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Picking winners or building them? Alliance, intellectual, and human capital as selection criteria in venture financing and performance of biotechnology startups

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Abstract

In the entrepreneurial setting, financial intermediaries such as venture capital firms (VCs) are perhaps the dominant source of selection shaping the environment within which new ventures evolve. VCs affect selection both by acting as a "scout" able to identify future potential and as a "coach" that can help realize it. Despite the large literature on the role of VCs in encouraging startups, it is generally taken for granted that VCs are expert scouts and coaches, and so the ways in which VCs actually enhance startup performance are not well understood. In this study, we examine whether VCs' emphasize picking winners or building them by comparing the effects of startups' alliance, intellectual, and human capital characteristics on VCs decisions to finance them with the effects of the same characteristics on future startup performance. Our findings point to a joint logic that combines the roles: VCs finance startups that have strong technology, but are at risk of failure in the short run, and so in need of management expertise. Our findings thus support the belief in VC expertise, but only to a point. VCs also appear to make a common attribution error overemphasizing startups' human capital when making their investment decisions.

Keywords: Alliance capital; Intellectual capital; Human capital

1. Introduction

In the evolutionary approach to organizational change, processes of variation, selection, and retention drive changes in the organizations and organizational routines that characterize

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a given organizational population (Aldrich, 1999). As long as variations arise and are subjected to consistent selection criteria, and positively selected variants are preserved and propagated, evolution will occur. These three mechanisms are very general; their operation does not depend on finding a social analog to features of biological evolution (Campbell, 1965).

In evolutionary models of entrepreneurship, entrepreneurs generate variation by founding new firms, pursuing different strategies, and attempting to combine different bundles of assets to do so. Selection is then generated by the decisions of external resource holders to allocate their resources among these firms (Aldrich, 1999). In the entrepreneurial setting, financial intermediaries such as venture capital firms (VCs) have been cited as perhaps the dominant source of selection (Anderson, 1999). VCs affect selection by providing financial resources to cash-hungry startups and by favoring new firms with, or requiring them to adopt, particular strategies, practices, or other characteristics. VCs may also provide management expertise or access to other capabilities that bolster the competitive advantage of startups that they fund (Hellmann and Puri, 2002). Further, because they are perceived to be "informed agents" able to identify particularly promising startups, their investment provides a certification benefit that can enable the startup to obtain other resources (Megginson and Weiss, 1991). Thus, VCs can affect selection by acting as what we term a "scout" able to identify potential and as a "coach" (Hellmann, 2000) that can help realize it.

In evolutionary terms, the VC industry constitutes an indirect vicarious selective system (Anderson, 1999). Vicarious selectors function to eliminate trials of variations that would be fundamentally detrimental to the fit or survival of a system or even to anticipate certain kinds of variations that might prove beneficial (Campbell, 1965). Through past trial-and-error learning, VCs may evolve vicarious selective systems (e.g., due diligence strategies), which systematically predispose them toward financing startups expressing certain variations and avoidance of others. In turn, in their role as an indirect vicarious selective system, VCs lower investors' costs of search and selection. Rather than waiting for direct selection to determine the success or failure of a startup, investors rely on VCs to identify startups that give off signals predictive of future success and to enhance the performance of startups that they select for funding. VCs that acquire effective vicarious selectors thrive as a result, and successful selectors may subsequently diffuse through the VC industry. VCs thus shape the environment within which new ventures evolve and are themselves subject to selection processes at a higher level.

In this paper, we examine whether VCs' vicarious selectors emphasize picking winners or building them. As Shepherd and Zacharakis (2002) note, although researchers have described in detail the criteria VCs use to choose which startups to fund, researchers have typically assumed that VCs are capable of identifying promising startups and consequently have primarily asked VCs to report their own decision criteria without exploring whether these criteria actually influence subsequent startup performance. Yet only a fraction of the firms VCs fund succeed (Gifford, 1997; Gorman and Sahlman, 1989), most achieving an average rate of return on invested capital suggesting that many VCs are unable to discover a "predictive template" (Aldrich and Kenworthy, 1999). Moreover, while research shows VC-backed startups outperform comparable non-VC-backed startups (e.g., Megginson and Weiss, 1991; Sandberg, 1986; Timmons, 1999), research has rarely sought to identify whether these differences are attributable to inherent differences between VC-backed and non-VC-backed startups or to the postinvestment benefits that accrue to the VC-backed firms. Existing research thus offers little insight into how VCs affect the startup selection process.

Given the importance of financial intermediaries to selection within an organizational population, this is an important gap in our knowledge and our research focus. One way to address this gap is to test the effectiveness of VCs predictive templates by comparing the effects of startups' characteristics on VCs decisions to finance them with the effects of the same characteristics on future startup performance. If VCs affect selection primarily by picking winners, then the startup characteristics that attract VC investment should also enhance their future performance. If, instead, VCs affect selection primarily by building winners, then the startup characteristics that attract VC investment need not be associated with future startup performance and may even affect it negatively.

Below, we outline in more detail the "scout" and "coach" views of VCs and the empirical implications of each view. We also identify startups' alliances (i.e., social capital), patents (i.e., intellectual capital), and top management (i.e., human capital) as key signals of startup potential. We suggest that, faced with great uncertainty about the quality of startups, VCs will rely heavily on the startups' partners, patents, and top management team characteristics to make judgments about their promise; and that in the race for capital, startups capable of attracting alliance partners, creating intellectual property, and possessing capable management will outperform comparable startups that lack such capabilities. Then, we estimate models of the effects of social, intellectual, and human capital on VC financings and compare these effects with estimates from models of startup performance in the Canadian biotechnology industry from 1991 to 2000. We conclude with a discussion of our findings and proposals for future research.

2. The role of the VC: scout or coach?

Researchers have devoted a great deal of attention to the influence of VCs on startup formation (Barry et al., 1990) on facilitating the success of specific entrepreneurial ventures (Jain and Kini, 1995) and on the rate and nature of innovation itself (Kortum and Lerner, 2000). The popular press has similarly identified VCs as the primary actors in encouraging and selecting among new entrepreneurial ventures going as far as to accompany celebrated venture capitalists on their "daily rounds" to document their personalities, activities, and decisions (Byrne, 2000).

Yet despite the large literature on the role of VCs in encouraging startups, little of this research has attempted to tease apart the multiple ways in which a VC might enhance a startup's performance. Most research has assumed that VCs are particularly good "scouts." That is, that they are particularly adept at identifying exceptionally promising startup ventures. Consequently, a positive relationship between a VC's investment in a startup and that startup's subsequent performance is seen as resulting from the VC's ability to identify preinvestment, which startups are more likely to enjoy superior performance in the future

(Chan, 1983; Shepherd et al., 2000). Further, since other resource holders recognize that VCs are good at identifying promising firms, a VC investment facilitates the funded startup's efforts to obtain other necessary resources (Megginson and Weiss, 1991; Stuart et al., 1999; Anand and Piskorski, 2000).

Another stream of research emphasizes instead that VCs are particularly good "coaches." That is, that they are particularly skilled at injecting expertise and sound business judgment into startup ventures (Hellmann, 2000). Consequently, a positive association between a VC's investment in a startup and that startup's subsequent performance stems not from the VC's ability to "pick winners," but rather from the VC's ability to ensure that the startup is well-managed postinvestment (Jain and Kini, 1995; Hellmann and Puri, 2002). Again, VC investment should facilitate the funded firm's efforts to obtain other necessary resources; but in this view, by signaling an infusion of management expertise.

Which of these roles dominates? Do VCs' vicarious selectors emphasize picking winners or identifying startups that the VC can build into winners? There is no research on this issue. In part, this is the result of both VC roles being positively associated with startups' subsequent performance. Additionally, many of the characteristics that affect preinvestment scouting also affect postinvestment coaching in the same direction—for example, the greater the geographic distance between VC and startup, the more difficult are both identifying superior firms preinvestment and monitoring them postinvestment (Sorenson and Stuart, 2001).

One way to disentangle these different effects is to assess whether or not the weights VCs assign to startup characteristics when deciding which startups to finance converge with the influences of these same characteristics on startup performance. If the VC investment–startup performance relationship is driven by VCs' ability to identify particularly promising startups, then startup characteristics should affect VCs' decisions to invest in the same way that they affect startups' performance. If, however, the VC investment–startup performance relationship is driven by VC's ability to provide management expertise and network contacts to the startup, then startup characteristics that affect VCs' investment decisions need not affect startups' performance in the same way; they may be either unrelated to or diverge in their effects. Thus, the greater the convergence between the effects of startup characteristics on VC investment decisions and startup performance, the greater the ability of VCs to "pick winners" and the more likely it is that the VC investment–startup performance relationship is attributable to the "VC as scout."

3. Valuing technology startups

Mobilizing resources to build a new organization is an undertaking laden with uncertainty and unforeseeable hazards. It is also an inherently social process because entrepreneurs must access financial and social capital and other types of resources through relationships with parties beyond the boundaries of their organizations. Because the quality and promise of a new venture is always a matter of some debate, however, the decision of external resource holders to invest time, capital, or other resources in a new organization is one that must be made in the face of considerable uncertainty about the startup's survival chances and financial prospects.

Many obstacles confront young companies (Stinchcombe, 1965). Startups often lack employee commitment, knowledge of their environment, and working relationships with customers and suppliers. Because they have little operating experience, startups frequently operate using immature and unrefined routines. Startups also tend to be small and so unable to withstand a sustained period of poor performance (Aldrich and Auster, 1986). These perils have led organizational sociologists to conclude that new organizations are highly vulnerable to direct selection, a notion succinctly portrayed as a liability of newness (Hannan and Freeman, 1984; Stinchcombe, 1965).

Because startups encounter so many hazards and because they have short-track records by which outsiders can evaluate their potential, there is considerable uncertainty about their value. This uncertainty is compounded for firms established to pursue commercial applications of new technologies (Aldrich and Fiol, 1994). Added to the usual hazards of inexperience, technology startups often require substantial resources to fund early stage and speculative development projects, while revenues cannot be expected until well into the future. New technology is, moreover, by its very nature highly uncertain: undeveloped markets follow unforeseen turns; "hyped" technologies disappear; technologies obsolesce rapidly; and unanticipated "kinks" derail once-promising projects (Tushman and Rosenkopf, 1992). New technology startups are thus particularly risky and uncertain.

Given these uncertainties, how do VCs assess the potential of startups and select their investments? VCs spend a great deal of time and effort seeking and assessing signals of a startup's promise and quality (Amit et al., 1990; Hall and Hofer, 1993). When unambiguous measures of performance do not exist or cannot be observed, investors look for other signs or certifications of future promise and quality (DiMaggio and Powell, 1983; Podolny, 1993). Newly founded ventures must assemble a range of resources and relationships to survive and thrive (Stinchcombe, 1965). Biotechnology startups require access to human, intellectual, alliance, and financial capital (Baum et al., 2000; Walker et al., 1997) and are often portrayed as engaging in a series of "races" to win over desirable managers and researchers, garner valuable patent rights, develop relationships with desirable partners, and obtain the financial resources necessary to support technology development (Amburgey et al., 1996). VC investment is typically viewed as the most critical form of capital (Anderson, 1999; Shepherd et al., 2000); while consistent with the classic signaling literature in economics (Spence, 1974), access to the other forms of capital is seen more as an important signal to VCs of a startup's future promise (e.g., Stuart et al., 1999). Thus, prior research implicates three broad types of signals that may affect VCs' assessments of startups: alliance capital, intellectual capital, and human capital.

3.1. Alliance capital

Interfirm alliances have the potential to alter the opportunities and constraints that startups face in their early years. A large body of research has examined the benefits that these ties confer on organizations in general and on new organizations in particular (Dyer and Singh, 1998). Alliances provide myriad advantages primarily associated with the direct or indirect access to complementary resources (Chung et al., 2000) and to knowledge and other assets for which arm's-length ties are inadequate (Liebeskind et al., 1996; Williamson, 1991). Alliances may also confer an aura of legitimacy (Baum and Oliver, 1991, 1992; Miner et al., 1990), which in turn facilitate acquisition of other resources. Alliance advantages are particularly strong when timely access to knowledge or resources is essential (Teece, 1992) or when ambiguous technologies lead actors to rely on indirect social indicators to assess firm performance (Stuart et al., 1999).

Baum and Oliver (1991), for example, show how links with municipal government and community agencies can moderate the liabilities of newness and smallness for day care centers suggesting that if young organizations obtain early external endorsements and access to resources, liabilities of newness and smallness may be avoided. Relatedly, Baum et al. (2000) find that biotechnology startups able to establish upstream alliances with universities and other organizations with scientific and technological expertise and downstream alliances with pharmaceutical, chemical, or marketing companies at the time of their founding exhibit significantly higher performance growth during their early years. Also, Stuart et al. (1999) show that new biotechnology firms that form equity-based links link to prominent partners IPO more quickly and at higher market valuations than those with less prominent partners.

Thus, a startup's alliances provide signals for both access to valuable resources and knowledge critical to early performance as well as serving as external endorsements by suggesting that the startup has earned positive evaluations from other knowledgeable actors.

3.2. Intellectual capital

Many scholars have noted the unique role of patents in biotechnology (e.g., Fligstein, 1996; Lerner, 1995; Powell and Brantley, 1992; Powell et al., 1996). Biotechnology firms compete in patent races with their rivals. Since patents are granted to the first party across the finish line, running second provides little if any benefit. Intellectual property protection for newly developed products and processes offers significant benefits for the winner of a patent race: a 20-year monopoly in the United States and Canada.

The appropriability regime surrounding biotechnology patents is particularly strong because patented compounds are difficult to circumvent (Lerner, 1995). As a result, a biotechnology firm with a patent is in a favorable position to obtain complementary assets and skills (Pisano, 1990) and is more likely to obtain VC financing and willing partners to support commercialization activities (Kenney, 1986; Lerner, 1994). New biotechnology firms with patents also IPO more quickly (Stuart et al., 1999). Relatedly, Austin (1993) shows that, post-IPO, new patent announcements increase biotechnology firms' market valuations. In addition, the frequent publicity surrounding patents pending indicates that they are exploited to signal patent race leads in the race for additional resources. Silverman and Baum (2002), for example, find a positive relationship between the number of pending patent applications that a biotechnology firm possesses and its survival chances.

Thus, the ability to stake technological claims is a critically important early signal of a startup's future potential. By signaling innovative capabilities, patents and patents pending help startups possessing them to acquire additional resources, increasing the likelihood that they will obtain VC financing.

3.3. Human capital

In the popular business press, VCs commonly report that "nothing is more important than people..." and, in particular, that they look "for people who have high levels of energy, are willing to work around the clock, and are still hungry for success" (Byrne, 2000, p. 96). In a recent review of the academic literature, Zacharakis and Meyer (2000) find, similarly, that top management team experience and skills are the most frequent selection criteria self-reported by VCs.

Other recent studies provide more direct evidence of startups' human capital on VCs and other investors' behavior. In a study of Silicon Valley startups across several industries, Burton et al. (2001) find, for example, that prominence of the prior employers of a startup's founding management team increases the likelihood that the startup will obtain external financing at the time of its founding. Moreover, demonstrating the greater importance of human capital signals under conditions of uncertainty; they report that the effects of founding managers' prior employer prominence held only for "innovative" (and not "incremental") startups. Gulati and Higgins (2003) find similar top management career experience effects on investment bank behavior. Specifically, more prestigious investment banks took on IPOs for U.S. biotechnology startups with top managers who had more prominent previous employers, although these affiliations did not, in turn, necessarily affect the IPO's valuation. Again, uncertainty moderates this effect with investment banks being more sensitive to human capital influences in selecting firms to represent when uncertainty is higher.

Zucker et al. (1998) find that the founding of new biotechnology firms depends importantly on the number of "star scientists," corroborating that human capital is a key factor in biotechnology. Thus, the identity and background of top management are widely regarded as important signals of a startup's future potential, increasing its chances of obtaining VC financing.

In sum, alliance, intellectual, and human capital have been shown to serve as key signals VCs use in their assessments of startups, presumably because these are believed to materially affect subsequent firm outcomes, a presumption that empirical evidence tends to corroborate.

4. Research methods

4.1. Data description

We tested our hypotheses using data describing the alliances, personnel, patents, performance, and organizational characteristics of biotechnology startups that began operations in Canada during the 10-year period between January 1, 1991, and December 31, 2000. We compiled life histories on all 204 startups that were founded during this period—69 (33.8%)

of which had ceased operations by the end of 2000—as well as 471 incumbents founded prior to 1991.

The data were obtained from Canadian Biotechnology, an annual directory of companies active in the biotechnology field in Canada published since 1991. The directory covers biotechnology firms operating in 13 sectors: agriculture, aquaculture, horticulture, human diagnostics, human therapeutics, human vaccines, forestry, engineering, environmental, food, beverage and fermentation, veterinary, and energy. It compiles self-reported data on a wide range of firm characteristics, including revenues, R&D activities, personnel, products, and alliance partners. Firms report foreign as well as domestic partners, thus capturing each firm's global alliances. We cross checked these data against *The Canadian Biotechnology Handbook*, which provides information for a more restrictive set of "core" Canadian biotechnology firms (i.e., firms entirely dedicated to biotechnology) and found no significant discrepancies in information for those firms represented in both sources. Data on patents issued to each startup were collected separately using the Micropatent database.

Notably, by incorporating information on all startups, our research design avoids the common sample selection problem of overrepresenting currently successful firms that can undermine inferences about factors producing organizational behavior and success (Berk, 1983).

4.2. Dependent variables and analysis

4.2.1. Financing

Data on pre-IPO financing of biotechnology startups by VCs and through private placements were compiled by the National Research Council of Canada.[1] Pre-IPO financing was measured as the yearly total financing (in 1991 dollars) received by a startup. During the observation period, the sample startups received 73 VC financings valued at C$316.59 million and 23 private placements valued at C$139.23 million (both in 1991 Canadian dollars).

4.2.2. Performance

We examined six dimensions of startups' performance. The first three measures gauge performance in terms of year-over-year revenue and R&D spending growth (both in 1991 dollars) and year-over-year employment growth in the number of dedicated R&D employees. We use absolute growth rather than percentage growth since the latter cannot be computed from founding since the values for these variables are zero initially for many startups and often in subsequent years as well.

Our fourth and fifth performance measures are the yearly number of patent applications by and patents granted to a startup. We identify each startup's yearly number of patents applied for but not yet granted and patents issued using the Micropatent database, which contains information on all patents granted in the United States. We used U.S. patent data because

[1] We are indebted to NRC's Denys Cooper for permitting us to use these data.

most Canadian biotechnology firms file patent applications in the United States first to obtain a 1-year protection during which they file in Canada, Europe, Japan, and elsewhere (Canadian Biotech, 1989, 1992). For startups that were subsidiaries, we included only those patents assigned to the subsidiary.[2]

Together, these five measures gauge startups' performance across a range of dimensions critical to early success: revenue generation, investment in innovation and innovative capabilities, success in recruiting human capital, and development of intellectual property. Our sixth and final performance measure is startup survival, which we measured as the failure of a startup or closure of a subsidiary as reported in Canadian Biotechnology. Changes in name or ownership of a firm or a subsidiary are not coded as failures.

4.2.3. Model specification

For the analysis, we pooled the yearly data and estimated models on the pooled cross sections using time series regression techniques. For each startup in our sample, we generated separate observations for each year of its existence, up to 10 years, and entered an observation for each startup for every year in which it existed. A startup founded in 1991 and still in existence at the end of 2000, for example, is represented by ten observations. Startups founded in later years and startups that exited by the end of 2000 are represented by fewer observations. Thus, the length of each startup's time series may differ because of when it was founded or failed during the observation period. Pooling the data in this way improves estimation efficiency and allows us to correct for the bias arising from the inclusion of a lagged dependent variable (Hannan and Young, 1977). Our database includes 1093 observations.[3]

Our seven dependent variables include censored, continuous, count, and event data, each requiring a different estimation technique, which we describe below.

We estimated changes in the continuous dependent variables, pre-IPO financing, revenue, R&D spending, and R&D employees using the following standard log-linear growth model, which is suitable for estimation with linear methods:

$$\ln(P_{it}) = \alpha\ln(P_{it-1}) + \beta x_{it-1} + \varepsilon_{it}$$

where P is a time-varying dependent variable, α is an adjustment parameter that indicates how current performance depends on prior performance, and β is a vector of parameters for the effects of independent and control variables.

Inclusion of the lagged dependent variable (P_{it-1}) to predict the current year's value (P_{it}) helps account for the possibility that our empirical models of startup performance suffer from specification bias due to unobserved heterogeneity (Jacobson, 1990), which enables us to

[2] Although our observation period ends December 31, 2000, we include information on patents granted up to May 31, 2002. We do this to limit truncation of the count patents granted due to the time lag between application and granting dates. Of all the granted patents that were applied for by firms in our database between 1985 and 1992, more than 75% were granted within 29 months of application. More than 92% were granted within 41 months of application. Thus, in our sample, a minority of 2000 inventive activity is likely omitted.

[3] The sample also included 9 startups founded in 2000 and observed for only 1 year, less than the minimum two observations required for inclusion in the analysis.

infer causal relationships between startup characteristics and performance with greater confidence. That is, if startups' human, intellectual, and alliance capital characteristics are themselves a result of unobserved factors related to performance, controlling for lagged performance should eliminate spurious effects resulting from such endogeneity. Inclusion of the lagged dependent variable results in a loss of 195 observations (one for each startup), reducing the sample from 1093 to 898 observations, and missing observations on independent variables described below reduce the final sample for the analysis to 852.

Pooling repeated observations on the same organizations is likely to violate the assumption of independence from observation to observation and result in the model's residuals being autocorrelated. First-order autocorrelation occurs when the disturbances in one time period are correlated with those in the previous time period resulting in incorrect variance estimates. This renders OLS estimates inefficient and for the model of interest (with lagged dependent variable included) autocorrelation generates biased estimates (Judge et al., 1980). Therefore, we estimated random-effects GLS models, which correct for autocorrelation of disturbances (Greene, 1993).[4]

A further estimation issue concerns possible sample selection bias due to attrition: if a startup fails, it leaves the sample without its final performance changes represented in the data. Therefore, we estimated models that corrected for possible sample selection bias due to attrition using Lee's (1983) generalization of Heckman's (1979) two-stage least-squares (2SLS) procedure.

The pre-IPO financing dependent variable is censored. That is, it is truncated at zero and highly skewed with many observations for which the value of financing is zero. When a variable is censored in this way, its distribution is a mixture of discrete and continuous distributions. The Tobit model is appropriate for such dependent variables (Greene, 1993). The general formulation of the Tobit model is:

$$P^*_{it} = \beta x_{it} + \varepsilon_{it},$$

$$P_{it} = 0 \text{ if } P^*_{it} \leq 0,$$

$$P_{it} = P^*_{it} \text{ if } P^*_{it} > 0$$

where P_{it} is the value of the dependent variable at time t and P^*_{it} is the unobserved value of the dependent variable subject to censoring for startup i at time t. As before, because we pool our data, we estimated a random-effects Tobit model and also included a Heckman (1979) correction to account for possible effects of startup attrition. For comparability, we estimate a log-linear specification of the model.

[4] A second potential estimation problem is heteroskedasticity, which violates the assumption of constant error variance and can bias coefficient standard errors. Although the error variance may become proportionately adjusted after including random effects, and so heteroskedasticity corrected, some heteroskedasticity may still nevertheless exist. The only truly accurate solution would be to use the multistep procedure outlined by Greene (1993, pp. 558–559). However, the short panels comprising our data set, most including fewer than 6 observations, limits the value of this approach (Bill Greene, personal communication).

Because patent applications and patents granted are count measures (i.e., the yearly number of patents applied for or granted to a startup), we used the pooled cross-section data to estimate the number of patent applications or grants expected to occur within an interval of time. A Poisson process provides a natural baseline model for such processes and is appropriate for relatively rare events (Coleman, 1981). The basic Poisson model for event count data is:

$$Pr(Y_{it} = y) = \exp\lambda(x_{it})[\lambda(x_{it})y/y!]$$

where both the probability of a startup i experiencing a given number of events in a time interval, $Pr(Y_{it}=y)$, and the variance of the number of events in each interval equal the rate, $\lambda(x_{it})$. Thus, the basic Poisson model makes the strong assumption that there is no heterogeneity in the sample. However, for count data, the variance may often exceed the mean. The presence of such overdispersion causes standard errors of parameters to be underestimated, resulting in overstatement of levels of statistical significance. In order to correct for overdispersion, we employ a negative binomial regression model, which allows the Poisson process to include heterogeneity by relaxing the assumption of equal mean and variance:

$$\lambda_{it} = \exp(\pi' x_{it})\varepsilon_{it}$$

where the error term, ε_{it}, follows a gamma distribution. The presence of ε_{it} produces overdispersion. The specification of overdispersion we use takes the form:

$$\mathrm{Var}(Y_{it}) = E(Y_{it})[1 + \alpha E(Y_{it})]$$

We estimated the model using a specification that accounts for the potential nonindependence of the repeated observations on each startup and also included a Heckman (1979) correction to account for possible effects of startup attrition noted above.

Finally, we estimate startups' exit rate using a random effects logistic regression model:

$$y_{it}^{*} = x_{it}\beta + u_i + \varepsilon_{it}$$

$$y_{it} = 1 \text{ if } y_{it}^{*} > 0, \text{and } 0 \text{ otherwise}$$

where u_i are independent draws from a normal distribution with zero mean and standard error σ_u. Again, the random effects control for the potential nonindependence of repeated observations on the same startup.

4.3. Independent variables[5]

4.3.1. Alliance capital

To estimate the influence of startups' "alliance capital" on their financing and performance, we construct a set of firm-specific variables that count, separately, the aggregate number

[5] All independent and control variables are lagged 1 year to avoid simultaneity problems.

of alliances each startup had at the start of each year in the three following categories: downstream alliances, with pharmaceutical firms, chemical firms, marketing firms; upstream alliances, with universities, research institutes, government labs, hospitals, industry associations; and horizontal alliances with rival biotechnology firms. We define rival biotechnology firms (startups and incumbents) as those operating in one or more of the same biotechnology sectors as the startup.

Downstream alliances link startups to sources of complementary assets including distribution channels, marketing expertise, and production facilities as well as financing that facilitate successful development and commercialization of a new product or process (Kogut et al., 1992). Upstream alliances link startups to sources of research know-how and technological expertise that can prove critical to the successful discovery and patenting of new products or processes (Argyres and Liebeskind, 1998). In contrast to vertical alliances, there is some evidence to suggest that horizontal alliances are more problematic and fraught with difficulty than vertical linkages, notably due to fear of proprietary information leakage and the propensity for learning races (Khanna et al., 1998). Silverman and Baum (2002) found, for example, that horizontal alliances, on average, raised a biotechnology firm's likelihood of failure.

4.3.2. Intellectual capital

We estimated the effects of startups' "intellectual capital" on their financing and performance using the patent applications and patents granted variables defined above. Additionally, to account for dynamic effects of startups' patenting activity, we included "time clocks" tracking the number of years since a startup had last applied for or been granted a patent. The time since patent application variable was set equal to zero until a startup applied for its first patent after which it counted the number of years since that application was made. The time clock was reset after each subsequent application. The time since patents granted variable was constructed in an identical manner for patents granted. These time clock variables capture potential decay (or growth) of the value of a startup's past patenting activity over time.

4.3.3. Human capital

We estimated "human capital" effects on financing and performance using four variables characterizing a startup's top management team, which included personnel in five roles: president, general manager, and directors of R&D, marketing, and operations. The first is the size (number of individuals) on the top management team. The second is the president's number of top management roles. Larger top management teams may possess greater human capital, as well as social capital. Greater concentration of roles in the president's hands may reflect a weakness in startup management (i.e., that the startup was either unable to attract or afford a full management team); or alternatively, it may reflect a highly capable entrepreneur. The third and fourth variables gauge the entrepreneurial activity and abilities of the startup's president. Some individuals appear more adept at creating new firms than others, owning multiple firms and being involved in multiple startups (Starr and Bygrave, 1992; Starr et al., 1993); "habitual" entrepreneurs have been observed in many industries (Aldrich and

Kenworthy, 1999). President's prior foundings counted the number of prior startups the startup's president was also president of since 1991, and president's other presidencies counts the number of other firms for which the startup's president is also concurrently president.

4.4. Control variables

Many other factors may influence startup's financing and performance. Accordingly, we control for a variety of additional startup characteristics and industry-specific environmental factors.

4.4.1. Startup characteristics

Each model included each other dependent variable (i.e., pre-IPO financing, revenue, R&D spending, and R&D employees), lagged, as a control.[6] High values on these variables may both increase the likelihood of financing as well as step up the pace of growth (Eisenhardt and Schoonhoven, 1990). We also included a financing time clock variable, time since last financing, to account for possible dynamic effects of prior financings. As with the other time clocks, this variable was set equal to zero until a startup received its first financing after which it counted the number of years since the financing occurred. The variable was reset after each subsequent round of financing.

One concern in this study is that a financing event requires interest from both a venture capitalist and the startup. A startup with a great deal of resources on hand could be attractive to venture capitalists but at the same time would not need to accept VC funding (for which it must give up some equity) because it has enough financial capital on hand already. To control for this, we construct a variable called net cash flow, which is the sum of cumulative capital infusions and revenues less R&D expenses. This is intended to serve as a rough proxy for the amount of cash available to the startup at the beginning of each observation year.

An important source of early seed capital for biotechnology startups in Canada is R&D grants from the National Research Council of Canada's Industrial Research Assistance Plan (IRAP). IRAP provides funding (up to C$350,000 per year) and expert assistance to small- and medium-sized high-technology firms for R&D projects emphasizing advancement of unproven technology to the point of performance testing and validation stages prior to commercialization. Therefore, in the models, we controlled IRAP grant (in millions of 1991 Canadian dollars) and also time since the last IRAP grant to allow for a dynamic effect of this funding.[1]

Financing and performance may also vary with the industry sector in which the startup operates. In particular, compared to nonmedical sectors, commercialization is most taxing for developments in human therapeutics and vaccines where rigorous clinical trials and regulations inhibit speedy implementation and somewhat less so for human diagnostics (about half of which are in vitro and half in vivo) (Powell and Brantley, 1992, pp. 18 and

[6] As noted above, lagged values of patent applications and patents granted are also included as measures of startups' intellectual capital.

369). Therefore, we control for possible differences between startups focused on human medical and nonmedical applications with a dummy variable, human medical sector, coded one for startups whose primary sector is human diagnostics, human therapeutics, or human vaccines and zero if otherwise. We also control for the degree of a startup's diversification, defined as the total number of sectors in which a startup is active.

Ownership differences may also influence initial performance. In particular, startups that are established as subsidiaries or joint ventures may have access to financial resources of their parent firm(s), and this may affect both their likelihood of obtaining venture financing as well as their early rate of growth and survival prospects. Therefore, we include a dummy variable coded one for startups with parent a firm (or firms) and zero if otherwise. Additionally, we control, with a dummy variable, for whether or not the startup was a university spinoff. University biotechnology spinoffs may possess systematically better access to cutting-edge academic resources or may benefit from university funds dedicated to technology transfer.

Finally, we control for startup age, defined as the number of years since founding, in our models to ensure that any significant effects of our alliance, intellectual property, and human capital variables were not simply a spurious result of aging-related processes.

4.4.2. Environmental factors

We also controlled for several factors influencing the carrying capacity for and intensity of competition within the biotechnology field in Canada. For each industry sector, we computed the total value of financing from all sources—IPOs and other public offerings as well as VC and private placements—and to all firms (startups and incumbents). Based on these sector-specific amounts, we constructed two variables. Own sector financing is the total financing (in 1991 dollars, logged) in a startup's primary sector. Other sector financing is the total financing (in 1991 dollars, logged) in all industry sectors other than the startup's primary sector.

The financing opportunities available to startups depend on the intensity of competition at the time the capital is added. If potential competition is not measured explicitly, then the effect of adding resources to the environment is assumed to be constant over time, and estimates for the effects of financing will suffer specification bias. Therefore, we include sector-specific measures of the potential for direct and diffuse competition. We measure the potential for direct competition with own sector density defined as the number of biotechnology firms (startups and incumbents) operating within a given industry sector. And we measure the potential for diffuse competition based on other sector density, the number of firms operating in all other industry sectors.

5. Results

Table 1 presents estimates for our analysis. Model 1 presents the estimates for the effects of alliance, intellectual, and human capital and the control variables on VC financings; Models 2–7 show identical models predicting startup performance and exit rates.

Table 1
Models of biotechnology startup financing, performance, and exit

	Pre-IPO financing	Revenues	R&D expenses	R&D employees	Patent applications	Patents granted	Exit
ln pre-IPO financing	0.249****	−0.001	−0.003	0.000	−0.013	−0.012	−0.042**
Time since last financing	0.184	−0.033	0.067****	0.010	0.202**	0.178***	0.576***
IRAP financing × 10 − 6	0.946**	−0.056	−0.047*	−0.039	0.496****	0.440***	−0.483
Time since IRAP financing	−0.301***	0.048***	0.019*	0.008	−0.189**	0.029*	−0.219
Startup age	−0.167***	0.027****	0.001	0.007	−0.285****	0.069**	−0.086
ln revenues	−0.019	0.042****	0.004*	0.002	0.007	−0.012	0.006
ln R&D expenses	0.027**	0.012***	0.046****	−0.011****	−0.020	−0.029**	0.023
Net cash flow	−0.021***	0.008****	0.001**	0.000	−0.063****	−0.003	−0.007
ln R&D employees	0.025**	0.065***	0.035**	0.924****	0.122*	0.142*	−0.252*
Human sector	0.469**	0.140**	0.078**	0.072**	0.389*	0.398*	0.630**
University spinoff	1.086****	−0.114	0.118**	0.077***	0.744****	0.061	−0.766**
Diversification	−0.171**	0.005	−0.007	−0.004	−0.315****	−0.092*	−0.124
Has parent firm	0.036	0.373****	0.173***	0.070**	1.341****	−0.088	0.996***
Own sector density	−0.023***	−0.001	0.000	0.000	−0.014****	−0.013***	−0.014*
ln own sector financings	0.026**	0.002	0.002*	0.002	0.043***	0.036***	−0.009
Other sector density	−0.014***	0.000	−0.001*	0.000	−0.003	−0.012****	−0.017**
ln other sector financings	0.209***	0.006	0.005	0.019*	0.064	0.181***	0.463****
Upstream alliances	0.006	−0.003	0.010**	0.010**	−0.052	0.017	0.071*
Downstream alliances	0.065**	0.018***	0.007**	0.014***	−0.099*	−0.109**	−0.097*
Horizontal alliances	0.317***	−0.047*	0.023*	−0.033**	0.048*	−0.150**	0.147**
Patent applications	0.419****	−0.017	−0.008	−0.004	0.078****	0.105****	−0.573**
Time since last patent application	0.176**	−0.018	0.039***	−0.023	0.117	0.042	−0.226
Patents granted	0.107**	0.024*	0.031***	−0.005	0.111***	0.177****	0.400
Time since last patent granted	−0.204*	−0.046*	−0.032*	0.010	−0.037	0.327***	0.307
TMT size	0.26***	0.044*	0.019	0.013	−0.036	0.129	−0.075
President’s number of roles	0.071*	0.008	0.005	0.010	−0.239***	0.011**	0.022
President’s number of prior foundings	−0.349**	0.004	−0.057*	−0.018	−0.122	0.232	−0.023
President’s number of other startups	1.608****	−0.051	0.045	0.003	0.825***	0.216	0.457*
Heckman correction (failure)	−6.533***	−0.924***	−0.759****	−0.317*	−18.217****	−31.325****	–
Constant	2.876	−0.394	−0.079	−0.216	0.448	0.190	−3.012
Observations (exits)	852	841	842	850	852	852	852 (69)
χ^2/Log-likelihood	237.31	558.21	431.78	8984.81	−416.162	−355.519	−194.731
Estimator	RE Tobit	RE GLS	RE GLS	RE GLS	Negative binomial	Negative binomial	RE logistic

* $P<.10$.
** $P<.05$.
*** $P<.01$.
**** $P<.001$.

5.1. Startup VC financing

5.1.1. Alliance capital

Startups with more downstream and horizontal, but not upstream, alliances obtained significantly more VC financing than startups with fewer such alliances. One explanation for this pattern of results may be an indication that the information about commercial viability signaled by a startup's vertical alliances is more important to VCs than the information they convey about the startup's resource access and endorsement (Calabrese et al., 2000).

Startups' downstream alliances indicate access to complementary assets, such as distribution channels, marketing and clinical trials expertise, and production facilities, and may involve infusions of financial capital, all of which are necessary for successful product development and commercialization. Downstream alliances also indicate that firms outside the biotechnology field—and closer to the market—believe in the technical feasibility and potential commercial viability of the startup's product or process. However, upstream alliances, which indicate access to cutting-edge research and know-how essential to the discovery and patenting of new products and processes, may provide more ambiguous signals about a startup's promise. VCs may interpret upstream alliances as an indication that the startup remains in an exploratory mode far from commercialization and perhaps even raising questions about its ultimate commercial viability.

Alternatively, downstream activities such as manufacturing and distribution may be far more scale intensive than upstream activities. Since scale-intensive activities are likely to present more severe obstacles to startups, downstream alliances (which obviate the need for a startup to conduct such activities itself) may therefore overcome more significant obstacles than upstream alliances. Whatever the specific mechanism at work, in hindsight, it is not entirely surprising that in the high-technology biotechnology industry, where the problem of competition is mitigated by firms' internalization of monopoly rents for innovative efforts, VCs financings are influenced more by startups' downstream rather than upstream alliance activities.

5.1.2. Intellectual capital

Startups with more, and more recent, patents granted obtained significantly more VC financing. Startups with more, and more distal, patent applications also obtained significantly more VC financing. Thus, VCs are more likely to fund startups that have won more patent races in the past and those that currently hold patent race leads. Falling behind in the race (i.e., letting time pass since the last patent granted), however, lowers the amount of VC financing a startup receives. The increase in VC financing as time passes since a startup's last patent application likely reflects the reduction of uncertainty and lower market risks VCs perceive as the startup proceeds from innovation to further development and commercialization of products and processes related to its patents.

5.1.3. Human capital

Startups with larger top management teams, presidents that take on a broader role, and presidents who currently act as president for other biotechnology startups obtained significantly more VC financing. Although only weakly significant ($P<.10$), the positive effect of a concentration of roles in the president's hands suggest it is taken more as a signal of a capable entrepreneur than of a weakness in startup management. This interpretation is consistent with the strong positive effect of a president's number of concurrent presidencies. An alternative account of this finding is that when presidents occupy multiple roles, the VC has greater leeway to apply its own management expertise to the startup.

Notably, the number of prior foundings in which a startup's president was involved has a negative impact on VC financing. With the number of concurrent presidencies controlled, this coefficient suggests that presidents who have experienced entrepreneurial failures in the past may find it more difficult to obtain VC financing for future startups. Thus, the apparent capabilities and entrepreneurial activity of a startup's president are vital to obtaining VC financing.

5.1.4. Effect size comparison

Thus, as we anticipated, all three forms of capital are implicated in VC financing decisions. In Table 2, we compare effect sizes of coefficients representing the three capitals to assess their relative importance to obtaining VC financing in our empirical setting. In the table, based on coefficients in Model 1, we show the estimated dollar value effect on startup VC financing (per year) for each variable evaluated at its mean and one standard deviation above its mean. For purposes of comparison, we also give both the dollar value change for increasing each variable from its mean to one standard deviation above its mean.

Table 2
Effect sizes of alliance, intellectual, and human capital on startup financing

Variable	Coefficient (β)	Variable mean	Variable S.D.	Impact evaluated at:		Dollar value increase (C$)
				Variable mean (C$)	Variable mean ± S.D. (C$)	
Upstream alliances	0.006	1.536	2.244	9256	22,935	13,678
Downstream alliances	0.065**	0.569	2.138	37,694	192,378	154,684
Horizontal alliances	0.317***	0.266	0.704	87,905	359,737	271,832
Patent applications	0.419****	0.323	1.207	144,832	898,193	753,361
Time since last patent application	0.176**	0.413	0.911	75,479	262,509	187,030
Patents granted	0.107**	0.267	1.020	28,959	147,584	118,625
Time since last patent granted	− 0.204*	0.168	0.576	− 33,696	− 140,793	− 107,097
TMT size	0.26***	3.074	1.178	1,224,046	2,021,147	797,101
President's number of roles	0.071*	2.319	1.318	178,957	294,648	115,691
President's number of prior foundings	− 0.349**	0.178	0.465	− 60,300	− 200,975	− 140,675
President's number of other startups	1.608****	0.119	0.345	211,168	1,110,762	899,594

* $P<.10$.
** $P<.05$.
*** $P<.01$.
**** $P<.001$.

The largest magnitude effects in dollar terms are associated with human capital. One standard deviation increases in the size of a startup's top management team, and its president's number of other presidencies increased the estimated value of VC financing from C$800,000 to C$900,000. A startup whose president currently acted as president for one other biotechnology startup is estimated to raise nearly C$4,000,000 more in VC financing per year. Although the human capital variables are clearly associated with the largest dollar increases, the effects of alliance and intellectual capital are also large—particularly patent applications—relative to the mean value of VC financing startups in our sample received annually, which was C$879,000 (S.D. = C$6,277,069). Nevertheless, in our empirical setting, human capital effects appear to predominate in VC financing decisions.

5.2. Startup performance

Models 2–7 present estimates for the startup performance models. The alliance variables generally have significant effects on performance, although the effects for upstream alliances are generally weaker and in some cases the alliance effects are detrimental to performance. Most of these negative effects are associated with horizontal alliances, which we anticipated given their more problematic nature and propensity for learning races. Several others were unexpected, however. Downstream alliances, while increasing startups' revenues, R&D expenditures and employment, and survival chances, also lowered startups' patenting activity. This unexpected result may reflect startups with downstream alliances being closer to commercialization and so less likely to produce innovative output. The patenting variables also have quite broad performance effects and more consistently enhance performance than alliances.[7]

In contrast, the human capital variables have limited impact on startup performance, and the few significant effects are split equally between enhancing and impeding performance. Given the large impact of human capital on VC financing decisions, the weak link between human capital and startup performance is surprising.

One possible explanation for this finding is that VCs make a common attribution error: placing emphasis on people (not situations) as causes (Ross, 1977) and so tending to overestimate entrepreneurs'—and their own—degree of control over their enterprises. In making this error, VCs overestimate the influence of entrepreneurs' actions and abilities on the success (or failure) of a new venture while simultaneously underestimating the influence of situational factors. They will also tend to attribute their successful investments to their own abilities to pick and build winners. This is especially true if there are few immediately negative investment results, which increases the likelihood that any false or superstitious beliefs will be reinforced, and limits the likelihood that they will question their

[7] While these findings are broadly consistent with earlier results reported in Baum et al. (2000) and Silverman and Baum (2002), there are some differences, which are likely attributable to (1) differences in the sample (e.g., the extended timeframe; startups only vs. all firms), (2) the inclusion of firm-specific financing and human capital variables, (3) differences in variable construction (e.g., aggregating upstream and downstream alliances), and (4) differences in model specification.

beliefs about the influence of entrepreneurs (March, 1981). These cognitive tendencies thus lead VCs to attribute success to what they think they are good at and attribute any failures that they do experience to their not trying hard enough (Levitt and March, 1988). As a result, there may be a tendency for VCs to place more emphasis on startups' human capital than on alliances and intellectual property when making their investment decisions. Notably, VCs' emphasis on entrepreneurs' track records may also provide a justification for funding startups that resonates with their own investors who are also prone to such attribution errors.

In sum, the evidence thus far suggests that VCs' vicarious selectors enable them to scout out more promising startups based on alliance and patent signals but are less effective at enabling them to identify more promising startups based on human capital signals. Rather, assertions about the importance of top management notwithstanding, VCs may identify those startups for which they can add value through "coaching" the top management.

5.3. Correspondence of predictors of startup financings and performance

To further disentangle the "scout" and "coach" explanations for the performance improvements that often follow VC investments, we now turn to assessing the whether or not the influence that startup's alliances, patents, and top managers have on VC's financing decisions converge with, are unrelated to, or diverge from their effects on startup performance. As we described above, greater alignment between the effects of startup's alliance, intellectual, and human capital on VC investment decisions and startup performance implies a greater the ability of VCs to "pick winners" and so supports the view that the VC investment–startup performance relationship is attributable to the "VC as scout."

To test for this convergence, we computed bivariate correlations among the estimates for the effects of alliance, intellectual, and human capital on VC financing in Model 1 with coefficients for the effects of these same variables on startup performance and survival presented in Models 2–7. Before computing the correlations, we standardized the coefficients (not reported in Table 1) for comparability. Table 3 presents the correlations. Panel "a" shows the correlations for all variables in the models (i.e., theoretical and control). Panel "b" shows the correlations among the alliance, patent, and human capital variables only. Notably, the magnitudes of the correlations increase markedly when restricted only to the variables expected to serve as signals VCs use to assess the promise of various startups. The first column of the correlation matrix in Panel "b" presents correlations between coefficients for the effects of alliance, patent, and human capital variables on VC financing and coefficients for their effects in the various performance models.

The correlations provide striking evidence both of convergence and of divergence. The strong positive correlation between the coefficients for the VC financing model and for the R&D expense and patent application models indicates very similar effects of alliances, patenting activity, and top management characteristics on VCs' financing decisions and startups ability to invest increasingly in R&D and submit patent applications over time. The correlations for the R&D employee and patents granted models are also positive, again indicating convergence, but their smaller magnitude points to a somewhat weaker alignment.

Table 3
Standardized coefficients correlations across dependent variables

	Pre-IPO financing	Revenues	R&D expenses	R&D employees	Patent applications	Patents granted	Exit
A. All variables							
Pre-IPO financing	1.000						
Revenues	− 0.162	1.000					
R&D expenses	0.342	0.720	1.000				
R&D employees	0.049	0.263	0.345	1.000			
Patent applications	0.533	0.547	0.717	0.145	1.000		
Patents granted	0.332	− 0.313	− 0.363	− 0.156	0.263	1.000	
Exit	0.074	0.790	0.614	0.132	0.383	− 0.320	1.000
B. Theoretical variables only							
Pre-IPO financing	1.000						
Revenues	− 0.747	1.000					
R&D expenses	0.799	− 0.468	1.000				
R&D employees	0.240	− 0.042	0.235	1.000			
Patent applications	0.988	− 0.773	0.745	0.228	1.000		
Patents granted	0.377	− 0.478	− 0.135	0.261	0.483	1.000	
Exit	0.756	− 0.758	0.499	0.277	0.799	0.609	1.000

Overall, then, VCs' appear to understand well the factors predicting these startups' technological performance and so to have "picked winners" in this regard.

In stark contrast, the strong negative correlation between the financing and revenue model coefficients indicates a sharp divergence of the effects of alliances, patents, and top manager characteristics on VCs' financing decisions and startups revenue growth. The same is true for startups' exit rate for which the large positive correlation indicates that the same alliance, patent, and top manager characteristics that led VCs to invest more heavily in them also increased the likelihood that the startup would fail.

Taken together, the convergent influence of alliance, intellectual, and human capital on VCs' financing decisions and startups' technological performance and divergent influence of these factors on startups' revenue growth and survival are suggestive of an integrated view of the scout and coach VC roles. On the one hand, VCs appear clearly to be able to pick "technological winners." On the other hand, they also appear interested in startups teetering on the brink of collapse, but to which, given their technological potential, VCs can add the greatest potential value postinvestment.

5.4. Discussion and conclusion

Although the influence of VCs on selection among startups has been extensively studied, little research has attempted to disentangle alternative explanations for the positive association between VC backing and a startup's subsequent success. This paper was motivated by this lacuna. Our broader motivation was to add to the evolutionary literature on entrepreneurship by identifying the degree to which VCs have evolved vicarious selectors that enable them to serve as an effective "scout" or "coach" in biotechnology.

Although prior scholarship uniformly associates VC investment with positive outcomes for startups, this relationship is predicated upon two distinct mechanisms. VCs may be able to identify, preinvestment, those startups that are particularly likely to exhibit superior future performance, thus picking winners. We termed this the "VC as scout" mechanism. Alternatively, VCs may provide postinvestment management expertise and connections, thus building winners—what Hellmann (2000) calls the "VC as coach" mechanism. We proposed that one way to disentangle these different effects was to assess whether the same startup characteristics that attract VCs funding are also associated with future startup performance. The greater the convergence between these effects, the greater the ability of VCs to "pick winners"; conversely, the less the convergence, the more likely that VCs build winners.

Drawing on prior research, we advanced startups' alliances, patents, and top managers as likely to influence VCs' investment decisions. In a study of Canadian biotechnology startups, we found that a startup's alliances and patents had broadly similar effects on both attracting VC investment and on subsequent startup performance. However, those top management team characteristics that attracted VC investment had little effect on subsequent performance of the startup. Our findings thus suggest that VCs do identify startups with "the right technological and relational stuff," but while they clearly are attracted to certain top management team characteristics, VCs do not identify startups with inherently superior top management teams.

Although the lack of connection between top management team characteristics and subsequent startup performance may appear surprising at first, it is consistent with some prior research. In a study of Silicon Valley-based electronics startups, Hellmann and Puri (2002) find that VC-backed firms change to outside management faster than non-VC-backed firms. They interpret this as evidence that VCs offer value to their investees via "professionalization" of the management team. This may indicate that when VCs identify top management team characteristics as important criteria in investment selection, they are concerned with characteristics associated with getting the venture to a particular next level rather than with taking it all the way to commercialization. More broadly, these results are consistent with attribution theory, which predicts and anticipates individuals placing undue emphasis on people, rather than situations, as causes of events (Ross, 1977). Given that VCs do not select on top management team characteristics that actually harm the future performance of the startup but rather have no systematic effect on it, such error may also generate superstitious learning (Levitt and March, 1988; March, 1981) in which the misperceived causes of success—choosing good people—become reified into the vicarious selector of the VC. As Shepherd and Zacharakis (2002) have noted, based on the presumption of VC expertise, little attention has been given to VC decision-making processes or their accuracy; our findings reinforce the need for such research.

Perhaps more intriguing, however, we find that the characteristics that lead to VC financing are highly correlated with the characteristics that trigger exit. Specifically, we find that VCs are attracted to firms that have technology that can lead to strong future performance but that are teetering on the edge of short-term failure. This pattern suggests that VCs select startups for funding based on a combined logic of "scouting" out strong technology (and relationships) and "coaching" via the injection of management skill. It also suggests that startups must take on certain characteristics that increase their short-term risk of failure in order to attract the venture funding that will enhance their long-run survival and performance. This finding is consistent with the idea in the organizational evolution literature that a firm may have to take actions that increase its risk of failure in the short run in order to improve its performance and survive in the long run (March, 1981). The finding may also reflect VCs' emphasis on picking "portfolios" of startups in which to invest rather than considering their investments independently. This latter interpretation is also consistent with classic economic notions of risk and return—since VCs traditionally seek extremely high returns, they are naturally attracted to more risky startups, and consequently a startup that is at low risk of failure may also offer a return too low to interest a VC. Future research designed to disentangle these possible interpretations would extend our analysis in an important way.[8]

Although there is much to learn from our study, it is not without limitations. One potential criticism of our study is that VCs are not interested in the performance metrics that we measure. More often than not, VCs earn returns on their investments either when another firm acquires the venture or when the venture's shares are sold on open exchanges in an initial public offering. VCs distribute to their investors the proceeds from acquisitions and the shares of funded firms that have become publicly traded. Consequently, like most vicarious selectors, they optimize achievement of a particular subgoal, not adaptation per se (Campbell, 1994). Their job is to maximize returns to the fund from acquisitions or public offerings, and these may not be perfectly correlated with the venture's long-run earnings or survival chances. To the extent that IPOs and acquisitions occur with more certainty, more quickly, or at higher valuations for startups with appropriate alliance, intellectual, or human capital, this concern is mitigated. Notably, the performance metrics we used appear likely to influence IPO likelihood, timing, and valuation. Stuart et al. (1999), for example, find that startups' patents and alliances positively influence IPO results in the U.S. biotechnology industry. Further, it is likely that the relative weight given to a startup's actual performance, as opposed to other more distant early signals of its worth, should increase with the age of the firm. As a firm garners a longer track record, this record becomes more reliable as an indicator of the firm's prospects. Hence, VCs must try to turn a startup's signals of superior future promise into actual superior performance in order to secure a timely, high-value IPO.

Our findings suggest to us at least three directions for future research. First, our data do not permit us to distinguish between VCs of varying abilities. We have interpreted our findings as suggesting that VCs select startups for funding based on a combined logic of scouting out and coaching. It may be, however, that some VCs are especially effective scouts and others especially effective coaches, and that our results mix these two vicarious selectors. It may also be that some VCs are simply better selectors than others along any dimension. Future research that distinguishes VC types and capabilities—based on partners' experience, prior investment track record, or some other metric—may uncover additional nuances within the VC selection process. For example, implicit in our discussion of the scouting role is the idea that VCs learn

[8] Thanks to Ramy Elitzur for conversations around this point.

strategies for identifying good investments. It is also possible, however, to "pick winners" by learning how to avoid poor investments (Moldoveanu, 2001). In the former case, a VC searches for signs that confirm the promise of an investment; in the latter case, the VC is sensitive to signs that disconfirm its promise. Whether VCs search for the "least inferior" or the "most promising" of the alternatives that confront them may represent an important distinction between the vicarious selectors VCs invoke to carry out due diligence.

Second, our study focuses on the biotechnology industry. Although the results appear consistent with some prior research on electronics startups in Silicon Valley (e.g., Burton et al., 2001; Hellmann and Puri, 2002), application of this study's methodology to other industries would provide evidence on the generalizability or lack thereof of our findings. Different sources of uncertainty in different industries (i.e., appropriability concerns, while essentially nonexistent in biotechnology, may be much greater in semiconductors) and different levels of "stickiness" of startup characteristics (i.e., human capital may be less fungible in biotechnology than in electronics if biotechnology startups rely on "star scientists" more than electronics firms) may, for example, generate different VC investment patterns and future startup performance across different industries. Of particular interest is identifying whether key startup characteristics are similar across all startups or whether they are contingent on the particular abilities of VCs to operate as scouts or coaches in different industries. Relatedly, in addition to assuming cross-sectional homogeneity in VCs vicarious selectors, we also assume that VC selection criteria are constant throughout our study period. While this may be a reasonable assumption over the relatively short 10-year span our data covers, examining longer time horizons would permit examination of the evolution of VCs' vicarious selectors themselves over time.

Although evidence suggests that VC-backed startups outperform non-VC-backed startups, the source of this performance advantage remains unclear, and so the source of VC value—both to startups and VC fund investors—also remains unclear. We offer some of the first empirical evidence regarding whether VCs emphasize picking winners or building them. Our findings point to a joint logic that combines elements of both roles. Our findings thus support the presumption of VC expertise but only to a point. VCs' financing decisions appear to be affected by cognitive tendencies that lead them to overemphasize startups' human capital when making their investment decisions. Given our results, we think future studies clarifying the role of VCs and treating startup valuation as a problematic inference process influenced by distorting factors including attribution errors can add greatly to the emerging evolutionary perspective on entrepreneurship.

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