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Venture Capitalists and Cooperative Start-up Commercialization Strategy

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This paper examines the possible impact of venture capital (VC) backing on the commercialization direction of technology-based start-ups by asking: To what extent (if at all) do VC-funded start-ups engage in cooperative commercialization strategies (strategic alliances or technology licensing, or both) relative to a comparable set of start-ups, and with what consequences? To address these questions, I assemble a novel data set that matches firms receiving a federal research and development subsidy through the U.S. Small Business Innovative Research program to VC-funded firms by observable characteristics in five technology-intensive industries. These data allow decoupling of cooperative activity resulting from start-up development via the passage of calendar time from that due to association with VCs. An analysis of the 696 start-ups in the sample (split by an external funding source) suggests substantial boosts in both cooperative activity associated with VC-backed firms and in the likelihood of an initial public offering.

Key words: entrepreneurial ventures; venture capital; cooperation; commercialization strategy; strategic alliances; initial public offerings
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1. Introduction

This paper examines the possible impact of venture capital (VC) funding on the commercialization direction of technology-based start-ups. It does so by considering ways in which VCs can help facilitate start-up cooperative commercialization strategies, here defined as pursuing strategic alliances and/or technology licensing. In particular, the paper addresses the question: To what extent (if at all) do VC-backed start-ups engage in cooperative commercialization strategies relative to a comparable set of start-ups, and with what consequences?

By now the strategic and organizational benefits of inter-firm collaboration—extending reach to complementary assets, conserving resources, and obtaining new competencies/learning—have been well documented across a number of locations and industries (e.g., Hagedoorn 1993, Gulati 1998, Khanna et al. 1998, Kale et al. 2000, Dyer 2000). Scholars who have examined performance effects associated with cooperative commercialization in the context of start-ups have also documented beneficial effects (e.g., Stuart et al. 1999, Stuart 2000) while recognizing that the necessary network resources change along with the development of the new venture (Hite and Hesterly 2001).

These benefits are balanced against their expected costs when organizations (particularly start-ups) consider the decision to self-commercialize or seek collaborative commercialization, leading to observed variation in commercialization strategy. Costs might include such categories as (1) transaction and search costs of locating the right partner, (2) governing the relationship to guard against the threat of partner expropriation, (3) making managers complacent in developing in-house skills and capabilities, as well as (4) revenue sharing (see Eisenhardt and Schoonhoven 1996 and Gulati 1998 and the references therein).

For start-ups, the obstacles to cooperative commercialization may be somewhat higher as a result of higher search costs for appropriate partners and/or unknown reputations to potential collaborators, and so new ventures typically face unequal opportunities to collaborate. Differences in social connectedness resulting from, for example, industry experience (Eisenhardt and Schoonhoven 1996) or industry social standing (Chung et al. 2000) may be significant contributors to this uneven landscape. As well, start-ups likely differ in their value offered to potential collaboration partners with respect to the ability for partners to learn from the alliance (e.g., Mowery et al. 1996, Khanna et al. 1998). To the extent that relatively unique resources and capabilities can be bidirectionally transferred between alliance partners without unilateral expropriation (Kale et al. 2000), cooperation will likely be facilitated. Bidirectional resource transfer may result from either technical capital such as radical innovations (Ahuja 2000a) or commercial capital such as downstream complementary assets (Teece 1986).

A mechanism that has not been systematically explored in facilitating collaborative tie formation for start-ups, however, is the potential role of venture capitalists. At first blush, it would seem that such a study would be straightforward. Addressing the research question, however, requires a method that will (1) establish an appropriate counterfactual to effects of VC funding, and (2) decouple cooperative activity resulting from start-up development connected with the passage of calendar time from cooperative activity due to association with VCs. Such a method would effectively set both an expected baseline in the level of cooperative activity for firms *without* venture funding, as well as measure boosts from that baseline once VC involvement is introduced. The usual constraint in social science of not being able to do real experiments—in this case not being able to randomly assign start-ups to sources of external funding—applies in this case as well. As a second-best solution, I use a method that matches firms in five technology-intensive four-digit SIC industries funded by a U.S. government research and development grant program, the Small Business Innovative Research (SBIR) program with VC-backed companies, based on observable firm characteristics. Using this method, I assemble a data set of 696 start-ups (split by an external funding source) and examine postfunding cooperative behavior, controlling for a host of factors, including prefunding cooperation levels. The results suggest substantial boosts in VC-funded cooperative activity, as well as an increased likelihood of undertaking initial public offerings.

Clearly, start-ups are not pursuing funding sources randomly (nor are VCs investing randomly), and so I take a number of steps to address these potential selection concerns. First, the empirical design takes into account institutional details about the funding sources in an effort to enhance comparability in the sample. For example, I restrict the SBIR firms to awardees within one of five technology sectors (the same sectors in which VCs concentrate the bulk of their investments). As well, I test the robustness of the results to variation in the degree to which I am able to match funded projects on observable characteristics. Second, in the empirics, I examine (and control for) correlates of the ability and desire to pursue a cooperative strategy, most importantly firms' level of prefunding cooperative activity. Also, I take advantage of the fact that there are some firms in the data set that received both SBIR and VC funding and examine their cooperative patterns. Finally, I use start-ups' geographic distance from VCs active in investing in the start-up's industry as an instrumental variable to address the possibility that VC funding is endogenously determined. While the results of the instrumental variable regressions are consistent, the results are statistically noisier. An interpretation that VC funding is correlated with cooperative start-up commercialization activity (rather than necessarily causing such activity) is therefore warranted.

The rest of this paper is organized as follows: Section 2 discusses the literature, §3 describes the method and data, and §4 presents empirical results. Section 5 contains concluding remarks.

2. Literature and Empirical Predictions

The literature on the business development and extra-financial effects of VC on start-ups suggests that in addition to serving as a financial intermediary funding entrepreneurial ventures, VC structure and governance improves, for example, start-up patent productivity (Kortum and Lerner 2000) and professionalization of start-up human resource practices (Hellmann and Puri 2002). Relative to even the mid-1990s, the growing importance of the U.S. VC industry as a channel of start-up funding suggests that the possible impact of VCs in affecting start-up commercialization strategy represents an important area of study.[1]

While the literature on strategic alliances and cooperative firm behavior generally is by now voluminous (see, for example, reviews of the literature contained in Gulati 1998), studies that explicitly consider issues that start-up innovators face as they pursue cooperative commercialization strategies is more modest. Cooperative commercialization strategies may be particularly important for start-ups because entrepreneurial ability to expand the boundaries of their firms through backward or forward integration, for example, may be limited due to binding resource constraints. From the perspective of start-ups, four problems are associated with forming strategic alliances and other cooperative relationships: (1) start-ups face high search costs in locating appropriate cooperation partners, (2) start-ups may not want to engage in cooperative activity because they fear expropriation, (3) start-ups are of unknown quality, and so would-be cooperative partners have difficulty evaluating them, and (4) start-ups are not sufficiently developed to engage in cooperative relationships. Each of these areas is discussed in turn, together with how venture capitalists may mitigate these obstacles to cooperative start-up strategies.

[1] Inflows to the VC industry, while sharply down from their Internet boom peaks, still represent a significant source of start-up funding. For example, as of the second quarter of 2003, the National Venture Capital Association indicated that some $84 billion in capital remained uninvested in the VC industry (http://www.ventureeconomics.com).

A first impediment to start-up cooperative behavior is simply that they face higher search costs for potential cooperation partner matching. This can result from start-ups' reluctance in broadcasting their product or service development, especially in settings in which ventures are privately held and entrepreneurs fear alerting potential competitors of their strategic direction (expropriation is an area that will be considered later). While researchers have highlighted the role of prior alliance networks as a source of information about firms' existence, capabilities, and needs that can lead firms to enter new alliances (e.g., Gulati 1995), de-novo start-ups may not have access to this channel relative to more established firms.

VC information intermediation may help start-ups get matched with cooperation partners due to their intensive due diligence and monitoring processes, together with their knowledge of the needs and capabilities of other firms. Because VCs are active in a range of activities and functions that span industrial segments, they are more likely than internal directors of the start-up to be aware of threats and opportunities in the business environment. VCs can therefore act as information intermediaries, providing privileged information access and reducing search costs for start-ups seeking appropriate cooperation partners (Burt 1992, Aoki 2000, Gans et al. 2002). Each additional investment extends the VC's network of information and contacts, which in turn can be important in helping the VC identify and participate in cooperative commercialization (Sorenson and Stuart 2001). In addition to the VC's role as a broker of pure information between parties, the VC's reputation as a trusted intermediary with known experience and credentials may be important in facilitating start-up cooperation (in the spirit of Granovetter 1985). More generally, the VC's informational advantages can help promote start-up inter-organizational collaboration as a result of enhanced access to potential partners, better timing in realizing the cooperation, and improved referrals to appropriate partners (Burt 1992). Consistent with this literature, Lindsey (2002) provides evidence regarding enhanced strategic alliance activity among start-up firms *within* VC portfolios. The focus of this paper is to understand whether VCs also help facilitate cooperative activity more generally for their start-up firms.

A second obstacle to start-up cooperation may be entrepreneurial fear of expropriation when negotiating with potential cooperation partners. Start-up idea disclosure is a necessary part of cooperation contracting, and the threat of entrepreneurial idea expropriation can affect both ex ante start-up innovation incentives (Arrow 1962) and start-up commercialization strategy (Gans et al. 2002). Also, the stylized fact is that patent effectiveness against expropriation concerns can vary dramatically across industries, with relatively weak perceived effectiveness across many industries (Levin et al. 1987).

Start-up involvement in a VC portfolio can mitigate appropriation concerns by increasing the cost to cooperation partner defection. By broadening the network in which the start-up is engaged (to incorporate the VC's network of contacts), defecting cooperation partners will face a larger potential penalty, because perverse behavior will be broadcast faster and more pervasively through the network. The form of the penalty for the offending party may be incurred either in the current period (dissolution or increased monitoring of contemporaneous collaborations) or in future periods (developing a bad reputation, resulting in fewer realized collaborations), or both. Knowing these costs to partner misbehavior, start-up innovators may be more willing to engage in cooperative behavior relative to a world in which they engaged in bilateral cooperation. Theoretical and empirical support for these ideas come from Coleman (1988) and Robinson and Stuart (2000).

A third potential obstacle to start-up collaborative commercialization is that start-ups may be of unknown quality to potential cooperation partners. The literature in this area observes that endorsements or certifications of reputable parties can signal to relatively uninformed outsiders the quality of the unknown start-up (Megginson and Weiss 1991, Stuart et al. 1999). Endorsements from known affiliates (such as VCs) may be particularly important for start-ups without established reputations or for start-ups with particularly uncertain technology. For "leasing" VC reputation, as well as for business development services, entrepreneurs are willing to accept a lower valuation on their start-up to affiliate with more reputable venture capitalists (Hsu 2004). There may thus be important intra-VC-industry differences in affiliation value for start-ups.

A final potential stumbling block to start-up cooperation may be that these firms are not yet sufficiently developed to be attractive to potential cooperation partners. Recent literature on the business development role of VCs has emphasized their ability to professionalize employment practices (Hellmann and Puri 2002) and boards of directors (Lerner 1995, Baker and Gompers 2003). Also, the VC's networks of contacts can provide important new venture linkages to suppliers and customers (Sorenson and Stuart 2001), follow-on investors (Bygrave and Timmons 1992), and investment bankers (Barry et al. 1990). Note that in contrast to the role of VCs conceptualized to address the first three start-up cooperation-formation areas, one of pure VC affiliation effects, the active VC role in promoting start-up business development is stressed in this fourth area. Taken as a whole, the foregoing discussion on how VCs may help facilitate start-up cooperation suggests a first set of empirical predictions in this study:

Hypothesis 1. *VC funding is associated with boosts in start-up cooperative behavior.*

Hypothesis 2. *VCs differ in reputation, and start-ups affiliated with higher reputation VCs forge more cooperative outcomes.*

A related line of research has examined the performance consequences of the VC's influence on new venture business development. While the literature has, as previously discussed, a limited treatment of the effect of VCs on new venture business development via cooperative behavior, there are a number of related studies on this topic. Hellmann and Puri (2000), for example, find that among a sample of technology-based start-ups in Silicon Valley, those funded by VCs brought their products to market faster. Shane and Stuart (2002) found a positive relationship between VC involvement and initial public offering (IPO) rates. More generally, the literature has examined at least three classes of mechanisms that might link VC involvement and new venture performance: (1) VC contributions to the structure and governance of start-ups, (2) business development effects, and (3) signaling/certification effects. Each is discussed in turn.

Using an agency perspective in which entrepreneurs and VCs have asymmetric information about the likelihood of start-up success, a first strand of literature relates VC involvement with start-up performance. Using methods such as contract structure, staged start-up funding, and entrepreneurial monitoring (perhaps by board of directors participation), this literature has found that VC as a financing institution both permits start-up funding and improves start-up performance (e.g., Gompers and Lerner 1999, Kaplan and Strömberg 2003).

In addition to entrepreneurial monitoring and financial intermediation services, a second strand of research, as discussed in the prior section, has highlighted the VC's role in new venture business development. VCs mentor entrepreneurs, act as a source of referrals, and participate in strategy setting (e.g., MacMillan et al. 1989, Gorman and Sahlman 1989), which may help in reaching observed business development milestones such as product development and speed to market (Hellmann and Puri 2000). Moreover, the VC's business development role may be even more important than their selection role of promising ventures (Brander et al. 2002). Also, VCs may help professionalize start-ups by improving firms' human resource management and corporate governance structures (e.g., Hellmann and Puri 2002, Baker and Gompers 2003).

Another business development effect is in alliance formation, as discussed in this paper. Alliance formation, in turn, has been linked to innovative performance, as measured by patent production. In the setting of biotechnology start-ups, Shan et al. (1994) and Baum et al. (2000) find that cooperative behavior is linked with innovative output. Similarly, Ahuja (2000b) found that direct and indirect network ties in the global chemicals industry are related to patent production. Researchers have also established a direct link between VC funding and innovative outcomes. Kortum and Lerner (2000) studied the differential patent productivity between different sources of entrepreneurial finance, and found that VC funding is more productive in this regard relative to corporate R&D outlays, controlling for technological opportunity.

A third mechanism in the literature, also briefly discussed in the previous section, examines the certification and signaling value that a reputable VC can impart on its associated start-ups. Stuart et al. (1999) find that the hazard of IPO increases with the reputation of entrepreneurial ventures' strategic alliance and investment bank affiliates. Shane and Stuart (2002) and Shane and Cable (2002) examine the link between direct and indirect VC social ties on the one hand, and IPO rates on the other hand, finding a positive association in both instances. A central premise of these papers is that there are performance implications of affiliating with resource providers with established reputations. In the setting considered in this paper, there may be a matching process at work such that VCs of a certain reputation can help signal quality start-ups to IPO underwriters of a commensurate quality (in the spirit of Barry et al. 1990 and Megginson and Weiss 1991). Because IPO underwriter reputation is linked to less variance in IPO returns (Carter and Manaster 1990), these network ties can have performance implications.

While business development milestones such as product development and cooperative activity are important, another important marker for technology-based start-ups is the ability to raise funds through an IPO. IPOs can serve several functions such as allowing firms to raise working capital for business development, allowing equity holders to achieve liquidity, introducing a currency (publicly-traded shares) through which acquisitions can be facilitated, and even spawning further entrepreneurship within a geographic region (Sorenson and Stuart 2003). IPOs are therefore examined as a measure of performance. Taken together, the foregoing discussion suggests a second set of empirical predictions:

Hypothesis 3. *VC funding is positively associated with the likelihood of a start-up firm IPO.*

Hypothesis 4. *VCs differ in reputation, and start-ups backed by more reputable VCs have an enhanced probability of achieving an IPO.*

Hypothesis 5. *Of the start-ups that go public, those that have VC backing have a more reputable IPO underwriter.*

3. Methodology, Data, and Variables

3.1. Methodology

To test the hypotheses developed in the previous section, we require a data set that contains both firms funded by VCs as well as "comparable" firms not funded by VCs, but which received external funding for business development. The challenge in empirically studying the impact of VC on start-up commercialization strategy is in establishing a baseline cooperation rate in which to compare the incremental role of venture capital. The empirical strategy used here is to match start-up firms by key observable characteristics (described in detail below) across two funding sources, VC and the U.S. SBIR program, and to control for as many of the remaining differences as possible. This method is attractive because it allows for separation between observed cooperative behaviors that results from the passage of calendar time from cooperative behaviors that result from affiliation with VCs.

To test the cooperation hypotheses, I regress the postfunding level of cooperation on the mode of external funding, the prefunding level of cooperation, and a set of control variables. To test the performance hypotheses, I estimate both the likelihood that a firm undergoes an IPO and the level of IPO underwriter reputation, using postfunding cooperation levels and a set of controls as right-hand-side variables. Before describing the data set and variables, it will be useful to examine some institutional details of the two external financing mechanisms, SBIR and VC, used in the study to understand the comparability of matched start-ups based on these funding sources.

3.1.1. The Small Business Innovative Research (SBIR) Program. The SBIR program, created by the U.S. Small Business Innovation Development Act of 1982, is administered through the U.S. Small Business Administration (SBA); American-owned, independent firms with 500 or fewer employees are eligible. Award winners are selected based on "small business qualification, degree of innovation, technical merit, and future market potential" (SBA, http://www.sba.gov/sbir/). Proposals are peer reviewed, and funds are awarded competitively. The SBIR program, aside from the required paper work, is a very "hands-off" R&D program in that unlike VC financing, the government through the SBIR program does not take an equity stake in exchange for the grant. Moreover, the program is the largest of its kind, having awarded \$1.5 billion in 2001, up from its first year of operation in 1983, during which it awarded \$45 million (SBA, http://www. sba.gov/sbir/).

The rationale for the program is to subsidize technology development in small firms, an activity which is believed to generate positive externalities (Acs and Audretsch 1988). Left on their own, these firms would likely underinvest relative to the socially-optimal level due to their inability to appropriate the full value of their invention (Arrow 1962). A second motive for public intervention is that capital markets may not be willing to invest in these young companies for informational or uncertainty reasons, and because the firm cannot place the results of R&D as collateral against a potential default, there may be a funding gap for these new enterprises. A U.S. Government Accounting Office (1995) report summarizes the three-fold legislative goals of the SBIR program: (1) to increase the rate of commercialization of innovations derived from federal research, (2) to enhance the "competitiveness" of small firms in technology-intensive industries, and (3) to enhance the participation of small firms as well as women and minority-owned businesses in the federal contracting process.

The selection mechanism for SBIR is on technical and commercial merit.[2] SBIR funding takes place in two stages, with Phase 1 earmarked for proof of concept and idea development and Phase 2 awards reserved for technology development and exploring their commercial potential. Phase 1 awards were capped at \$100,000 during the sample period (ending in 1999), while Phase 2 awards were capped at \$750,000 during the sample period. Only those firms with a Phase 1 award are considered for a Phase 2 award. The overall ratio of awards granted to "proposals received" within each government agency was relatively constant in the 1991–1993 period, ranging from 8% (for the Department of Energy) to 28% (for the National Institutes of Health). For the period 1991–1993, for all 11 participating federal agencies, the average ratio of funded Phase 1 proposals to proposals received was 13.3% (U.S. Government Accounting Office 1995). Phase 2 awards were much more competitive, at about a 5% acceptance rate on average.

[2] Political "capture" effects (Stigler 1971) do not seem plausible in this context due to the sheer number of agencies and referees involved in the grant-making process. Based on my qualitative interviews with two dozen Boston-area SBIR recipients (usually product development managers within the firms) during the summer of 1998, companies seemed to participate in the SBIR program for a multitude of reasons, ranging from straightforwardly seeking a subsidy to R&D expenditure to validating a project for internal political reasons.

By 2004, the SBIR program had become both more selective (the Department of Defense awarded one in eight Phase 1 applicants, and one in three of those winners went on to win a Phase 2 award) and larger, awarding $2 billion annually (Olson 2004). For more details of the SBIR program, see Wallsten (1998) and Lerner (1999).

3.1.2. Exploiting Differences in Financing Mechanisms. External funding via the VC and SBIR programs exhibit important similarities and differences, and so this subsection is designed to highlight these institutional features to inform an appropriate empirical sampling strategy for the study.

VCs select the firms they wish to fund by reviewing business plans and by considering both the technical and commercial merits of an idea; SBIR program administrators use the same selection criteria, although selection is through a peer-review process. While there is undoubtedly a selection process at work such that some entrepreneurs will choose to pursue VC funding, there is theoretical and empirical evidence that those entrepreneurs that seek and receive VC funding are not necessarily "better." Amit et al. (1990) in an asymmetric information model find that lower ability entrepreneurs pursue VC funding, while higher ability ones retain equity in-house. In the context of the SBIR program, Lerner (1999) provides empirical evidence that SBIR firms performed better commercially than matched VC-backed firms if the SBIR organization was located in a zip code that had high levels of early-stage VC activity, and interprets the evidence as suggestive that SBIR awards play an important role in certifying firm quality to the private investment community. The empirical design and analysis in this paper will also take into account potential selection issues.

A second difference between the financing mechanisms is the industrial representation of their investments. VCs tend to concentrate their investments in a much narrower range of technical projects—particularly in the communications, information technology, and biotechnology sectors—relative to the SBIR program.[3] To address this issue, sampled SBIR projects are restricted to encompass only those in which VCs concentrate their investments (in five high-technology sectors).

Despite these differences in selecting projects between the two financing mechanisms, there are many similarities in the inputs to—and characteristics of—the SBIR and VC financed projects. First, from a numerical standpoint, the selectivity of projects from both funding sources is very competitive, especially when VC funding is compared to SBIR Phase 2 funding (the strategy taken in the data collection effort). In addition, the levels of funding for successful VC and SBIR recipients have not been that different historically (Lerner 1999), although this has clearly changed since the mid-1990s. Meanwhile, because successful SBIR Phase 2 recipients typically receive multiple awards for development, the average project may have received comparable levels of outside funding. Also, the age of organizations at the time that they received external financing (VC or SBIR) has been historically comparable (Lerner 1999). In sum, while SBIR and VC represent different funding sources, controlled comparisons of projects funded by each will help us isolate the effect of VC association on start-up commercialization strategy.

3.2. Data

A list of Phase 2 SBIR funded firms from 1988 through 1999 was generously provided to me by the SBA. Restricting the sample to Phase 2 SBIR recipients was meant to establish relative uniformity in the overall sample by comparing projects in which the main uncertainty is commercial rather than technical. This list of SBIR awardees was further restricted to those operating in one of five SIC industries: biotechnology (SIC 2836), industrial machinery and equipment (SIC 35), electronic and electrical equipment (SIC 36), scientific instruments (SIC 38), and pre-packaged computer software (SIC 7372). From this list of Phase 2 awardees, I sampled every fifth SBIR-backed company. This effort led to identification of 661 SBIR-backed firms. The following information was then retrieved for these firms from the *Corptech Directory of Technology Companies* (1998): year of funding, year of founding, and geographic location. I then tried to identify a venture-backed match for each of the firms by using the following hierarchical procedure: the SIC industry had to match, the year of funding had to match, the year of founding had to match, and the geographic location (at the state level) had to match. If no match was found using all four criteria, the geographic location constraint was dropped. If no match was found using the remaining three criteria, the year of founding criteria was dropped. The funding year and SIC industry match was always retained (no match was declared otherwise). I eliminated those venture-backed start-ups that had received SBIR funding (an uncommon event). This process yielded identification of 454 VC-backed firms.

To find cooperation data, I relied on the Securities Data Corporation (SDC) Platinum Alliances database to obtain strategic alliance and licensing data. I gathered counts of cooperation events using the year

[3] For VC statistics on investments by industrial area, see the Pricewaterhouse-Coopers "Money Tree" http://www.pwcmoneytree.com.

in which the firm received external funding (SBIR or VC) as the dividing line between pre- and post-cooperation events. For technology licenses, the event was counted only if it was the target firm licensing out. For strategic alliances, extension announcements were excluded from the counts, as were alliance termination notices. When the scope of the collaboration extended across type (e.g., R&D and marketing), the primary function was coded. In this manner, R&D alliances were separately coded from sales and marketing alliances.

Unfortunately, 53.6% of the SBIR-backed firms were not included in the SDC database, as compared to 14.3% of the VC-backed firms. Because these measures of postfunding cooperation are the dependent variables in the analyses, this reduced the usable number of observations to a total of 696 (composed of start-up firms matched on at least industry and funding year).[4] Perhaps it is not surprising that SDC would carry better coverage for VC-backed firms, because these firms are more visible. The disparity in the coverage, however, does raise questions of comparability of the subsamples in the study, especially relative to the original matching procedure. Collecting other firm-level variables, however, should mitigate concerns about other factors that might affect observed variation in cooperation levels.

Additional databases are used to compile further information about these firms: *Venture Economics* is consulted for financing amounts and experience of VCs; *SDC Platinum's Public Offerings* database provides IPO data; the *Corptech Directory* provides industry, location, sales, and employee information; and the U.S. Patent and Trademark Office provides patent data. The following section describes the data used in the empirical analysis (Table 1 provides descriptive statistics of the variables).

3.3. Variable Description

3.3.1. Dependent Variables. Cooperation is measured through count variables. *Postfunding R&D alliances* is the number of R&D alliances following the introduction of external funding (mean = 1.1). The empirical analysis also explores different definitions of cooperation, using postfunding sales and marketing alliances, postfunding technology licenses, and an aggregate measure, *postfunding cooperation events*, which counts the number of R&D alliances, sales and marketing alliances, and technology licenses following the introduction of external funding (mean = 2.3). In the empirical analysis, I will make use of logarithmic transformations of both dependent and independent variables—which will be denoted by the prefix "L" to the variable name. These transformations are defined as $\log(1 + \text{variable})$.[5]

A second set of dependent variables examines performance consequences. *IPO* is a dummy variable = 1 if an initial public offering was achieved as of January 2002 (mean = 0.37). *IB reputation* is a measure of investment bank underwriter reputation taken from Carter et al. (1998) (mean = 7.3). The variable ranges from a low of zero to a high of nine, and is based on underwriter placement in tombstone announcements.

3.3.2. Independent Variables. The two independent variables of most interest are *VC funded* and *SBIR and VC funded*. The former measure takes the value of 1 if the start-up only received VC funding during the sample period, which ended January 2002 (mean = 0.56). The variable *SBIR and VC funded* takes a value of 1 if a start-up that was initially SBIR funded subsequently received VC funding by the end of the sample period (mean = 0.18). Data to code both these variables are from the *Venture Economics* database. The third population of firms, those that only received SBIR funding (mean = 0.26), represents the balance of the sample (it is the excluded variable in the three-way analysis). As a measure of VC reputation, *prior VC IPOs* is the number of companies a VC firm had taken public in the year prior to funding the target start-up (mean = 43). *Prior VC IPOs*, of course, can only be constructed for the subsample that was VC funded. Prior VC performance can assist VCs in raising subsequent investment funds, and to the extent that IPOs are a highly visible measure of VC performance, attaining a track record in bringing start-ups to the public market can contribute to VC reputation. An alternative measure of VC reputation is *Bonacich VC centrality* (mean = 0.14), which is based on the

[4] To address the issue of bias as a result of missing observations of the dependent variable, I performed t-tests of equal means of key independent variables within the funding source subsamples and found that, consistent with expectations, smaller firms as measured by employees and sales tended to be missing more often from the database. Also, a team of research assistants researched missing cooperative event data using Google searches, corporate websites, and the Lexis-Nexis database. Empirical results using these more complete data are stronger than those reported in the empirical tables. Because many of these additional observations contain no cooperative events, and because of the variety of data sources used to compile the data set, I report more conservative estimates from a single data source (SDC) here. Results from the expanded data set are available from the author on request.

[5] The results presented in the empirical tables are largely robust to a variety of functional form specifications: linear, semi-log, and log-linear. With no ex ante theory guiding functional form specification, I chose the form with the best overall fit across the empirical specifications: logged postfunding cooperative events as the dependent variable, together with logged right-hand-side variables with the exception of linear year effects. Also, the results are robust to zero-inflated negative binomial regressions of cooperation counts (not transformed into logs), which allows for different processes leading to observed zero values of the dependent variable.

Table 1 Summary Statistics and Variable Definitions

Variable	Definition	Mean	Std. dev.
Dependent variables			
(1) *Postfunding R&D alliances*	Count of R&D alliances signed after external funding, as of Jan. 2002.	1.09	4.62
(2) *Postfunding cooperation events*	Count of R&D alliances, sales and marketing alliances, and technology licenses signed after external funding, as of Jan. 2002.	2.30	8.68
(3) *IPO*	Dummy = 1 if an initial public offering was achieved as of Jan. 2002.	0.37	0.48
(4) *IB reputation*	0–9 rating (9 is high) of investment banker reputation according to Carter et al. (1998).	7.29	2.68
Start-up characteristics and measures			
(5) *VC funded*	Dummy = 1 if a start-up only received VC funding as of Jan. 2002.	0.56	0.50
(6) *SBIR and VC funded*	Dummy = 1 if a start-up initially received SBIR funding and subsequently received VC funding.	0.18	0.38
(7) *Prefunding R&D alliances*	Count of R&D alliances signed before external funding, as of Jan. 2002.	0.42	1.53
(8) *Prefunding cooperative events*	Count of R&D alliances, sales and marketing alliances, and technology licenses signed before external funding, as of Jan. 2002.	1.00	2.78
(9) *Year founded*	Year start-up was founded.	1981.72	7.56
(10) *Year funded*	Year start-up received external funding.	1993.57	3.47
(11) *Total dollar inflows*	Net present value (in millions of 1999 dollars) of the sum of external funding.	15.59	26.21
(12) *Employees*	Number of employees at a start-up in the year prior to external funding.	166.51	445.55
(13) *Patents*	Count of the number of patent applications in the month and year prior to receiving external funding.	5.95	19.04
(14) *VC density by industry*	Geographic density of VCs with investment experience in the start-up's industry (see text).	13.50	11.78
Venture capitalist reputation measures			
(15) *Prior VC IPOs*	Count of a VC's prior number of IPOs up to the year of start-up funding.	43.11	50.01
(16) *Bonacich VC centrality*	Centrality score based on the number and reputation of other VC firms with which the focal VC firm forms investment syndicates (Bonacich 1987).	0.15	0.16
Industry controls			
Industry dummies	Dummy = 1 indicating the start-up's industrial representation in one of the following: biotechnology (15% of sample), software (25%), electronic equipment (24%), industrial equipment (12%), or scientific/medical instruments (24%).		

Note. The natural logarithm of a variable, X, will be denoted by LX.

number and reputation of other VC firms with which the focal VC firm forms investment syndicates in the year before the focal start-up received VC funding. The measure is based on a standard measure of centrality in the network sociology literature (Bonacich 1987).[6]

A second set of independent variables control for prefunding cooperative activity, either in *prefunding R&D alliances* (mean = 0.42) or in aggregate alliance and licensing *prefunding cooperative events* (mean = 1.00). Both these data are also from the SDC Platinum Alliances database.

A third set of control variables is defined for year of start-up founding, *year founded* (mean = July 1981), based on data from various annual issues of the *Corptech Directory of Technology Companies* listings. The variable *year funded* (mean = June 1993) is based on data from the SBA and *Venture Economics* databases. These same databases were used to compile the 1999 net present value of *total dollar inflows* from external sources (mean = \$15.6 million).

I also controlled for prefunding levels of employees and patents. Because the pairwise correlation between prefunding sales and prefunding employ-

[6] Applied to the VC setting, I follow Podolny (2001) and Piskorski (2004) in defining centrality as: $C_t = a\sum_{k=0}^{\infty}\beta^k R_t^{k+1}\mathbf{1}$, where R_t is a matrix with elements $R_{ii't}$ denoting the number of times VC i and i' jointly funded a new venture in time t, $\mathbf{1}$ is a column vector of 1s, a is an arbitrary scaling coefficient, and β is a weighting parameter that is set by convention in the network sociology literature to three-fourths of the reciprocal of the maximum eigenvalue of R_t (when $\beta > 0$, each firm's centrality is an increasing function of the centralities of the firms it is linked with).

Table 2 Pairwise Correlation Matrix

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
(1)	1															
(2)	0.97*	1														
(3)	0.15*	0.17*	1													
(4)	0.19*	0.18*	NA	1												
(5)	0.05	0.04	0.26*	0.22*	1											
(6)	0.00	0.02	0.16*	−0.04	−0.32*	1										
(7)	0.13*	0.12*	0.28*	0.06	0.06	0.06	1									
(8)	0.17*	0.16*	0.33*	0.05	0.07	0.09*	0.89*	1								
(9)	0.02	0.02	−0.02	0.21*	0.16*	0.03	0.01	0.04	1							
(10)	−0.14*	−0.17*	−0.00	0.04	0.19*	−0.08	0.12*	0.15*	0.17*	1						
(11)	0.02	0.04	0.27*	0.18*	0.46*	−0.13*	0.14*	0.13*	0.13*	0.08*	1					
(12)	0.27*	0.23*	0.27*	0.12	0.23*	−0.04	0.29*	0.39*	−0.09*	0.05	0.18*	1				
(13)	0.06	0.06	0.08*	0.09	0.06*	0.03	0.19*	0.19*	0.02	0.07*	0.03	0.32*	1			
(14)	−0.02	−0.02	0.04	0.11	0.25*	−0.08	0.09*	0.09*	0.21*	0.23*	0.19*	−0.03	0.04	1		
(15)	0.05	0.03	0.19*	0.02	NA	NA	0.05	0.08	−0.04	−0.21*	0.07	0.03	−0.03	0.00	1	
(16)	0.03	−0.01	0.18*	0.09	NA	NA	0.07	0.12*	0.09	0.11	0.11	−0.06	−0.05	0.09	0.33*	1

Note. Numbers correspond to the numbering of variables from Table 1; * denotes the correlation is significant at the 5% level.

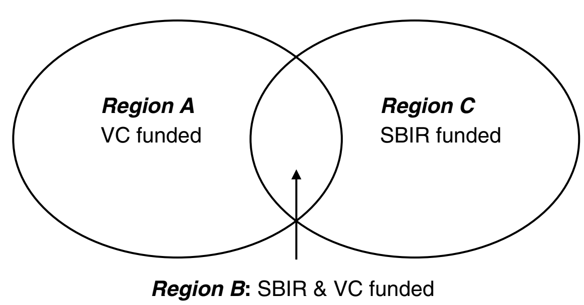
ment levels is 99%, I use only the employee measure of firm size (from *Corptech*) in the empirics (mean = 167 employees). Finally, the variable *prefunding patents* is a count of patent applications in the month and year prior to receiving external funding (mean = 6). Finally, I include a set of industry controls for biotechnology (15% of the sample), software (25% of the sample), electronic equipment (24%), industrial equipment (12%), and scientific/medical equipment (24%). The location and industry data are from *Corptech* and *Venture Economics*. Table 2 presents the pairwise correlation matrix for the variables.

4. Empirical Results

Before discussing the empirical results, it is important to re-emphasize that there are three types of firms in the sample. Figure 1 contains a schematic of these firms. Firms located in region "A" in the figure were initially VC funded and remained in that status (recall that VC firms that were subsequently SBIR funded were eliminated). Firms in region "B" were initially SBIR funded and subsequently VC funded. Firms in region "C" were initially SBIR funded and remained that way. The empirical tables evaluate the hypothesized relationships by comparing these three groups of firms and checking the robustness of the results to a variety of econometric issues.[7]

Table 3 presents R&D alliance OLS regressions, where the dependent variable is the log of start-up *postfunding R&D alliances*. The first specification is parsimonious, only including the variables *VC funded* and *L prefunding R&D alliances*. The *VC funded* variable is positive and significant at the 7% level, suggesting that compared to the SBIR sample of firms (for the moment disregard the distinction with SBIR-funded firms that subsequently received VC funds), VC-backed firms received a boost to their postfunding R&D alliances, controlling for prefunding levels of R&D alliance behavior (which is itself statistically and economically significant). The next specification adds in the *SBIR and VC funded* variable. The *VC funded* result is strengthened statistically and economically while the *SBIR and VC funded* estimate is also positive though statistically insignificant. Throughout the empirical tables, statistical tests of the null hypothesis that the *VC funded* effect is equal to that of the *SBIR and VC funded* effect are presented when appropriate (the *VC funded* effect is more robust throughout). The coefficients on *VC funded* and *SBIR and VC funded* should be interpreted in relation to the omitted category—those firms that were exclusively SBIR funded. A third specification adds to the prior one a variety of further controls: age effects (*year founded* and *year funded*), resource and size effects (the log values of *total dollar inflows*, *prefunding patents*, and *employees*), as well as industry controls for *biotechnology*, *software*, *electrical equipment*, and *scientific instru-*

Figure 1 Types of Firms in the Data Set



[7] The author thanks an anonymous reviewer for suggesting this structure.

Table 3 R&D Alliance OLS Regressions

	Dependent variable = *L postfunding R&D alliances*			
	Entire sample $N = 696$ observations			SBIR sample $N = 307$ observations
Independent variables	(3-1)	(3-2)	(3-3)	(3-4)
VC funded	0.088* (0.048)	0.150*** (0.056)	0.134** (0.058)	
SBIR and VC funded		0.154** (0.074)	0.108 (0.071)	0.143** (0.067)
L prefunding R&D alliances	0.443*** (0.052)	0.424*** (0.053)	0.365*** (0.055)	0.469*** (0.085)
Year founded			0.000 (0.000)	
Year funded			−0.049*** (0.007)	
L total dollar inflows			0.034 (0.023)	
L employees			0.026** (0.013)	
L prefunding patents			0.070*** (0.026)	
Industry dummies			Yes	
Constant	0.223*** (0.037)	0.165*** (0.046)	97.942*** (13.409)	0.161*** (0.041)
F test probability of H_0: *VC funded = SBIR and VC funded*		0.95	0.71	

Note. *, **, or *** indicate statistical significance at the 10%, 5%, or 1% level, respectively.

ments (*industrial equipment* is the excluded category).[8] The *VC funded* variable remains significant, while the *SBIR and VC funded* variable falls from statistical significance. Throughout these specifications, the *prefunding R&D alliances* effect is, as expected, positive and highly significant (at the 1% statistical significance level), with magnitudes ranging from 0.37 to 0.44, a result in line with prior studies using lagged dependent variables as a regressor. The estimates also suggest that larger firms as measured by employees and those firms with more prefunding patents have more R&D alliances. Also, firms that were funded more recently tended to have fewer R&D alliances, all else equal, a result perhaps due to the length of ex post funding "treatment" the firms have received. The final specification presented in Table 3 examines the SBIR subsample and regresses the log of *postfunding R&D alliances* on *SBIR and VC funded* and the log of *prefunding R&D alliances*. The estimates suggest that the SBIR firms that subsequently received VC funding experienced a boost in R&D alliance activity relative to those SBIR-funded firms that did not. Taken as a whole, the results in Table 3 show that VC funding is associated with increased start-up R&D alliance activity.

R&D alliance activity may be just one indicator of cooperative start-up commercialization strategy. I therefore explored other definitions of cooperative behavior, including sales and marketing alliances, technology licensing, and outright start-up acquisition. In the interest of conserving space, I briefly describe the motivation and results for each concept of cooperation.[9] Start-ups frequently find the cost of acquiring complementary assets, such as a sales force or specialized distribution channels, to be a significant obstacle to self-commercialization (Teece 1986, Gans et al. 2002). Sales and marketing alliances to access such complementary assets may therefore be an important means of business development. A second conceptualization of start-up cooperation is technology licensing. There has been increasing interest in this activity, especially in technology-intensive sectors (e.g., Arora et al. 2001, Gans et al. 2002). Using similar empirical specifications as those found in Table 3, regressions of sales and marketing strategic alliances and of technology licenses suggest similar boosts of these cooperative activities associated with VC funding. A third possible definition of start-up cooperative activity is to be acquired, as this activity, like the others previously mentioned, also has the effect of mitigating direct competition following start-up innovation. Start-up acquisitions, however, can result in a relatively successful entrepreneurial outcome if favorable terms, including price, are reached; alternatively, acquisitions can be associated with an unfavorable entrepreneurial outcome if the deal terms are not optimal, resulting from a weak entrepreneurial bargaining position. Ideally, one would like to examine deal terms in the acquisition event relative to a benchmark (for example, terms struck in the most recent private financing round) to better interpret the favorability of the event. Unfortunately, I am not able to collect this type of information for the acquisitions in the sample. Perhaps not surprisingly, then, when I regress acquisitions on my right-hand side variables, neither *VC funded* nor *SBIR and VC funded* are statistically different from zero.

To examine a performance consequence of VC funding, Table 4 presents probit regressions of the probability a start-up experienced an IPO of stock as of January 2002. The reported coefficients represent marginal effects, and I follow a similar specification structure as in Table 3. The first specification is a parsimonious specification with only two regressors: *VC funded* and the log of *postfunding R&D alliances*.

[8] The Yale measures for the strength of intellectual property (Levin et al. 1987) are also included (at the industry level) in an unreported specification to capture the possibility that the included industry dummy variables do not adequately capture the appropriability regime. Including these variables does not overturn the robustness of the main external funding effects.

[9] It is easy to see that the results do not change, as the pairwise correlation between the definitions of cooperation is 97%.

Table 4 IPO Probit Regressions

	Dependent variable = *prob*(*IPO by Jan. 2002*) (Marginal effects reported)			
	Entire sample $N = 696$ observations			SBIR sample $N = 307$ observations
Independent variables	(4-1)	(4-2)	(4-3)	(4-4)
VC funded	0.123*** (0.038)	0.226*** (0.045)	0.178*** (0.056)	
SBIR and VC funded		0.253*** (0.063)	0.179*** (0.067)	0.224*** (0.056)
L postfunding R&D alliances	0.284*** (0.032)	0.272*** (0.032)	0.244*** (0.035)	0.229*** (0.047)
Year founded			0.000 (0.000)	
Year funded			0.004 (0.006)	
L total dollar inflows			0.063*** (0.020)	
L employees			0.046*** (0.011)	
L prefunding patents			0.049** (0.023)	
Industry dummies			Yes	
Log likelihood	−404.326	−396.153	−364.770	−159.496
χ^2 test probability of H_0: *VC funded* = *SBIR and VC funded*		0.82	0.88	

Note. *, **, or *** indicate statistical significance at the 10%, 5%, or 1% level, respectively.

I include the latter variable because such alliances proxy for stage of business development, which is likely important for a start-up's readiness for an IPO. The *VC funded* estimate is positive and statistically significant at the 1% level, which, of course, should be interpreted in relation to firms that were initially SBIR funded. Entering in the *SBIR and VC funded* variable both establishes the significance of this variable (positive and significant at the 1% level) and strengthens the *VC funded* result. These results can be interpreted as relative to those firms that only received SBIR funding. Furthermore, these results remain robust to the introduction of the full slate of firm and industry controls, as shown in (4-3) (Table 4). The specification also reveals that ventures with more total funding inflows, employees, and prefunding patents are more likely to undergo an IPO. In a final specification, (4-4), an analysis of the within-SBIR sample shows that those firms that subsequently received VC funding were associated with a 22% increase in the likelihood of an IPO, controlling for postfunding R&D alliances (which itself is statistically significant at the 1% level—a result that holds in all the Table 4 specifications). Similar results (unreported) are achieved by excluding merger and acquisitions events from the analysis, by including pre and postfunding alliances on the right-hand side, and by using a Cox hazard regression on yearly data (the clock starts when the start-up is founded, and failure occurs when the start-up undergoes an IPO).

The analyses conducted thus far have been based on the assumption that there are no endogeneity issues or selection issues based on unobservable (to the researcher) processes in these data. However, we know that far from the gold standard situation of random assignment of funding sources to entrepreneurial firms, we are in a world in which entrepreneurs are purposive and select funding sources. In particular, it could be the case that entrepreneurs who see the most need for a cooperative commercialization strategy differentially seek out VC in ways not captured by the control variables. Tables 5 and 6 address this issue for both the R&D alliance and IPO results, as well as the concern that the final matches of SBIR- and VC-funded firms, while well intentioned ex ante, ended up yielding rather heterogeneous subsamples due to missing data. To address the endogeneity issue, I employ an instrumental variables strategy in which I use *VC density by industry*, a measure of the geographic density of VCs investing in the start-up's industry relative to the start-up's location. The measure is constructed based on the same type of density

Table 5 R&D Alliance Robustness Regressions

	Dependent variable = *L postfunding R&D alliances*		
	Instrumental var. regression *VC density by industry* instruments for *VC funded* Entire sample $N = 696$ observations	OLS regressions "Better matched" sample $N = 394$ observations	
Independent variables	(5-1)	(5-2)	(5-3)
VC funded	0.242 (0.277)	0.263*** (0.082)	0.215** (0.091)
SBIR and VC funded	0.150 (0.191)	0.298*** (0.110)	0.236** (0.111)
L prefunding R&D alliances	0.365*** (0.060)	0.535*** (0.069)	0.471*** (0.074)
Year founded	0.000 (0.000)		0.002 (0.006)
Year funded	−0.051*** (0.008)		−0.047*** (0.010)
L total dollar inflows			0.031 (0.033)
L employees	0.029** (0.014)		0.027 (0.018)
L prefunding patents	0.070*** (0.026)		0.068* (0.038)
Industry dummies	Yes		Yes
Constant	100.775*** (15.171)	0.093 (0.072)	90.808*** (20.427)
F test probability of H_0: *VC funded* = *SBIR and VC funded*	0.42	0.70	0.84

Note. *, **, or *** indicate statistical significance at the 10%, 5%, or 1% level, respectively.

Table 6 IPO Robustness Regressions

	Dependent variable = *prob*(*IPO by Jan. 2002*) (Marginal effects reported)		
	Instrumental var. regression *VC density by industry* instruments for *VC funded* Entire sample $N = 696$ observations	Probit regressions "Better matched" sample $N = 394$ observations	
Independent variables	(6-1)	(6-2)	(6-3)
VC funded	0.430* (0.206)	0.254*** (0.062)	0.197*** (0.075)
SBIR and VC funded	0.361** (0.158)	0.205** (0.097)	0.150 (0.106)
L postfunding R&D alliances	0.220*** (0.039)	0.232*** (0.039)	0.192*** (0.043)
Year founded	0.000* (0.000)		−0.008 (0.006)
Year funded	−0.003 (0.007)		−0.001 (0.008)
L total dollar inflows			0.062** (0.027)
L employees	0.124*** (0.030)		0.032*** (0.015)
L prefunding patents	0.046** (0.024)		0.031 (0.033)
Industry dummies	Yes		Yes
Log likelihood	−354.80	−229.423	−210.697
χ^2 test probability of H_0: *VC funded* = *SBIR and VC funded*	0.33	0.33	0.50

Note. *, **, or *** indicate statistical significance at the 10%, 5%, or 1% level, respectively.

measure as that found in Stuart and Sorenson (2003):

$$\sum_j \left\{ \frac{1}{[1+d(ij)]} \right\} \quad \text{for VC } j$$

with investment experience in start-up i's industry (summed across all U.S. VC firms with investment experience in i's industry).[10] The instrumental variable diagnostics on *VC density by industry* are good: the variable is related to *VC funded* but not correlated with the dependent variables on a pairwise basis. The results from the fully-specified regression models using *VC density by industry* as an instrument for *VC funded* are presented in (5-1) (Table 5) and (6-1) (Table 6).[11] In these regressions, *VC funded* and *SBIR and VC funded* are estimated with positive coefficients, although they are statistically significant at conventional levels only in the IPO regression (in both specifications, the coefficients are estimated with larger effects compared to (3-3) and (4-3), but are estimated with less precision).[12]

A second robustness issue treated in Tables 5 and 6 is the matching procedure that generated the sample. Due to missing data on the dependent variable, the final sample was not as comparable as originally intended. I therefore examine the subsamples of data varying in ex ante match quality. Tables 3 and 4, the main empirical tables in this paper, analyze the sample in which observations match on industry and funding year. The final two columns of Tables 5 and 6 present regressions imposing the additional constraint of matching on founding year (reducing the sample to 394 observations). The *VC funded* and *SBIR and VC funded* results are robust. When the final matching criterion, state-level geography, is imposed, the sample drops in size to 136. In parsimonious specifications (those analogous to (3-2) and (4-2)) using this sample, the *VC funded* and *SBIR and VC funded* results are statistically significant at conventional levels, although the *SBIR and VC funded* result falls from statistical significance in the IPO regression. The results become

[10] The distance between i and j is defined as $d(ij) = 687.56 * \{\arccos[\sin(\text{lat}\, i) * \sin(\text{lat}\, j) + \cos(\text{lat}\, i) * \cos(\text{lat}\, j) * \cos(\Delta)]\}$, where the units for latitude (lat) are measured in radians, and Δ is the absolute value of the difference between the longitude of i and the longitude of j in radians. The constant, 687.56, converts the distance into units of five miles. This distance measure takes into account the large geographic area in the continental U.S. (and adjusts for the earth's curvature relative to a Euclidean distance measure). Olav Sorenson generously provided these data, and I thank an anonymous referee for suggesting the instrument.

[11] The *total dollar inflows* variable is excluded from the specification because its pairwise correlation with VC funded is 0.46 (and I have only one instrumental variable). I also evaluated another instrument, *California-located start-up*, a dummy equal one if the start-up is located in California (mean = 0.28). This variable is likely to be associated with VC funding due to the propensity for VCs to invest locally (e.g., Gompers and Lerner 1999) and the geographic distribution of technology-based start-ups. The variable may, however, be related to the dependent variables in this study, particularly given Saxenian's (1994) findings. The results based on this instrumental variable are strong economically and statistically. The results for *VC density by industry* are reported in the paper, however, because it is perhaps a better instrument.

[12] In the IPO regressions, because the dependent variable is binary, I employ Newey's (1987) simultaneous estimation method. While the current empirical strategy deals with the general problem of nonzero correlation between the error term and the right-hand-side variables by instrumenting for the endogenous variable, I also employ a Heckman (1979) type two-stage model in which both stages are qualitative dependent variables (Van de Ven and Van Praag 1981) to accommodate selection of VC funding based on unobservables. In the first stage, I regress the probability of receiving VC funding on *VC density by industry*, *prefunding R&D alliances*, *year founded*, *employees*, and *prefunding patents*. Note that the first two of these variables are excluded from the second-stage (IPO likelihood) equations, and so act as instrumental variables. The resulting Mill's ratio is used as an additional regressor in a second-stage IPO probit. The results are similar to those reported in Tables 4 and 6 (the Heckman-adjusted predicted probabilities of IPO conditional on VC funding are actually larger than the predicted probit and instrumental variable effects). I do not formally report the results because a chi-squared test of ρ, the cross-equation correlation of the error terms, does not reject the hypothesis that ρ is statistically different than zero. A similar approach and results also hold for Heckman adjustments of the R&D alliance equations.

noisy when industry and other start-up controls are introduced (unreported regressions).

To explore possible differential effects of more reputable VCs, Table 7 examines the subsample of firms that received VC backing, and looks for heterogeneous start-up value associated with more reputable VCs. I use two variables to proxy for VC reputation. *Prior VC IPOs* counts the number of firms the VC firm had taken public before the focal venture financing. A second measure of VC reputation is Bonacich's (1987) centrality score, which in this empirical setting is based on the reputation of VC investment syndicates in the year prior to the funding event. Reassuringly, these two measures of VC reputation are pairwise correlated at the 33% level (and statistically significant at the 5% level). I therefore use only one measure at a time and report the best fit in Table 7. The first two columns of Table 7 report OLS regressions of the log of *postfunding R&D alliances* using first a parsimonious, then a fully specified model of control variables together with *prior VC IPOs* as the measure of VC reputation. Across both specifications, the measure of VC reputation is positive and significant at conventional levels. In the final two columns of the table, I use a similar set of specifications to explore the role of VC reputation on IPOs. In these regressions, because one might believe that it is uninteresting to use prior IPO rates to predict future IPO rates, I use the *Bonacich VC centrality* measure, which can be interpreted as a measure of the information (and quality of information) available to the VC, which in turn affects both ability to select higher quality investments and to add value to the entrepreneur. Again, the measure of VC reputation is positive and significant (at the 1% level), indicating that VCs appear to differ in value to start-ups depending on their reputation, a finding consistent with Hsu (2004).

To further investigate the hypothesized matching of VCs with reputable investment banking underwriters, I examine the correlates to investment banker reputation in the within-IPO subsample. Table 8 reports OLS regressions of investment banker reputation for the sample of start-ups that realized an IPO. The measure of investment banker reputation is the 0–9 scale developed by Carter et al. (1998), which is based on tombstone placement. The results indicate that both *VC funded* and *SBIR and VC funded* are positive and significantly related to *investment bank reputation*. This suggests that relative to firms funded only through the SBIR program, those firms that have received VC

Table 7 VC Reputation Regressions (Within-VC Sample)

	Ever-received VC sample $N = 512$ observations			
	L postfunding R&D alliances OLS regressions		IPO probit regressions (Marginal effects reported)	
Independent variables	(7-1)	(7-2)	(7-3)	(7-4)
L prior VC IPOs	0.098*** (0.028)	0.066** (0.028)		
Bonacich VC centrality			0.581*** (0.210)	0.526*** (0.213)
SBIR and VC funded	0.209 (0.181)	0.196 (0.180)	0.036 (0.067)	0.011 (0.076)
L prefunding R&D alliances	0.391*** (0.058)	0.276*** (0.062)		
L postfunding R&D alliances			0.308*** (0.038)	0.272*** (0.042)
L total dollar inflows		0.046* (0.027)		0.061*** (0.023)
L employees		0.037*** (0.015)		0.046*** (0.012)
L prefunding patents		0.050 (0.033)		0.045 (0.029)
Industry dummies		Yes		Yes
Constant	0.119 (0.170)	−0.199 (0.193)		
Log likelihood			−306.238	−279.755
Prob > F/Prob > χ^2	0.00	0.00	0.00	0.00

Note. *, **, or *** indicate statistical significance at the 10%, 5%, or 1% level, respectively.

Table 8 Investment Banker Reputation OLS Regressions (Within-IPO Sample)

	Dependent variable = investment bank reputation on 0–9 scale (from Carter et al. 1998) $N = 237$	
Independent variables	(8-1)	(8-2)
VC funded	2.217*** (0.532)	1.500** (0.668)
SBIR and VC funded	1.653*** (0.597)	1.477** (0.607)
L postfunding alliances	0.631*** (0.199)	0.378* (0.223)
Year founded		−0.001 (0.001)
Year funded		−0.032 (0.051)
L total dollar inflows		0.183 (0.204)
L employees		0.201 (0.159)
L prefunding patents		0.491*** (0.168)
Industry dummies		Yes
Constant	5.014*** (0.496)	68.439 (102.043)
F test probability of H_0: *VC funded = SBIR and VC funded*	0.16	0.97

Note. *, **, or *** indicate statistical significance at the 10%, 5%, or 1% level, respectively.

funding are brought public by more reputable IPO underwriters.

5. Conclusion and Discussion

This paper examined the possible impact of venture capital (VC) backing on the commercialization direction of technology-based start-ups by asking: To what extent (if at all) do VC-backed start-ups engage in cooperative commercialization strategies (strategic alliances and/or technology licensing), and with what consequences? To decouple cooperative activity resulting from start-up development associated with the passage of calendar time from cooperative activity due to association with VCs, I assembled a novel data set that matched firms receiving a federal R&D subsidy through the U.S. Small Business Innovative Research Program to VC-backed firms by observable characteristics in five technology-intensive SIC industries. An analysis of the resulting 696 start-ups (split by external funding source) suggests substantial boosts in VC-backed cooperative activity, as well as increased likelihoods of start-up IPOs, with accentuated results for more reputable VCs. Given the empirical design, an interpretation of the results that VC funding is correlated with cooperative start-up commercialization activity (rather than necessarily causing such activity) is warranted.

Three alternate explanations for the observed empirical patterns are worth discussing. First, while the chosen methodology establishes a baseline to evaluate the role of VCs in cooperative commercialization strategy, the method comes at the cost of introducing a possible selection issue: VCs may select certain types of start-ups to fund in ways that are unobserved. Another possibility is that certain types of entrepreneurs (higher quality or those seeking to take a commercialization strategy) choose to be considered for VC funding, again in unobserved ways.[13] A reverse causality interpretation would be in order if start-ups that wished to engage in cooperative activity are more likely to seek VC relative to SBIR funding. Absent the gold standard of a natural experiment or random assignment of ventures to external funding sources, I have taken a second-best external funding matching approach in this paper. While the approach is not perfect, I have taken three steps to mitigate the possibility that pure selection effects are driving the results. First, the premise that only higher-quality entrepreneurs choose to be considered for VC funding might not be correct (Amit et al. 1990, Lerner 1999). Second, the empirical design takes into account institutional details about the funding sources in an effort to enhance comparability in the sample. Specifically, I restrict the SBIR firms to Phase 2 awardees within one of five technology sectors (the same sectors in which VCs concentrate the bulk of their investments). Also, I test the robustness of the results to variation in the degree to which I am able to match funded projects on observable characteristics. Finally, in the empirical analysis, I take a number of steps to address the selection concerns. First, I examine (and control for) correlates of the ability and desire to pursue a cooperative strategy: firm size, age, technological base, and prefunding cooperative activity. Second, I take advantage of the fact that there are some firms in the data set that received both SBIR and VC funding. The estimated empirical boosts in cooperative activity and performance in this subsample (as well as in the ventures that received only VC funding) relative to the SBIR firms is reassuring.[14] Finally, I use an instrumental variable strategy to account for the possibility that VC funding is endogenous to start-up commercialization strategy. This analysis, while consistent with a VC effect in spurring cooperative start-up behavior, is statistically noisier.

A second possible alternative explanation for the empirical patterns is that the top management teams (TMTs) at start-ups that were backed by VCs were better connected socially relative to the teams that would receive SBIR funding. Eisenhardt and Schoonhoven (1996) suggest that differences in social connectivity of TMTs are significantly related to variation in alliance formation in their sample of semiconductor firms. Because pre-existing social relations of start-up TMTs is likely correlated with the ability to attract VC funding (Shane and Stuart 2002, Shane and Cable 2002), the same factors that explain start-up venture funding may explain alliance formation, and so enhanced alliance formation may be independent of the role of VCs in this regard. Because the empirical analysis examines the *relative* boost to alliance formation of VC-funded compared to SBIR-funded firms in the pre and postfunding eras, the social connectedness alternate explanation would have to account for the unequal marginal increase in alliance formation associated with the VC-backed firms.

A third potential alternative explanation is that because VCs are more likely to fund firms that emphasize more innovative strategies (Hellmann and Puri 2000), while more radical technological innovations by start-ups is positively associated with alliance

[13] An economic equilibrium analysis of the selection issue in the setting of VCs and entrepreneurs can consider the analysis from either actor's viewpoint, as Hellmann and Puri (2000) have discussed. Therefore, the same estimation procedures can be used no matter who is selecting whom.

[14] Similarly, an analysis of the within-SBIR sample reveals that those firms also receiving VC experienced increases in cooperative activity and in IPO likelihood.

formation (Ahuja 2000a), it may be difficult to disentangle the influence of VC action from pre-existing technological development in explaining alliance formation. The empirical analysis does control for patent counts in the month and year prior to external funding to capture the variation in patent-measured innovativeness at the start-ups. Also, the results are consistent with Kortum and Lerner's (2000) finding that innovation (patent) boosts are associated with the VC institution relative to corporate research and development.

In addition to these possible alternative explanations, three potential limitations of the analyses should be noted. First, only counts of cooperative activity were examined, rather than their size or importance. Second, I did not examine the characteristics of the cooperation partner, which is likely to be important in assessing value (and learning potential) to the start-up (e.g., Stuart 2000). Because I did not collect information about the size distribution of cooperation partners, I do not make claims about the market structure implications of the boost in start-up cooperative activity. An informal examination of cooperation partners, however, reveals more established firms (rather than fellow start-ups). Finally, there may be unobserved or unmeasured factors such as founder reputation/imprinting effects and possible business strategy effects that are important determinants of cooperative activity and/or IPO likelihood (e.g., Baum et al. 2000, Hellmann and Puri 2000).

Two possible areas for future research are suggested from this work. First, it would be interesting to look more deeply into the real effects of start-up cooperation on geographic locales. For example, there may be processes of spiraling entrepreneurial activity such that VC funding leads to enhanced start-up cooperative activity, higher rates of IPO, more entrepreneurial activity, and to renewed VC funding in a region—beginning the cycle afresh. Second, while Shane and Cable (2002) and Hsu (2003) have begun to examine how start-up entrepreneurs develop relationships with VCs in the first place, this paper suggests that a deeper understanding of that process might be worthwhile.

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