Database; firm financing information is from Thomson's Venture Economics. These data are supplemented with information from public filings and other public sources (company web sites and popular press). The database of strategic alliances and joint ventures is compiled from company press releases, news wires, and trade journals. The data cover a cross-section of industries, include both public and private firms, and span alliances from January 1987 through June 2001. Only alliances between U.S. firms are considered because the venture financing information cannot be considered comprehensive for international firms.[2] Company information in the strategic alliance data set includes the main SIC code for each parent company, its status as a public or private entity, and its state of headquarters. For each observation in the database, a broad description of the alliance purpose is given (such as marketing or research and development), the alliance date, and an SIC code for the alliance activity. More detailed information about the alliance activity is sometimes included in a text description, but this information is not systematically coded across alliances. The financing information in Venture Economics is collected from reporting venture capital firms and public sources, and includes financing round information such as the date and amount of investment and the participating venture capitalists. From Venture Economics' inception in 1970 to June 2001, the data cover 54,722 financing rounds for 23,767 companies by

[2] Privatizations and spinouts, which are included in the database for historical reasons, and oil and gas exploration agreements are excluded from the study.

over 1,500 venture capitalists.[3] This database has been used in many studies on venture capital, including Gompers (1995), Lerner (1995), Kaplan and Schoar (2005), and Gompers et al. (2007).

The two databases are matched on company name to recover venture financing information for participants in alliances.[4] Of the 16,818 unique firms in the alliance data, 3,032 are venture-backed, or roughly 18%. Though only 18% of the firms in initial alliances are venture-backed, 44% of the alliances involve at least one venture-backed firm. These data are supplemented with information on CEO age, as a proxy for a company's network, collected from SEC filings, company web sites, news articles, and biographical databases such as ZoomInfo. This information is obtained for 20,730 of the 24,311 alliances. The data are first merged on ticker and year with information from SEC proxy statements. Each company is then hand-checked to see if age information could be recorded from a later filing. For companies that were publicly traded at the time of the alliance or that went public later, over 99% of CEO ages are collected using information from public filings. Each company that was venture-backed or that formed an alliance with a venture-backed firm is then further hand-checked against the alternative sources listed above. For these firms, 86% of CEO ages are obtained. For the subset of alliances that share a common venture capitalist, CEO age is recorded for 96% of the observations.

The research question focuses on whether a company's venture capitalist appears to foster new relationships that culminate in the creation of alliances, where an alliance is defined as the initial affiliation of two firms. In alliances where more than two firms participate, each pairing of firms is treated as one alliance. Table I shows the total number of initial alliances over time, as well as the number of alliances in which one firm received venture backing and in which both firms received venture backing. The last two columns of Table I show the composition of the alliances by public status. Almost half (47%) of alliances occur between one private firm and one publicly traded firm. Some 29% of alliances occur between two private firms, while 25% are between two public firms.

Table II displays the alliances by described purpose, where more than one purpose can be coded for each alliance. The categories are marketing, manufacturing, technology licensing, royalty, funding, research and development, supply, original equipment manufacturing (OEM), joint ventures, and unknown. A large fraction of the alliances are coded as "unknown," and the uncategorized segment grew over time. The size of this category compels its inclusion. The most frequently coded alliance purpose category is marketing agreements, followed by technology licensing, and then R&D alliances. Joint ventures are categorized separately and with no further details. They are roughly as frequent as marketing alliances.

[3] See Kaplan, Sensoy, and Strömberg (2002) for an evaluation of this database. In brief, it is found to be generally free from bias, though it oversamples California companies and large rounds.

[4] Because of the large number of observations in each database, a program is used to aid in matching. The program eliminates nonidentifying information (such as Co, Corp, PLC), removes spaces, and performs case-insensitive matching on the core name.

Table I

Alliances by Year, Venture Backing, and Public Status

Table I shows the number of alliances, defined as initial bilateral pairs, in each year from 1987 to June 2001. The first column shows the total number of alliances each year. The second two columns show the venture-backed status of companies in the alliances. The next two columns show the public status of companies in the alliances. The unreported columns are (a) neither venture-backed and (b) both private.

Year	Total Number	Exactly One Venture-Backed	Both Venture-Backed	Exactly One Public	Both Public
1987	102	46	14	54	26
1988	181	73	14	95	56
1989	180	67	28	82	53
1990	1,056	383	139	547	242
1991	1,709	624	221	843	415
1992	1,826	697	239	892	481
1993	2,186	800	197	1,052	554
1994	2,578	817	257	1,154	584
1995	2,412	730	219	1,146	528
1996	1,546	535	183	736	527
1997	2,016	670	223	991	594
1998	2,200	726	190	1,055	545
1999	2,843	967	333	1,318	766
2000	2,577	802	235	1,069	475
2001	899	255	43	339	124
Total	24,311	8,192	2,535	11,373	5,970

Alliances are more commonplace within and across particular industries. Industry pairs as defined by four-digit SIC codes are an important feature of the estimation procedure, which is discussed in Section III. Approximately 20% of alliances are within a single SIC-code. Prepackaged software is the dominant industry category. Within-industry software alliances are the most frequent category with 861 alliances, followed by the prepackaged software category paired with electronic computers with 668 alliances. Within-industry alliances for companies in pharmaceutical preparations ranks third, followed by the prepackaged software category paired with computer programming services, information-retrieval services, and integrated systems design. The 10 most frequent industry pairs comprise roughly 16% of the data.

II. A Simple Test for the Propensity to Ally

Are alliances more frequent within venture capital portfolios? One way to test this question is to condition on venture-backed firms. In the empirical analysis developed in Section III, the data include both venture and nonventure-backed firms that were active in forming alliances. One can extend the analysis to firms that did not enter alliances in a univariate test by analyzing the subset of firms that received venture capital financing.

Table II

Alliances by Described Purpose

This table shows the number of alliances in each year categorized by the alliance type code. The possible categories are marketing, manufacturing, licensing, royalty, funding, R&D, supply, original equipment manufacturing, joint venture, and unknown. An alliance may have more than one type of code.

Year	Marketing	Manufacturing	Licensing	Royalty	Funding	R&D	Supply	OEM	JV	Unknown
1987	14	1	15	0	0	11	2	6	42	17
1988	27	4	18	0	0	18	4	11	104	17
1989	35	3	34	0	0	25	2	4	87	17
1990	340	33	127	5	22	131	54	20	360	77
1991	595	31	189	7	47	240	114	94	531	47
1992	787	54	180	6	35	327	46	84	304	120
1993	737	78	217	4	56	415	28	60	553	148
1994	757	82	321	6	13	479	35	44	685	236
1995	632	108	476	5	3	212	26	52	771	226
1996	305	32	290	10	3	183	8	7	482	279
1997	361	66	427	11	4	237	18	13	468	455
1998	353	120	442	3	1	81	32	92	353	747
1999	319	150	358	1	1	62	27	30	403	1,510
2000	277	76	62	0	4	34	18	15	471	1,629
2001	156	26	33	0	0	49	47	5	79	505
Total	5,695	864	3,289	58	189	2,504	461	537	5,693	6,030

For each venture capital firm, two ratios are computed. The first is the *Total Alliance Ratio*. The *Total Alliance Ratio* is defined as

$$\frac{A_j}{n_j(n-1)} = \frac{\text{alliance nodes in } j\text{'s portfolio}}{\text{possible number of alliance nodes}}, \tag{1}$$

where j indexes each venture capital firm, n_j is the number of companies in VC j's portfolio, and n is the total number of venture-backed firms. This measure is meant to capture the extent to which companies within a given portfolio form strategic alliances or joint ventures with any other firm, regardless of which venture firm invested. It accounts for alliances involving the portfolio firms, both those that involve pairings with venture-backed firms external to the portfolio and those within it. In assigning a particular alliance to a particular portfolio, it is useful to think of participating companies as origination points. Thus, it is not alliances that are counted, but companies that enter a particular alliance. Each company can be counted more than once; in particular, it can be counted as many times as the number of unique alliance partners it has. This number is normalized by the possible number of such alliance origination points for the portfolio. An alliance ratio of one would mean that each company formed an alliance with every other company.

The second ratio is the *Within-Portfolio Ratio*. The *Within-Portfolio Ratio* is defined as

$$\frac{W_j}{n_j(n_j-1)} = \frac{\text{alliance nodes that begin and end in } j\text{'s portfolio}}{\text{possible number of alliance nodes within } j\text{'s portfolio}}. \tag{2}$$

The numerator again counts companies as originating points in an alliance, but only considers alliances that occur between two firms in the same portfolio. It is normalized by the number of possible within-portfolio alliance "nodes." If the *Within-Portfolio Ratio* is larger than the *Total Alliance Ratio*, there are disproportionately more alliances occurring within the same venture capital portfolio. Table III shows the results of the paired t-test of the ratios for each venture capital portfolio. The *Within-Portfolio Ratio* is small, at 0.24%, but two orders of magnitude above the baseline measure. The difference is statistically significant at the 99% level. The small magnitude of the two ratios should not be surprising. Many of these venture-backed firms never become viable companies, and hence they would not form strategic alliances. Nor would one expect a large fraction of the number of theoretically possible alliances to take place.

While this univariate test supports the idea that venture capitalists are fostering interaction among their portfolio firms, it lacks controls for firm and venture capitalist characteristics. Further, one would not expect that the only potential alliance partners for any venture-backed company are other venture-backed firms. The next section develops an estimation framework to address these issues.

Table III

Propensity to Ally within or across VC Portfolios

Table III provides a paired t-test between a VC's *Within-Portfolio Ratio* and its T*otal Alliance Ratio*. The *Within-Portfolio Ratio* is the number of within-portfolio alliance nodes within the VC's own portfolio divided by the number of possible nodes ($N^2 - N$). The *Total Alliance Ratio* is the total number of alliance nodes in the VC's portfolio divided by the possible number of such nodes. Reported ratios and errors are scaled by 100.

Variable	Mean	Standard Error	Observations
Within-portfolio ratio	0.2433	0.0599	2,521
Total alliance ratio	0.0016	0.0001	2,521
t-statistic	4.0374	p-value	0.0001

III. Estimation Framework: The Sequenced Conditional Logit

This section introduces the model and variables used in the alliance pairing estimation.

A. Determining the Set of Possible Alliances

In order to determine whether the presence of a common VC investor increases the probability of two particular firms forming an alliance, the framework must distinguish pairs of firms that are more likely to form an alliance from the set of firms that could have formed alliances but did not. The data used in estimation, then, are the set of potential alliances from which actual alliances could have formed.

Because alliances are formed with a specific purpose in mind, a company's industry is a natural way to restrict the choice set of companies with which the firm might have formed an alliance. A firm typically has some particular project in mind when forming an alliance and is seeking a firm that has a complementary skill set. A particular example may be instructive. Suppose a small biotechnology company forms an alliance with a large pharmaceutical company in order to develop a drug. If the alliance activity code were used to identify other firms who also had an alliance focused on drug development, it would likely identify two distinct sets of firms. The first set would be small biotechnology companies like the example firm and the second would be large pharmaceutical companies. It is really only the second set that is similar to the firm with which the example company actually formed an alliance. It is reasonable not to condition on alliance purpose since large pharmaceutical companies that formed commercialization alliances (not drug development alliances) might also have been suitable choices for the example firm.

Therefore, for each firm observed in an alliance, one would want to include the set of firms from the industry of its *partner* as the potential choices. Because not all companies in the partner's industry would be seeking an alliance in the original firm's industry, it makes sense to further restrict the potential alliance partners to companies from the partner industry that formed alliances with the original firm's industry.[5]

For a given firm, limiting the choice of alliance partners in this way has the strength of eliminating companies that may have lacked the complementary assets to be a desirable alliance partner for that firm. It also eliminates companies that might have found an alliance with another firm in the given firm's industry to be undesirable.[6] Further, the analysis is conditional on the firm having formed an alliance. This is reasonable since it indicates an inclination to ally. If one were to include the set of firms that did not form alliances, the number of pairs generated would be immense and, in any event, these data are not observed.

B. Probability Model

The model is based on the idea of sequential sampling, with alliances selected from a pool of possible alliances in a series of rounds. In the model, the coefficients indicate the characteristics that are associated with a high likelihood of an alliance being formed between a particular pair of firms. Because the parameterization of the probabilities follows the logistic distribution, the resulting likelihood function can be thought of as a sequenced conditional logit. The model is similar to the standard conditional logit (Chamberlain (1980)), but differs in allowing the set of conditioning outcomes (in this case, alliances) to vary as alliances are formed over time.

The model is

$$\Pr(Alliance = 1) = \frac{\exp\left(X_s^t \beta\right)}{\sum_{s \in S} \exp\left(X_s^t \beta\right)}, \tag{3}$$

where X is vector of explanatory variables and β a vector of coefficients, t indexes the time of the alliance, and S is the set of feasible alliances constructed from companies in the alliance partner's industry. The set S varies as alliances in a particular industry pair are formed. Each firm pair is parameterized with a potentiality of $e^{X\beta}$, where X represents firm pair characteristics at time t. The probability of each alliance, which is just the potentiality of the realized

[5] Formally, let $I \equiv$ set of observed industries and let $P \equiv$ set of industry pairs. Define $p \in P$, where $p = \{i, j\}$ with $i, j \in I$. Define $S^p \subset S$ to be the set of strategic alliances for industry pair p. Let $\gamma(\bullet)$ denote a firm's industry. If company pair $\{a, b\} \in S^p$, where $a \neq b$ and $\gamma(a) = i$ and $\gamma(b) = j$, then there exists $d = \{a, b'\}$ and $d' = \{b, a'\}$ such that $\gamma(b') = j$ and $\gamma(a') = i$. Both d and d' are elements of S, with $d \in D$ as the realized alliance.

[6] An additional motivation is to keep the data set to a manageable size. It is possible, of course, to have a wider choice set. For robustness, the requirement that the potential partner firm must also have an alliance with a member of the original firm's industry is relaxed, and the blurred boundary effect is robust to this alternative specification of potential alliance pairs.

alliance divided by the sum of the potentialities of all feasible alliances, follows the logistic function.[7]

Two variations of the model are developed. They differ with respect to assumptions about the maximum number of alliances a firm could have formed, or "alliance capacity." A firm's alliance capacity is the number of alliances it has a positive probability of entering. In the first version, alliance capacity is fixed at the number of alliances observed for a given firm; in the second, a firm can form any number of alliances, but the number of previous alliances formed by the members of the pair can affect the probability of forming an additional alliance. In both versions, the probability of each observed firm pair that enters an alliance at a particular point in time is calculated from the set of potential alliances, which changes over time.

Imagine a sequential process, where, in the first round, an alliance is selected based on characteristics of the pair. In one version of the model, all unselected pairs remain potential alliances, except those involving the selected entities (both actual and counterfactual). In the second version, the number of alliances a firm can form is unconstrained. Therefore, only the selected alliance is removed from the set of potential alliances, but the counterfactual alliances constructed from the members of the pair remain as potential alliances. In the next stage, another pair is selected, and so forth, with pairs involving selected entities removed at each stage. For an illustration of the model's mechanics in a simple example, see Figure 1.

This model is designed to allow for the possibility that firms' alliance choices may not be independent from one another. It is clear that treating each potential alliance as independent in this framework would be erroneous. The data are composed of firm pairs, and each firm appears in multiple observations. Because many of these firms might interact in markets where the choice of one firm's alliance partner precludes that partner from collaborating with a third firm, there is an interdependence among choices.[8] Statistically, this means that, viewed as random events, realizations of potential alliances are correlated. Proper estimation should account for these correlations. Because standard discrete choice models such as the logit or probit assume independence across all observations, estimates using traditional logit or probit estimates would be biased (Chamberlain (1980)). Further, because firms in the alliance pairs are not on distinct

[7] For an industry pair, the likelihood can be expressed as the product of N_p terms,

$$L^p = \left(\frac{\exp(X^1_{s_1}\beta)}{\sum\limits_{s\in S^P}\exp(X^t_s\beta)}\right)\left(\frac{\exp(X^2_{s_2}\beta)}{\sum\limits_{s\in S^{Pf}(s_1)}\exp(X^t_s\beta)}\right)\left(\frac{\exp(X^3_{s_3}\beta)}{\sum\limits_{s\in S^{Pf}(s_1,s_2)}\exp(X^t_s\beta)}\right)\cdots\left(\frac{\exp(X^t_{s_{N_p}}\beta)}{\sum\limits_{s\in S^{Pf}(s_1,s_2\cdots s_{N_p-1})}\exp(X^t_s\beta)}\right).$$

The likelihood function is then the joint probability of the observed alliances. Multiplying across all industry pairs,

$$L = \prod_{p\in P} L^P(s_1,\ldots,s_{N_p}).$$

[8] The management literature refers to this phenomenon as "lock-out" (Gulati, Nohria, and Zaheer (2000)).

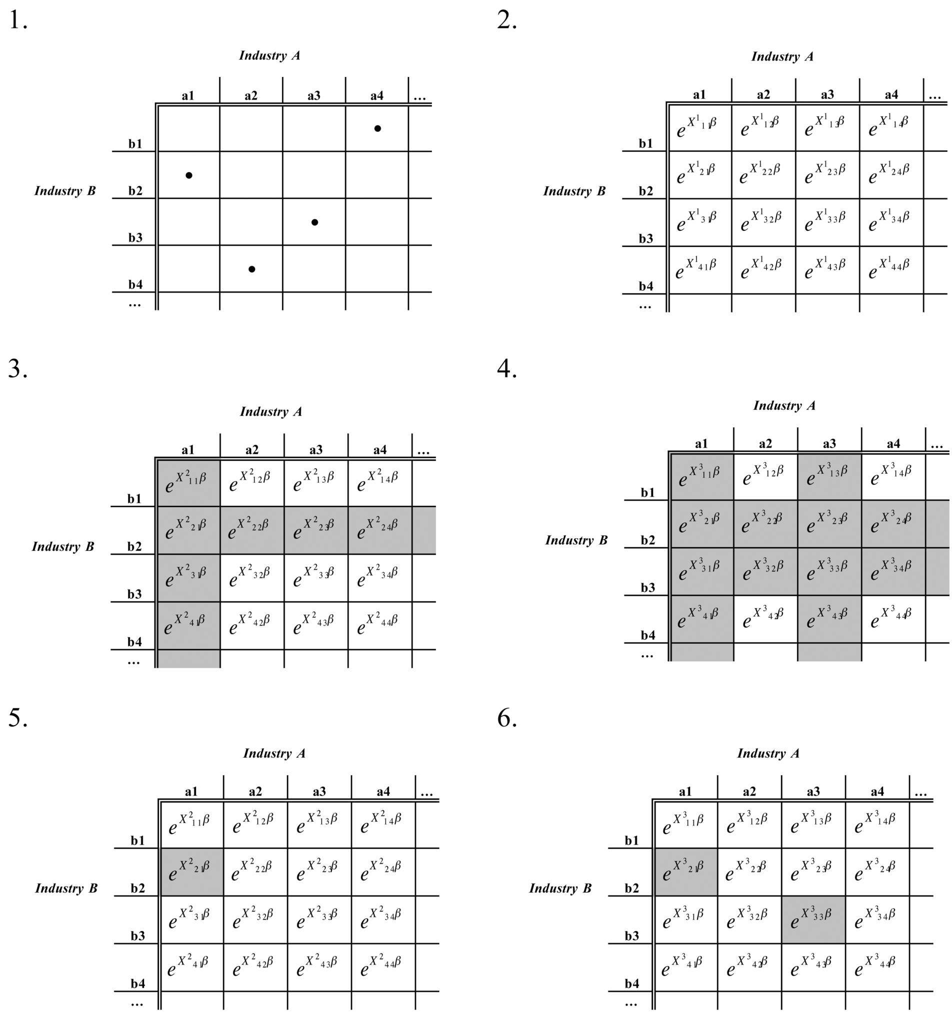

Figure 1. An illustration of the sequenced conditional logit. Suppose there are two industries, A and B, with alliances between pairs of firms from each industry. The observed data are depicted by the dots in the grid of box 1, with alliances between the following firms: (a1,b2), (a2,b4), (a3,b3), and (a4,b1). Each potential alliance in the grid has a potential realization based on its characteristics given by $e^{X\beta}$, as shown in box 2. Suppose the first alliance is (a1,b2). The probability of that event is simply $e^{X^1_{21}\beta}$ divided by the sum of all of the potentialities in the grid. In the fixed capacity version of the model, neither firm a1 nor firm b2 can enter another alliance. Thus, potential pairs formed by firms a1 and b2 will be removed from the set of potential alliances, as represented by the shaded region in box 3. In the variable capacity version, only the selected alliance is removed from the set of potential alliances. The potential alliances constructed from the selected firms are allowed to remain, as depicted in box 5. Suppose the second alliance formed is the alliance between firms a3 and b3. The probability of that event would be $e^{X^2_{33}\beta}$ divided by the sum of the remaining potentialities at the time the alliance was drawn, which are the expressions in the unshaded area of box 3 for the fixed capacity version and box 5 for the variable capacity version. For the next alliance, the potential alliances and associated probabilities are shown by the unshaded area in box 4 for the fixed capacity version and box 6 for the variable capacity version. The process continues until the penultimate alliance is selected. For alliances that occur between firms within the same industry, firms are not permitted to self-match and the redundant pairs are eliminated before the first alliance. If a firm has more than one alliance, its row or column of potentialities is not eliminated until it forms its last alliance.

"sides" of a market, it is impossible to use fixed effects or error clustering to control for correlations across the same firm.

The main advantage of this model is that it accounts for the interdependence in both dimensions simultaneously. It includes more information from the observable data as well. The order in which the alliances occur is used to eliminate firms from the market in a manner consistent with the data. The fixed capacity implementation also provides a rationale for including only companies from the alliance database as eligible in constructing potential pairs. Any firm not in the data presumably had no alliances, and therefore had capacity fixed at zero. A weakness of this version may be the extreme assumption of fixed capacity. However, it is a natural extension of the conditional logit framework, which imposes the same restriction in a single dimension. Because it is difficult to imagine that no firm in the alliance database could have formed a single additional alliance beyond what was actually observed, the assumption is relaxed in the variable capacity version of the model.

C. Variable Definitions

Because the unit of observation is a pair of firms that enter an alliance, the variables used in this estimation pertain to the pair forming the alliance rather than each individual firm. The variables include both the characteristics of the companies in the alliances and characteristics of venture capitalists, if any, which were involved in funding the companies in the pair. The variable capacity version of the model includes an additional control for the number of previous alliances for the two firms, which changes within the estimation. Industry controls are implicit in the data construction since probabilities are computed separately for each industry pair. Summary statistics for the observed alliances are presented in Table IV.

The variable of interest is *Common VC*, which is an indicator variable that takes the value of one if the company pair shared a common venture capital investor, and zero otherwise. Because venture backing itself mechanically affects the probability that two firms may share a common VC and may also be associated with firm characteristics that affect the formation of alliances, controls for whether one or both firms in the alliance pair received venture backing prior to the alliance are included. In particular, *One Venture-Backed* is an indicator variable signifying whether at least one firm in the company pair was venture-backed, and *Both Venture-Backed* is an indicator variable signifying whether both companies were venture-backed, though not necessarily by the same VC.

The public status of the alliance participants may also affect the companies' probability of entering alliances. Asymmetric information can exist between any two entities, but private firms that lack financial reporting requirements may be less transparent financially and may have had less time to develop a reputation than public firms. Further, venture capitalists are likely more active in the life of the private firms in their portfolio in which they still have a significant financial interest. While VCs may remain involved as a Board member or informal advisor for a more mature firm, they generally exit large

Table IV

Summary Statistics for Observed Initial Alliance Pairs

Table IV shows summary statistics for the observed alliances. *Common VC* is an indicator variable that takes the value one if the company pair shares a common investor, and zero otherwise. *Both VC* is an indicator variable for whether both companies are venture-backed. *One VC* is an indicator variable signifying at least one firm in the company pair is venture-backed. *Both Public* is an indicator variable signifying that both firms are publicly traded at the time of initial pairing. *One Public* is an indicator variable signifying that at least one firm in the company pair is publicly traded at the time of the initial pairing. *Same State* takes a value of one if the companies in the pair are in the same state, and zero otherwise. *CEO Age* is the log of the sum of the CEO ages of the two firms. *Early Stage* takes a value of one if either company in the alliance received VC funding at an early stage, and zero otherwise. *Round Amount* is the natural log of one plus the average first round amount of the companies. *Number VCs* is the natural log of one plus the total number of venture capital (VC) firms involved in funding the alliance participants. *IPO Rate* is natural log of one plus the proportion of companies in the funding VCs' portfolios that had a public offering. *VC Experience* is the natural log of one plus the average age, in years, of the funding VC firms calculated from their first entry into the Venture Economics database. VC *Industry Focus* is the natural log of one plus the proportion of companies that the funding VCs financed in the alliance participant's two-digit SIC code *VC Stage Focus* is the natural log of one plus the proportion of companies in which the funding VCs invested at an early stage.

Variable Name	Number of Observations	Mean	Standard Deviation	Minimum	Maximum
Common VC	24,311	0.0234	0.1513	0	1
Both VC	24,311	0.1043	0.3056	0	1
One VC	24,311	0.4412	0.4965	0	1
Both public	24,311	0.2456	0.4304	0	1
One public	24,311	0.7133	0.4522	0	1
Same state	20,872	0.2381	0.4259	0	1
CEO age	20,730	4.6455	0.1577	3.8501	5.2933
Early stage	24,311	0.2334	0.4230	0	1
Round amount	24,311	2.6554	4.0230	0	13.9617
Number VCs	24,311	0.1463	0.5946	0	3.8501
IPO rate	24,311	0.0181	0.0727	0	0.5404
VC experience	24,311	0.1109	0.4541	0	2.9704
VC industry focus	24,311	0.0172	0.0730	0	0.6931
VC stage focus	24,311	0.0254	0.1013	0	0.6931

financial positions shortly after the IPO. One may therefore expect that any common investor effect "wears off" as both firms in the alliance become more mature. Accordingly, *One Public* is a dummy variable indicating at least one firm in the company pair was publicly traded at the time of the initial pairing, and *Both Public* is a dummy variable indicating that both firms were publicly traded at the time of initial pairing. These variables are included as controls throughout the analysis and are also interacted with the *CommonVC* variable for some tests.

Geographic proximity may affect the likelihood of two firms pairing in an alliance. It also controls for the possibility that two firms located near one another may meet through channels other than their VC. The variable *Same*

State is an indicator variable that takes a value of one if the companies in the pair are headquartered in the same state, and zero otherwise.

Ideally, one would control for all firm-specific factors that affect the possibility that two firms meet in an alliance. Of particular importance, however, is some measure of a firm's network independent of their venture capitalist. For young firms, a company's network is substantially similar to that of key employees involved with the firm since the firm has had little time to develop an independent reputation (Eisenhardt and Schoonhoven (1996)). To proxy for the firms' networks, *CEO Age*, a control for the sum of the ages of the two CEOs of the firms involved in the alliance, is included, transformed by the natural log. Alternative definitions such as a control for the least experienced, most experienced, or average of the two CEO ages can be used and produce similar results. For venture-backed firms, additional controls that capture firm development at the time of funding are included. The variable *Early Stage* takes a value of one if either company receives its first funding at the seed or early stages of development as coded by Venture Economics, and zero otherwise. The variable *Round Amount* is the natural log of the company's first-round financing amount.

In addition to firm-specific controls, several characteristics of the funding VCs are included as well. These variables account for differences among funding VCs and, because better-quality companies have been shown to sort to better-quality VCs (Sørensen (2007)), may control for otherwise unobservable measures of company quality. In addition, prior literature documents that venture capitalists tend to focus by industry or stage, such that these characteristics of the VC could affect a firm's potential to ally within the network. The variable definitions for the venture capitalist controls, transformed as the natural log of one plus the variable for use in the regressions, are as follows: *Number VCs* is the total number of venture capital firms involved in funding the alliance participants; *IPO Rate* is the proportion of companies in the funding VCs' portfolios that had a public offering; *VC Experience* is the average age, in years, of the funding VC firms calculated from their first entry into the Venture Economics database; *VC Industry Focus* is the average across VCs of the proportion of companies in the portfolio in the alliance participant's industry, measured at the two-digit SIC code level;[9] and *VC Stage Focus* is the average across VCs of the proportion of companies in the portfolio in which a company is first funded at an early stage.

IV. Blurred Firm Boundary Effect

The empirical task in this section is twofold. The first task is to test for the presence of a blurred boundary effect using the estimation method outlined

[9] SIC codes are missing for a large fraction of the Venture Economics database. Venture Economics industry codes are available, but do not have a one-to-one correspondence to SIC codes at any level. From the observations where both industry codes are available, I construct a mapping from Venture Economics codes to two-digit SIC codes based on the most frequent occurrences between the two codes and use the mapped SIC code where missing.

above. The second is to draw inferences from the types of alliances for which an effect is present about the role the venture capitalist plays in the phenomenon.

A. Testing for a Blurred Boundary Effect

Does sharing a common venture investor increase the probability of two firms pairing in an alliance? Table V presents the results of the maximum likelihood estimations under the alternative assumptions of fixed and variable capacity. An observation is a realized alliance. There are 18,527 observations used in the estimation. The coefficients can be interpreted as measuring factors that influenced the realization of a particular pair relative to the set of potential pairs in that alliance market.

In the fixed capacity estimation of Column I and the variable capacity estimation of Column III, the coefficient estimate on the *CommonVC* variable is positive and statistically significant, indicating that sharing a venture capitalist increases the probability that two firms will form an alliance. The coefficients on the VC backing controls are positive as well, though only the control for at least one venture-backed firm is statistically significant across specifications. Both controls for public status indicate a negative relation with the probability of forming an alliance, indicating that alliances between private firms are more likely than their frequency in the set of counterfactual alliances would predict. The variable *SameState* does not significantly affect alliance formation in the estimation, and *CEOAge*, as a proxy for the firm's own network, shows a positive effect on the formation of alliances across specifications.

The venture funding controls indicate that the more money firms received in the first round of financing, the less likely it is that they enter an alliance, perhaps because they have more internal resources. Consistent with similar intuition, there is some evidence in the fixed capacity estimation that firms funded at an earlier stage are more likely to enter alliances. Firms funded by VCs with an early-stage focus are associated with a higher probability of pairing in an alliance, whereas, quite surprisingly, firms funded by more experienced VCs on average are associated with a lower probability of alliance pairing. This result could stem from a number of factors. For example, firms with more internal capabilities, and therefore in need of fewer alliances, may be funded by more experienced VCs. Alternatively, it is possible that younger VCs, in an attempt to build reputation, engage in an unusual amount of alliance activity on behalf of their firms.

In the variable capacity version of the model, the coefficient on the variable measuring previous alliance activity is negative, indicating that the likelihood of two firms pairing in an alliance decreases with each additional alliance for one of the pair's members. The associated marginal effects are not obvious from the coefficient magnitudes. In sequenced models, the measured probabilities change as alliance histories develop; reported calculations here for implied marginal probabilities are prior to any alliances having been formed. In both the fixed and variable capacity models, the base probability of two companies entering an alliance is close to 12%. The probability increases a somewhat

Table V

Testing for a Blurred Boundary Effect

Table V presents the results of the maximum likelihood estimation of the sequenced conditional logit model with fixed and variable alliance capacities. The unit of observation is a realized alliance. The independent variables are: *CommonVC*, which takes the value of one if the company pair shares a common investor, and zero otherwise; *CommonVC* ∗ *Private*, a variable that takes the value of one if the company pair shares a common investor and at least one firm in the alliance is private, and zero otherwise; *CommonVC* ∗ *Public*, a variable that takes the value of one if the company pair shares a common investor and both firms in the alliance are public, and zero otherwise; and *Previous Alliances,* which tracks the number of alliances realized by the firm pair in the estimation. The other variables are defined as in Table IV. Standard errors are in parentheses. *, **, or *** means the coefficient is statistically significant at the 10%, 5%, or 1% level.

	Fixed Capacity		Variable Capacity	
	I	II	III	IV
CommonVC	0.1218**		0.1897***	
	(0.055)		(0.055)	
CommonVC ∗ private		0.2994***		0.4529***
		(0.079)		(0.078)
CommonVC ∗ Both public		0.0077		0.0303
		(0.068)		(0.067)
Both VC	0.1469***	0.1503***	0.0652	0.0700*
	(0.041)	(0.041)	(0.041)	(0.041)
One VC	0.1702***	0.1688***	0.1461***	0.1442***
	(0.029)	(0.029)	(0.029)	(0.029)
Both public	−0.2071***	−0.1935***	−0.1318***	−0.1114***
	(0.022)	(0.022)	(0.022)	(0.022)
One public	−0.1759***	−0.1775***	−0.1399***	−0.1427***
	(0.027)	(0.027)	(0.027)	(0.023)
Same state	0.0335	0.0323	0.0169	0.0150
	(0.022)	(0.022)	(0.022)	(0.022)
CEO age	0.2635***	0.2629***	0.4081***	0.4067***
	(0.063)	(0.063)	(0.062)	(0.062)
Early stage	0.0607*	0.0601*	−0.0046	−0.0059
	(0.032)	(0.032)	(0.032)	(0.032)
Round amount	−0.0235***	−0.0235***	−0.0159***	−0.0158***
	(0.004)	(0.004)	(0.004)	(0.004)
Number VCs	−0.0589	−0.0661	−0.1229**	−0.1366**
	(0.048)	(0.048)	(0.048)	(0.048)
IPO rate	−0.2354	−0.1632	0.4837	0.5960
	(0.471)	(0.471)	(0.461)	(0.001)
VC experience	−0.4165***	−0.4336***	−0.4016***	−0.4231***
	(0.051)	(0.051)	(0.051)	(0.051)
VC industry focus	0.4052	0.4375	0.1311	0.1438
	(0.279)	(0.279)	(0.281)	(0.281)
VC stage focus	1.6303***	1.6488***	1.7488***	1.7966***
	(0.396)	(0.395)	(0.391)	(0.390)
Previous alliances			−0.0046***	−0.0046***
			(0.000)	(0.000)
	$N = 18{,}527$		$N = 18{,}527$	
	Prob $> \chi^2 = 0.000$		Prob $> \chi^2 = 0.000$	

modest 12.92% to 13.46% in the fixed capacity version and 20.93% to 14.27% in the variable capacity version when the two firms share a common VC investor. A summary of the implied probability calculations for the sequenced models reported throughout the text is contained in Table IX. The economic magnitudes increase substantially in the extensions discussed below.

B. Inferences from Public versus Private Firms

The next step is to separate the effect for alliances containing private firms, which may be less well known and where VCs are likely active. For these estimations, venture backing of a company is considered permanent, so a company is never removed from a VC's portfolio. Venture capitalists can sit on the board of directors long after a company goes public (Gompers and Lerner (1998)), and one can imagine informal ties with the management even if the venture firm has no formal presence in the company. If the venture capital community were involved in fostering relationships, however, one would expect this pattern of support to exist while the company is still private. Further, asymmetric information is likely greater for private firms, who lack the reporting requirements, analyst coverage, and track record of public firms. If the data were to show that the blurred boundary effect is present and strongest between two mature, publicly traded firms, one would question the role the venture capitalist played in facilitating the alliance since venture capitalists are presumably most active in managing their portfolio of private firms. Thus, if venture capitalists use the information they have about their portfolio firms to help facilitate relationships with other firms, the effect should be stronger for alliances containing at least one private firm.

Columns II and IV of Table V show the results from estimations of each sequenced conditional logit version with the *CommonVC* variable divided into separate variables for alliances containing public versus private firms. The $CommonVC * Private$ variable, defined as $CommonVC * (1 - BothPublic)$, takes a value of one if at least one firm in the shared VC pair is private. The $CommonVC * Private$ coefficient is positive and statistically significant. This blurred boundary effect does not extend to alliances between two public firms. The coefficients are statistically different from one another at the 99% confidence level in both specifications.

The associated increases in probability for the coefficients in Table V are economically meaningful as well. The fixed capacity estimation implies a 34.9% increase in the probability of an alliance containing a private firm being formed if the two firms share a common VC. The variable capacity model implies a 57.0% increase in the probability from a base of 11.8% to 18.5%. Both versions of the estimation find a blurred boundary effect confined to alliances involving at least one private firm that is positive, statistically significant, and economically meaningful.

This finding is consistent with venture capitalists being active in fostering relationships in the early stages of a company's life and maintaining relationships with firms after they have gone public. It is also evidence that venture capitalists either use the information they have gathered about their portfolio firms to find appropriate alliance partners or that VCs can effectively lend their reputation within their network to mitigate hold-up problems, and that these alliance partners are disproportionately firms with which the venture capitalist has a prior relationship.

C. Additional Inferences on the Value of a Shared VC

If VCs facilitate alliances that may otherwise not take place because of incomplete contracting problems from asymmetric information or risk of expropriation, *CommonVC* alliances are likely to be concentrated in particular areas. Research and development is one obvious area where unforeseen contingencies, and therefore the risks of opportunism, are likely to arise. Marketing arrangements, where a firm becomes intimately acquainted with its alliance partner's product and end customers, also are subject to such risks.[10] Because R&D and marketing alliances are more likely to require specific investments and to be characterized by greater uncertainty ex ante, one might expect sharing a VC to be more important for these types of alliances.

To test this hypothesis, the *CommonVC* variable is split into categories by alliance purpose: R&D, marketing, and an "other" category. The results of the estimation are presented in Columns I and III of Table VI. The blurred boundary effect, as measured by the *CommonVC* interaction coefficients, is concentrated in marketing and R&D alliances. Both of these coefficients are statistically different from the default category, and from one another. The coefficients on the other controls are similar to the previous results. The implied probabilities associated with each of these alliance purpose categories are significant. The coefficients indicate that sharing a common VC investor increases the likelihood of an R&D alliance pair occurring by 69% to 86%. For marketing alliances, the estimates indicate a 28% to 36% increase in probability associated with sharing a common VC.

To test whether anticipated expropriation may be a factor in determining which companies pair in alliances, pairs of firms that are more likely to be direct competitors are of interest. If a company is collaborating with a firm in its same industry, the firms could be more concerned about competitive threats from sharing information and thus more worried about opportunistic behavior following alliance formation. In this case, one would expect any governance role of the venture capitalist to be more important in alliances involving firms from the same industry and less important when involving firms that do not compete directly.

Columns II and IV of Table VI report results where the *CommonVC* variable is again split, but this time according to whether the pair of alliance firms are from the same industry or different industries. In both the fixed and variable capacity versions of the estimation, the coefficient on the same-industry *CommonVC*

[10] Allen and Phillips (2000) use R&D and advertising expenditures to identify industries in which alliances are most likely to create information asymmetries or require asset-specific investment.

Table VI

Blurred Boundary Effect by Alliance Type

Table VI presents the results of the maximum likelihood estimation of the sequenced conditional logit model with fixed and variable alliance capacities. The unit of observation is a realized alliance. In Columns I and III, the *CommonVC* variable is interacted with indicator variables according to alliance purpose: R&D, marketing, or other. In specifications II and IV, the *CommonVC* variable is interacted with indicator variables according to whether the firms are in the same or different industries. The control variables are defined as before. Standard errors are in parentheses. *, **, or *** means the coefficient is statistically significant at the 10%, 5%, or 1% level.

	Fixed Capacity		Variable Capacity	
	I	II	III	IV
CommonVC * R&D	0.5265***		0.6245***	
	(0.103)		(0.099)	
CommonVC * marketing	0.2508***		0.3019***	
	(0.088)		(0.087)	
CommonVC * other	−0.0609		−0.0293	
	(0.071)		(0.071)	
CommonVC * same		0.4121***		0.4490***
		(0.101)		(0.099)
CommonVC * cross		0.0381		0.1131*
		(0.061)		(0.061)
Both VC	0.1353***	0.1504***	0.0564	0.0686*
	(0.041)	(0.041)	(0.041)	(0.041)
One VC	0.1675***	0.1700***	0.1434***	0.1459***
	(0.029)	(0.029)	(0.029)	(0.029)
Both public	−0.2075***	−0.2070***	−0.1324***	−0.1316***
	(0.022)	(0.022)	(0.022)	(0.022)
One public	−0.1765***	−0.1762***	−0.1404***	−0.1401***
	(0.027)	(0.027)	(0.027)	(0.027)
Same state	0.0340	0.0320	0.0174	0.0157
	(0.022)	(0.022)	(0.022)	(0.022)
CEO age	0.2655***	0.2602***	0.4070***	0.4054***
	(0.063)	(0.063)	(0.062)	(0.062)
Early stage	0.0631*	0.0607*	−0.0017	−0.0049
	(0.032)	(0.032)	(0.032)	(0.032)
Round amount	−0.0233***	−0.0236***	−0.0157***	−0.0159***
	(0.004)	(0.004)	(0.004)	(0.004)
Number VCs	−0.0627	−0.0548	−0.1253***	−0.1185**
	(0.048)	(0.048)	(0.048)	(0.048)
IPO rate	−0.2364	−0.2781	0.4576	0.4494
	(0.473)	(0.471)	(0.462)	(0.461)
VC experience	−0.4052***	−0.4186***	−0.3920***	−0.4052***
	(0.051)	(0.051)	(0.051)	(0.051)
VC industry focus	0.4482	0.4430	0.1945	0.1638
	(0.281)	(0.279)	(0.283)	(0.281)
VC stage focus	1.5999***	1.6128***	1.7250***	1.7316***
	(0.397)	(0.396)	(0.392)	(0.391)
Previous alliances			−0.0045***	−0.0046***
			(0.000)	(0.000)
	$N = 18{,}523$		$N = 18{,}523$	
	Prob $> \chi^2 = 0.000$		Prob $> \chi^2 = 0.000$	

coefficient is much larger than the cross-industry coefficient. The cross-industry coefficient is not statistically significant at the 95% level in either version of the model, though it is borderline significant in the variable capacity version of the model. For alliances in which the firms are from the same industry, both versions of the model produce a positive and statistically significant coefficient estimate. The implications for associated increases in probabilities for firms in the same industry that share a common VC to pair in an alliance are 51% to 57%.

V. Probability of Exit

While prior literature shows that announcements of alliances are met, on average, with positive reactions in the public equity markets, it is possible that a complex set of incentives overrides this general result for private venture-backed firms. A common measure for the success of a private venture-backed firm is a successful exit, either through an initial public offering or acquisition. This section examines success differentials for companies with alliances formed within their venture capitalists' portfolio.

In this section, the sample consists of all companies in Venture Economics funded since 1987, the year the alliance database begins, through 2001. The dependent variable in each specification is one of two exit measures, a binary variable indicating exit through IPO or a binary variable indicating exit either through IPO or acquisition. The variable of interest is an indicator variable for whether a company had a *Within-Portfolio Alliance*. This variable takes a value of one if the company entered into a strategic alliance with another firm that shares a common venture capitalist after the company's first venture capital investment but before any exit, if applicable, and zero otherwise. In addition, the variable *Any Alliance* is equal to one if the company had any strategic alliance, within portfolio or otherwise, after its first funding round but before any exit, and zero otherwise. The *Within-Portfolio Alliances* are a subset of *Any Alliances*. Company controls include the stage at the time of the first venture round, the natural log of the amount of first-round financing, the natural log of the number of investors, a geography control for whether the company is located in the venture capital clusters of California or Massachusetts (similar to the same state control from the previous section), industry indicators based on one-digit Venture Economics codes, and year controls for the year of the first venture round. The venture capital firm-level variables are defined as before, averaged over the company rather than a company pair.

Because selection on unobservable factors may simultaneously lead a firm to an alliance and a successful exit, both a probit model predicting exit and a bivariate probit model simultaneously predicting exit and alliances within the portfolio are employed. Two specifications are considered for each model. The first considers only the *Within-Portfolio Alliance* association with exit. The second specification takes the existence of an alliance as given (within or outside the portfolio), and asks whether having a *Within-Portfolio Alliance* enhances or reduces the firm's chances of exit.

Table VII provides results from a set of probit regressions, where success is defined as exit via IPO or, alternatively, as exit through an IPO or acquisition. Column I shows that a *Within-Portfolio Alliance* is positively associated with an IPO, with a marginal increase in probability of about 25%. The control variables have intuitive signs, with companies funded at earlier stages less likely to go public. Companies in California and Massachusetts, where riskier firms are more likely to receive financing, are less likely to go IPO. In contrast, companies with larger first-round financing amounts are more likely to experience a successful exit. The venture capitalist variables also help to explain positive outcomes. The more successful the VC firms, as measured by the average IPO rate, the more likely the particular firm is to go public. Industry focus is positively associated with a firm's success, whereas early-stage focus is negatively correlated with a firm's success, which may indicate a more risky investment in a firm even after controlling for the firm's stage at funding. Average VC experience does not have a statistically significant relationship with a firm's IPO prospects, but this is after controlling specifically for the VC average IPO rate.

In the second specification, Column II, the variable *Any Alliance* is added. The coefficient on *Any Alliance* is positive and significant, indicating that alliances in general are associated with successful outcomes. The magnitude of the coefficient on *Within-Portfolio Alliances* drops by a little more than half, but it should be noted that this coefficient is now measuring the additional association of a within-portfolio alliance with a successful outcome over and above the value of an alliance. The coefficient is still positive and highly statistically significant, corresponding to a marginal increase in probability of 8.6%.

Columns III and IV present these same specifications for the measure of success that also includes acquisitions. Results are largely consistent, though geographic cluster of the company and a company's first-round size no longer have statistical significance. The number of VCs involved is positively associated with exit. Most notably, in column IV, the magnitudes of the coefficients for *Any Alliance* and *Within-Portfolio Alliance* are quite similar, which would indicate that a within-portfolio alliance is twice as likely to be associated with an IPO or acquisition relative to alliances in general. Estimated marginal effects from the *Within-Portfolio Alliance* coefficient are approximately 42% in the specification without the *Any Alliance* control and 24% with the control included.[11]

A natural concern is one of selection. Many of the unobservable factors that contribute to a company's success could also make it a very attractive alliance partner. Thus, the positive relation between a within-portfolio alliance and a successful exit could merely indicate that VCs were facilitating alliances for higher-quality companies and that the company would have been poised for a successful exit sans alliance. To control for this possibility, a method that simultaneously estimates the probability of a within-portfolio alliance and a

[11] A similar analysis with venture capital firms as the unit of observation also shows a positive relation between a firm's *Within-Portfolio Ratio* and its proportion of IPO exits.

Table VII

Probability of Exit for Venture-Backed Companies with Alliances

Table VII presents results of probit estimations where the unit of observation is a venture-backed firm. The dependent variable takes a value of one if the company exits as defined in the column headings, and zero otherwise. The independent variables are: *Within-Portfolio Alliance*, an indicator variable that takes a value of one if the company had an alliance with another company that shared a common VC, and zero otherwise; *Any Alliance*, an indicator variable that takes a value of one if the company entered into any strategic alliance, and zero otherwise; *Geographic Cluster*, which takes the value of one if the company was located in California or Massachusetts, and zero otherwise; *Early Stage*, which takes the value of one if the company received VC funding at an early stage, and zero otherwise; *Round Amount*, the natural log of one plus the first-round financing amount; *Number VCs,* the natural log of one plus the total number of VC firms involved in funding the company; *IPO Rate,* the natural log of one plus the proportion of companies in the funding VCs' portfolios that had a public offering; *VC Experience*, the natural log of one plus the average age, in years, of the funding VC firms; *VC Industry Focus*, the natural log of one plus the proportion of companies that the funding VCs financed in the company's industry; and *VC Stage Focus,* the natural log of one plus the proportion of companies in which the funding VCs invested at an early stage. Fixed effects for the industry and the year of the first round of VC financing are included but not reported. White heteroskedasticity-adjusted standard errors are in parentheses. *, **, or *** means the coefficient is statistically significant at the 10%, 5%, or 1% level.

	IPO		IPO or Acquisition	
Dependent Variable	I	II	III	IV
Within-portfolio alliance	0.9832***	0.4559***	1.1248***	0.6681***
	(0.087)	(0.092)	(0.096)	(0.099)
Any alliance		0.7924***		0.6207***
		(0.046)		(0.041)
Geographic cluster	−0.0651*	−0.0755*	−0.0349	−0.0404
	(0.039)	(0.040)	(0.032)	(0.032)
Early stage	−0.1675***	−0.1667***	−0.2014***	−0.1983***
	(0.042)	(0.043)	(0.034)	(0.035)
Round amount	0.0346***	0.0271***	0.0073	0.0013
	(0.008)	(0.008)	(0.006)	(0.007)
Number VCs	0.0043	−0.0169	0.0862**	0.0765***
	(0.050)	(0.036)	(0.041)	(0.041)
IPO rate	6.5920***	6.4809***	4.3677***	4.1839***
	(0.304)	(0.309)	(0.246)	(0.247)
VC experience	0.0304	0.0288	0.0061	0.0050
	(0.031)	(0.032)	(0.025)	(0.025)
VC stage focus	−0.8455***	−0.7811***	−0.3284**	−0.2413*
	(0.179)	(0.181)	(0.143)	(0.145)
VC industry focus	0.3682**	0.2428	0.3373***	0.2567**
	(0.155)	(0.158)	(0.130)	(0.130)
Constant	−1.9528***	−1.9851***	−1.3214***	−0.8427***
	(0.154)	(0.157)	(0.109)	(0.122)
Industry and year controls included but not reported				
	$N = 9{,}406$		$N = 9{,}406$	
	Prob > $\chi^2 = 0.000$		Prob > $\chi^2 = 0.000$	

successful outcome for a company is needed. Because these dependent variables are binary, the bivariate probit is an appropriate model. For better identification, a control that predicts a within-portfolio alliance but that is uncorrelated with a company's success (after controlling for other factors) is included in the

Within-Portfolio Alliance equation. The variable is a variation of the *Within-Portfolio Ratio*, defined in Section II, averaged across the VC firms for the company. I recalculate this ratio for each VC firm, this time excluding the company whose exit is in question from the numerator in the calculation.[12] The idea is that because this variable measures other within-portfolio alliances in a VC's portfolio, it is correlated with the probability that a particular firm may be more likely to enter such an alliance, and it is likely to be exogenous to a specific firm's success, particularly after controlling for the venture capitalists' IPO rates. Table VIII, Panel A presents results for the bivariate probit estimation with success measured by IPOs.

Column I (and III) presents the results for the "first-stage" equation, predicting a *Within-Portfolio Alliance*. The coefficient on the *Within-Portfolio Ratio* is large and statistically significant. Many observable factors are positively associated with the probability that a firm enters this type of alliance, including being funded at an early stage, having a larger first round, having more investors, and being located in a VC cluster state of California or Massachusetts. A VC firm's industry focus and higher-quality firms, measured by IPO rates, also increase the probability of a within-portfolio alliance. The IPO equation in Column II shows that even while simultaneously controlling for factors that would influence the likelihood of within-portfolio alliances, such alliances are valuable to firms. There is a positive coefficient on *Within-Portfolio Alliance* that can be interpreted as causal for successful exits. Further, *rho*, the correlation between the errors of the two equations, is negative, indicating that selection on unobservable factors is counter to the argument that alliances within a VC's portfolio are targeted toward firms that were likely to be more successful anyway. In the second specification of Panel A, *Any Alliance* is added to the IPO equation as an exogenous variable. In this specification, one takes an alliance as given and asks if there is any additional value from a within-portfolio alliance. The coefficient estimate remains positive and statistically significant. The coefficient on *Any Alliance* is also positive and significant. Again, *rho* is negative. After controlling for observable factors that may make a company more likely to enter a within-portfolio alliance, these alliances confer an additional probability of success to the firm beyond alliances more generally.

Considering both IPOs and Acquisitions (Panel B) tells a similar story. Estimates for the *Within-Portfolio Alliance* equation are similar in magnitude and sign to the previous models. In the first specification, where only the *Within-Portfolio Alliance* variable is included, there is a positive and significant effect on the probability of a successful exit. Again, *rho* is negative and statistically significant, indicating that firms that were less likely to exit via an IPO or acquisition are more likely to form within-portfolio alliances or that firms more likely to exit are less likely to form these alliances. In the last specification, which controls for the existence of *Any Alliances* for the firm, the coefficients

[12] Results are robust to using the ratio defined in Section II without any adjustments as well as excluding all within-portfolio alliance nodes from the company's alliance partners from the calculation.

Table VIII

Probability of Exit and Formation of Within-Portfolio Alliances

Table VIII presents results of bivariate probit estimations where the unit of observation is a venture-backed firm. The first dependent variable takes a value of one if the company had a *Within-Portfolio Alliance*, an alliance with another company that shared a common VC investor, and zero otherwise. The second dependent variable takes a value of one if the company exits by IPO (Panel A) or by IPO or Acquisition (Panel B). The independent variables are: *Any Alliance*, an indicator variable that takes a value of one if the company enters into any strategic alliance, and zero otherwise; *Geographic Cluster,* which indicates the company is located in California or Massachusetts; *Early Stage*, which indicates the company received VC funding at an early stage; *Round Amount*, the natural log of one plus the first round financing amount; *Number VCs,* the natural log of one plus the total number of VC firms involved in funding the company; *IPO Rate,* the natural log of one plus the proportion of companies in the funding VCs' portfolios that had a public offering; *VC Experience*, the natural log of one plus the average age, in years, of the funding VC firms; *VC Industry Focus*, the natural log of one plus the proportion of companies that the funding VCs financed in the company's industry; and *VC Stage Focus,* the natural log of one plus the proportion of companies in which the funding VCs invested at an early stage. Fixed effects for the industry and the year of the first round of VC financing are included but not reported. White heteroskedasticity-adjusted standard errors are in parentheses. *, **, or *** means the coefficient is statistically significant at the 10%, 5%, or 1% level.

Dependent Variable:	WP Alliance I	IPO II	WP Alliance III	IPO IV
		Panel A		
Within-portfolio alliance		1.5389***		0.9752***
		(0.252)		(0.292)
Any alliance				0.7879***
				(0.046)
VC within portfolio ratio	44.5238***		43.7075**	
	(17.069)		(16.688)	
Geographic cluster	0.2573***	−0.0753*	0.2568***	−0.0851**
	(0.070)	(0.039)	(0.070)	(0.040)
Early stage	0.2403***	−0.1746***	0.2387***	−0.1736***
	(0.079)	(0.042)	(0.079)	(0.043)
Round amount	0.1051***	0.0327***	0.1034***	0.0255***
	(0.028)	(0.008)	(0.028)	(0.008)
Number VCs	0.1593**	0.0002	0.1592**	−0.0208
	(0.075)	(0.050)	(0.075)	(0.050)
IPO rate	2.4574***	6.4805***	3.2057***	6.3781***
	(0.413)	(0.306)	(0.511)	(0.311)
VC experience	0.1431*	0.0255	0.1431**	0.0242
	(0.073)	(0.031)	(0.073)	(0.031)
VC stage focus	−0.1995	−0.8356***	−0.1901	−0.7731***
	(0.328)	(0.178)	(0.328)	(0.180)
VC industry focus	0.7901***	0.3239**	0.7942***	0.2021
	(0.255)	(0.157)	(0.255)	(0.160)
Constant	−4.802***	−2.4855***	−4.7922***	−2.4232***
	(0.412)	(0.144)	(0.409)	(0.147)
Industry and year controls included but not reported				
Rho	−0.2755**		−0.2554*	
	(0.120)		(0.137)	
	$N = 9{,}406$		$N = 9{,}406$	
	Prob $> \chi^2 = 0.000$		Prob $> \chi^2 = 0.000$	

(*continued*)

Table VIII—*Continued*

Dependent variable	WP Alliance I	IPO or Acquisition II	WP Alliance III	IPO or Acquisition IV
		Panel B		
Within portfolio alliance		2.0105***		1.5124***
		(0.190)		(0.220)
Any alliance				0.6091***
				(0.040)
VC within portfolio ratio	43.7097***		41.8979***	
	(16.605)		(15.952)	
Geographic cluster	0.2526***	−0.0487	0.2519***	−0.0534
	(0.069)	(0.032)	(0.069)	(0.033)
Early stage	0.2314***	−0.2108***	0.2290***	−0.2076***
	(0.078)	(0.034)	(0.078)	(0.034)
Round amount	0.1089***	0.0053	0.1058***	−0.0006
	(0.027)	(0.006)	(0.027)	(0.006)
Number VCs	0.1630**	0.0783*	0.1617**	0.0690*
	(0.075)	(0.041)	(0.074)	(0.041)
IPO rate	3.2164***	4.2149***	3.2391***	4.0451***
	(0.512)	(0.245)	(0.512)	(0.247)
VC experience	3.2164**	0.0022	0.1433**	0.0014
	(0.512)	(0.024)	(0.072)	(0.025)
VC stage focus	−0.1748	−0.3161**	−0.1556	−0.2309
	(0.326)	(0.142)	(0.327)	(0.143)
VC industry focus	0.7418***	0.2746**	0.7482***	0.1994
	(0.252)	(0.131)	(0.252)	(0.131)
Constant	−4.8128***	−1.2630***	−4.7922***	−1.2156***
	(0.403)	(0.109)	(0.400)	(0.109)
Industry and year controls included but not reported				
Rho	−0.4570***		−0.4293***	
	(0.092)		(0.107)	
	$N = 9{,}406$		$N = 9{,}406$	
	Prob $> \chi^2 = 0.000$		Prob $> \chi^2 = 0.000$	

on both *Within-Portfolio Alliance* and *Any Alliance* are positive and significant. This result is consistent with VCs intervening in the case of a struggling firm, providing a relatively less attractive firm with an alliance that results in an IPO or acquisition. The marginal effects implied by the *Within-Portfolio Alliance* coefficients in Column IV are economically meaningful, indicating a 21% increase in probability of exit for Panel A and 56% for Panel B.

VI. Robustness and Alternative Explanations

The findings above suggest that venture capitalists play a role in facilitating alliances for their portfolio firms and that these alliances are valuable. There are three areas that warrant further discussion. The first pertains to the set of feasible alliances. The second is whether clustering on unobservable factors could have produced the same empirical results. The third concerns the interpretation of the results.

Table IX

Implied Changes in Probability for Sequenced Models

Table IX presents the calculated probabilities implied by the *CommonVC* coefficient estimates. For each specification, the base probability is the calculated probability with the *CommonVC* variable evaluated at zero and all other variables evaluated at their means prior to any alliances having been formed. The *CommonVC* column reflects the probability calculation with the *CommonVC* variable of interest set to one and all other controls at their means.

	Full Sample			VC Subsample		
	Base	Common VC	Percent Change	Base	Common VC	Percent Change
Fixed capacity	0.1192	0.1346	12.92%	0.1043	0.1201	15.15%
Variable capacity	0.1180	0.1427	20.93%	0.1867	0.2335	25.07%
Fixed capacity: at least one private	0.1192	0.1608	34.90%	0.1042	0.1398	34.17%
Variable capacity: at least one private	0.1179	0.1851	57.00%	0.1867	0.2970	59.08%
Fixed capacity: R&D	0.1192	0.2017	69.21%	0.1042	0.1848	77.35%
Variable capacity: R&D	0.1179	0.2196	86.26%	0.1867	0.3626	94.22%
Fixed capacity: marketing	0.1192	0.1531	28.44%	0.1042	0.1328	27.45%
Variable capacity: marketing	0.1179	0.1602	35.88%	0.1867	0.2545	36.31%
Fixed capacity: same industry	0.1192	0.1800	51.01%	0.1042	0.1597	53.26%
Variable capacity: same industry	0.1180	0.1851	56.86%	0.1869	0.2959	58.32%

A. Alliances with at Least One Venture-Backed Firm

The main estimation results presented above include alliances with both venture and nonventure firms. One concern might be that alliances that involve a venture-backed firm share certain unobservable characteristics. Though the estimations contain controls for venture capital backing, the coefficients could be affected by introducing choices of alliance partners that are not true potential choices for the venture-backed companies in the sample. These factors could produce estimates that may not be the most relevant for the phenomenon at hand.

For robustness, all previously reported models are also estimated for the subsample of alliances that contain at least one venture-backed firm. Within this restricted subsample, the same pattern of results emerges. The associated marginal probabilities for this subsample are reported, along with base probabilities, in Table IX. The implied probabilities of *CommonVC* overall and by public and private status are quite similar to the full sample estimations. Dividing the *CommonVC* variable by alliance purpose shows an increase in marginal probabilities for R&D alliances, to a range of 77% to 94%, and magnitudes for marketing alliances similar to those of the full estimation, at 27% to 36%. For pairs of firms that compete in the same industry, sharing a common VC implies a 53% to 58% increase in probability that the two firms will form an alliance. The results are still economically meaningful in each case.

B. Clustering

Another concern might be the issue of firms clustering on unobservable factors, such that firms likely to pair in a strategic alliance are also likely to be funded by a particular VC, regardless of any purposeful selection or value-enhancing efforts by the VC. It has been suggested that this could come about through VC industry specialization. For this to be true, a very specialized pattern of VC funding across industries would have to be present. Since VCs tend to focus on a distinct set of industries, it is very unlikely that a single VC dominates an alliance industry pair to the exclusion of other VCs. Thus, while one might expect that alliances between venture-backed firms were more frequent in a particular industry pair, it does not follow that alliances would be between firms of the same VC. Further, if it were the case that the observed industry classifications were not specialized enough to adequately control for industry, it is unclear why the pattern would cease to hold for public firms and across alliance types.

Another source of clustering could stem from the firms "knowing" each other before the venture backing. In all of these observed alliances, the VC funding occurred before the alliance. Exposure to entrepreneurial activity and other networks, however, may lead entrepreneurs to have many of the same contacts. Though the estimation attempts to control for such effects by defining variables for the ages of the chief executives and the development of the company at the time of VC funding, it is difficult to know the extent to which prior business relationships might contaminate the results. Gompers, Lerner, and Scharfstein (2005), in studying entrepreneurial spawning, find that spawned firms tend to be in businesses less related to the parent company, making collaborations between those firms somewhat less likely. Further, to the extent business proximity controls for prior contact, the estimations do control for the firms located in the same state.

C. Interpretation of Results

A further worry might be with the interpretation of the blurred boundary effect. Perhaps something other than information asymmetries or contracting difficulties are driving the results. It is well known that association with prominent partners, including venture capitalists, can have a certification effect whereby a firm can signal its quality (see, e.g., Barry et al. (1990), Hsu (2004), and Megginson and Weiss (1991)). It is possible that venture capitalists are seeking alliances for their portfolio firms prior to a firm's public offering or to garner attention before raising future funds, similar to the grandstanding by young venture capital firms documented by Gompers (1996). The blurred boundary effect still exists between alliances where both firms are private (unreported results), where it is less likely that the alliance partner is well known. Further, if this were the sole purpose of the alliances, it is unclear why the blurred boundary effect would be concentrated in R&D and marketing alliances or between firms in the same industry.

In order for certification by the venture capitalist to be driving the results, the certification effect would have to be asymmetric; that is, a potential alliance partner would have to give more weight to a firm's association with a venture capitalist that also funded it. If interaction with a VC involves learning information about the VC that may not be captured by its reputation to other parties, then certification could be asymmetric, though this differs from the traditional notion of certification to the entire market. Thus, these findings are only somewhat consistent with a certification role for the venture capitalists in facilitating alliances. One would have to believe that the signal of quality must be stronger within the portfolio than the signal external to the portfolio. In short, while alternative explanations for a blurred boundary effect do exist, it is difficult to find one consistent with all of the empirical evidence presented.

VII. Conclusion

This paper explores the role that venture capitalists play in facilitating alliances for their portfolio firms. It adds to the literature on the role financial intermediaries play in building new companies, showing that venture capitalists help to develop networks for their portfolio companies. In the more traditional view, financial intermediaries collect information about individual firms for screening or monitoring purposes. Here, this activity is shown to have a positive externality. While a growing body of literature seeks to explore ways in which specialized intermediaries such as venture capitalists solve asymmetric information problems between investors and entrepreneurial firms, relatively less attention has been devoted to studying the role that these intermediaries may play in overcoming information and contracting problems between entrepreneurial firms.

This is the first study to evaluate empirically the role of venture capitalists in facilitating alliances within their portfolios. In any application where there are two decision makers, the assumptions of traditional discrete choice models involving independence of counterfactual choices can be problematic (see also Sørensen (2007)). The analytical framework developed in this paper can be applied in a variety of settings where the order of observations is observed. Using an estimation framework that allows one company's choice of alliance partner to affect the probability of the remaining available choices, sharing a common venture capitalist is shown to increase the probability of two firms collaborating through a joint venture or strategic alliance. Further, the pattern of observed alliances is consistent with the venture capitalist helping to overcome asymmetric information problems or expropriation risks in contracting. These findings hold for the full sample of all firms that enter alliances and also the subset of alliances that involve at least one venture-backed firm. The confirmation that there are a disproportionate number of alliances within a VC's portfolio suggests that VCs do play a role in fostering relationships, and the exit regressions demonstrate that these relationships are valuable to firms. This finding is of particular importance to entrepreneurs who anticipate needing access to alliance partners and also has implications for which companies are funded by which venture capital firms.

The idea of strategic alliances or other forms of corporate support for young firms is not new. Within the corporate venture capital setting, Gompers and Lerner (2000) document that corporate VCs that invest in related areas perform as well as independent VCs, and that such performance could be through selection or value-added support. Santhanakrishnan (2003) explores this idea further and shows that support in the product market appears to have a positive effect. The fact that independent venture capitalists are also important in facilitating alliances changes the traditional calculus for an entrepreneur who may have thought that a corporate VC was the most direct route to a key strategic alliance. If independent VCs can potentially match portfolio firms with a variety of appropriate alliance partners as compared to an alliance with only the corporate VC, the ensuing outcome may be a less constrained optimization.

Also, because network externalities increase exponentially with size, these empirical results imply that the size of each venture capital firm's portfolio may be important in exploiting value-enhancing opportunities with other firms. Hochberg, Lu, and Ljungqvist (2007) find, using network quality measures from the sociology literature, that VCs with high measures of network quality experience better investment performance. This paper offers a mechanism through which these superior returns may occur. Further, many alliances that share a common investor involve one public and one private firm, suggesting that the capabilities of more mature firms are important in strategic alliances with private firms. Without a history of relationships with more mature firms, it may be more difficult for a new venture capitalist to provide the resources needed for a successful start-up. In addition to pure skill, this type of path-dependence could be at play in explaining Kaplan and Schoar's (2005) findings of persistence in VC returns.

The empirical evidence of a blurred boundary effect and its importance to the success of young firms represent a dimension of VC value-added services previously undocumented in the literature. By identifying the types of alliances for which sharing a common investor matters, this paper suggests that incomplete contracting problems are important for young firms and provides a new mechanism through which they may be overcome.

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