Venture Capital Firms and Entrepreneurship:  
A Study of Start-Up Companies and Their Funding

Emilio J. Castilla*  
The Wharton School  
University of Pennsylvania  
Management Department

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Abstract

Research on what determines the performance of start-up companies is characterized by a sharp debate in the literature of economic sociology and the sociology of the economy. There is one extreme view proposing that in the long run, a rational market takes care of allocating scarce resources such as venture capital funding to the most potentially profitable and exciting business plans. By contrast, a more sociological social network perspective highlights how entrepreneurial efforts and economic activities are more successful when embedded in a densely connected network of social actors. My research adds to the study of new organizations’ performance by examining the different economic, regional, and sociological factors influencing the performance of venture capital funded start-up companies (between 1995 and 1998) in the United States. I find evidence that after controlling for the economic characteristics of portfolio investments, network variables still play an important role in explaining start-up companies’ success. Companies backed by venture capital firms involved in more dense patterns of co-investments are more likely to go public (or to merge / get acquired) than start-ups funded by isolated venture capital firms. In addition, the success of a company in the public market seems to be significantly enhanced when its funding comes from a syndication network of venture capital firms with at least one highly central and structurally autonomous venture capital investor. Most importantly, my analyses also show that the same network structure seems to predict the survival of the newly-created company, finding support to the often ignored argument in economic sociology that social ties, under certain circumstances, can result in the funding of non-profitable business ventures as well.
Introduction

For decades now, we have seen a stream of theoretical and empirical studies examining how social relations shape economic processes and institutions (for a review, see: Swedberg 1997, Granovetter 1973 and 1985; Burt 1992; and Baron and Hannan 1994). Most sociological work in this area has studied the broader social context of the economy and economic activity, identifying the important social actors and the connections between them. In the literature of regional studies only, economist sociologists have argued that dense network structures (like the one in Silicon Valley) provide the support that facilitates and even accelerates the process of starting new technology-oriented businesses. Thus, it has been argued that this support structure is what fostered the Valley’s tremendous economic growth in the 1980s and 1990s (Saxenian 1990 and 1994; Florida and Kenney 1987; Nohria 1992). While most of these studies have tended to provide very little (or even no) empirical evidence of such claims across different technology regions, they have proposed different theoretical mechanisms (and explanations) for why and under which conditions social relations might benefit economic and social processes.

Only recently, a few studies have started to empirically examine some of these underlying mechanisms explaining the success of companies located in different industrial regions and to consider how the particular network structure of relevant social actors in different locations and regions could have facilitated the process of starting new businesses (see Baron, Hannan, and Burton 2001; Castilla 2003; Castilla, Hwang, Granovetter, and Granovetter 2000; Powell, White, Koput, and Owen-Smith 2003; and Sorensen and Stuart 2001). While much progress has been made in understanding the social basis of economic phenomena such as the funding and success of start-up companies, still important questions remain unanswered. First, we still know very little about the relationship between different economic, regional, and sociological (including social network) factors and the performance of newly created companies. For example, despite the fact that work on industrial clusters has focused on the spatial concentration of industries and the advantages of agglomeration externalities and/or knowledge spillovers, we still have not been able to distinguish between the returns an organization might gain from locating itself near other firms and the importance of other (non-spatial) cross-organizational ties. A second important trend in this line of research within economic sociology is to overemphasize the benefits of embeddedness to firms. Evidence for the benefits of embeddedness has accumulated with particular speed in the literature on organizations. Thus, it has been demonstrated that cross-
organizational networks can potentially increase a company’s access to crucial private
information and resources (Granovetter 1985; Podolny 1993) and/or facilitate and increase the
performance of any new venture (Sorenson and Stuart 2001). However, alternative (and often
ignored in this literature) mechanisms can explain the exact opposite, and consequently account
for how social networks can in fact have negative consequences on company performance.
Because social actors prefer to exchange with known partners (i.e., those with whom they have
prior relationships), the propensity to avoid activities with new actors can ultimately result in
inefficient exchanges and non money-making outcomes. Without direct measures of company
location, information about the local economic activities and employment, it is difficult to
distinguish among these singular arguments when it comes to understanding organizational
performance. Also the field’s lack of information on the wide array of company’s outcomes
(such as initial public offering (IPO), merger or acquisition, or bankruptcy) renders us incapable
of adjudicating among these two competing accounts in the embeddedness research stream.

One way to make progress on this subject is to directly examine the relationship between the
different economic, regional, and sociological factors and the performance of start-up companies.
Using performance data for all company investments for a sample of venture capital firms in the
United States, I examine how the economic characteristics of the investment, the location of the
start-up company, and the properties of the syndication networks of venture capital firms interact
with the long-term technological and performance trends of start-up companies, placing
particular emphasis on venture investing and on networks of venture investors in the United
States. Performance data includes organizational outcomes such as going public, going defunct
or bankrupt, as well as being involved in mergers and acquisitions. I present my arguments as
follows. I start with the economic assumption that a rational market takes care of allocating
scarce resources such as venture capital funding to the most potentially profitable business plans.
Then I move toward alternative, sometimes complementary explanations that account for the
success of start-up companies and venture capital financing. Thus, I test the proposition,
common in recent studies of economic geography, that any unit of space (such as a city or a
region) with a high diversity of social actors and economic activities promotes the success of
newly established companies. A sociological perspective highlights how entrepreneurial efforts
and economic activities are more successful when embedded in a densely connected network of
social actors (Castilla, Hwang, Granovetter, and Granovetter 2000). Thus, economic growth
depends on densely networked interactions of subsets of actors specialized in converting science-based inventions into commercial innovations —what has been called a regional “ecology” or “habitat” of innovation (Lee, Miller, Hancock, and Rowen 2002). Here I incorporate information about the network of venture capital firms in predicting start-up firm success and performance. I use network methods that enable us to identify the most influential and central venture capital firms and to examine their impact on the entrepreneurial companies in which they invest. I also add to my empirical model information about the quality of this network of venture capitalist firms investing in a given start-up company. The aggregate of trust, reputation, experience, familiarity, and other social dimensions of previous or simultaneous interactions constitutes social capital, which can be the critical determinant of any company’s capacity to innovate and therefore to be successful in the market. By integrating existing research on organizational performance, this paper has implications for the literature on innovation and regional development and for the work of economic geographers and science/technology policymakers.

I have three major goals with this research. The studying of the success or failure of newly created start-up companies has important theoretical and empirical implications for future studies in the area of firm performance in economic sociology. Research on what determines organizational performance (more specifically start-up firm performance) is characterized by a sharp debate in the field of economic sociology and sociology of the economy. On the one hand, there is the extreme view which proposes that in the long run, a rational market takes care of allocating scarce resources such as venture capital funding to the most potentially profitable and exciting business plans. By contrast, the sociological view highlights how entrepreneurial efforts and economic activities are more successful when embedded in a densely connected network of social actors. Most sociological work in this area has studied the broader social context of the economy and economic activity, identifying the important social actors and the connections between them. A common concern among economists, though, is that these analyses in sociological network terms often overlook the logical implications of economic theories of information, incentives, and reputation. While many economists have become increasingly interested in modeling social relations in economic terms, economists and sociologists still have much to gain by broadening the scope of their work, expanding their interaction, and
productively influencing each other’s research. For this reason, integrating and clarifying these different insights about social structures and the economy is central to this study.

Second, to date, little is still known about which social relations (or under which circumstances social ties) might facilitate or derail economic processes. In this sense, we still have not formulated and tested the different mechanisms by which social relations matter in the economy. To explain the benefits of social embeddedness to firms, researchers have typically highlighted (at least) two mechanisms through which social networks might produce more efficient organizations. The first one puts emphasis on the access to private information that these networks provide prior to any economic transaction (consistent with Granovetter 1985; Podolny 1993). The second mechanism highlights how cross-organizational networks can potentially facilitate and increase the performance of any new venture (Sorenson and Stuart 2001). While all these factors are likely to explain why embedded exchange is more efficient in many important contexts, there is still no reason to discard the importance of alternative (and very often ignored) mechanisms that can account for the negative consequences on performance of embedded economic transactions. Network ties might substitute the due-diligence behind the process of searching and evaluating information which could be gathered about the quality of the potential exchange actors and their offerings. Another related argument has to do with the fact that social networks can sometimes increase the sense of obligation of exchange and reciprocity among the set of embedded actors (Polanyi 1944). This sense of obligation does not necessarily result in efficient outcomes. By examining different new business venture outcomes, this paper explores the role of social networks of one particularly crucial type of firm at this time, the venture capital firm, in explaining both the success and the failure of their investee companies.

This paper has an important third goal. The economic and sociological accounts described above are still incomplete because they ignore the literature that discusses how geographic location affects the likelihood of a start-up company’s success. A large body of literature, mainly theoretical and in the fields of regional economics and economic geography has been devoted to the spatial concentration of industries. Much research in this area has focused on agglomeration externalities, and therefore analyzes the advantages an organization might gain from locating itself near other firms. This literature also highlights how “knowledge spillovers” between geographically proximate firms serve to create self-reinforcing regional advantages in terms of innovative capacity (see Solow 1994 and Romer 1994). Much recent work on industrial
clusters additionally analyzes how information on new technologies and innovations diffuses within limited areas that contain many social actors working on similar problems and activities. When people with common professional interests cluster in physical space, informal social and professional networks emerge—that in turn serve to disseminate information about new technologies, promising market opportunities, or important technical answers to difficult questions (Piore and Sabel 1984; Saxenian 1994; Almeida and Kogut 1997; see Sorenson and Stuart 2001 for a review of some of this work in economic geography). In this paper, I also test the proposition, common in recent studies of economic geography, that any unit of space (such as a city or a region) with a high diversity of social actors and economic activities promotes the success of newly established companies.

In the next section, I provide a set of testable hypotheses that can offer some understanding of the different mechanisms in the literature underlying the success (as well as failure) of start-up companies. In the empirical setting section, I briefly describe the venture capital industry and the data I will be analyzing in this paper. I then present the empirical results about the impact of venture capital funding on the process of going public, as well as on start-up performance for a sample of 4,160 start-up firms in the United States which received venture funding from 1995 up to 1998. In the conclusion, I discuss the results of my analyses and suggest directions for future research on social networks on the one hand, and firm performance and regional development on the other.

Theory Review and Hypotheses

In this section, I begin with a literature review of the various theoretical propositions explaining the effects of venture capital funding characteristics and other regional factors on start-up companies’ success. I start controlling for the economic arguments about how the amount of funding and the number of investors signal the quality of a start-up company’s business plan. I continue with central propositions from the vast literature on geography, regional economics, and technology and innovation, focusing on the idea that innovation and entrepreneurship require a location where complex interactions among diverse economic actors and activities can take place. The proposition here is that diversity (rather than specialization) of economic actors and activities is crucial to innovation and to entrepreneurs’ ability to turn new knowledge into successful business enterprises. I continue with central propositions in the
economic sociology and social networks literature about how networks of social actors produce important organizational outcomes. Here I examine the proposition that entrepreneurial efforts are more successful when embedded in a densely connected network of social actors (Granovetter 1985).

**Venture Capital Funding, Industry, and Other Controls**

At the core of the economic theory lies the assumption that venture capitalists and any other investors will only invest in the most potentially profitable firms. Thus, those start-up companies with the greatest potential to succeed and to generate revenue should receive the most funding from venture capital firms. In this sense, venture capital funding (more specifically, the amount of money and the number of investors a given start-up company acquires) are important (and reasonable) signals to the market about the potential profitability and success of exciting business plans. In the aggregate, this leads to the important assumption that start-up companies receiving higher amounts of venture capital funding (as well as start-up companies with a higher number of investors) perform better than those receiving lower amounts of venture capital funding (or those with a lower number of venture capital investors).

Also, it is worth reminding that firms backed by venture capital firms find it difficult to meet their financing needs through traditional mechanisms. Gompers and Lerner (1999) highlight four factors that may limit access to venture capital for some of the most promising firms: uncertainty, asymmetric information, the nature of the firm’s assets, and the conditions in relevant financial and product markets. At any time, these four factors determine the financing choices that a firm faces and therefore also determine the likelihood of its going public. I therefore control for the industry of the start-up company by including several dummy variables for firms in the biotechnology, business services, communications, consumer, healthcare, industrial, and software and information industries, the seven most common types of industries in my sample of firms (these seven categories account for more than 75 percent of all investments during the period of analysis of this study). I also control for the stage of the investee company by including several dummy variables for companies in the initial/seed, first, second, third, and fourth and beyond stages (also for the bridge/mezzanine, and follow-on stages).
Diversity of social actors and economic activities

The previous section emphasized how venture capital funding and the number of investors in a given start-up project (as well as other industry or product line and investment stage) can predict the start-up company’s economic success. However, these economic accounts are still incomplete because they ignore the literature that discusses how geographic location affects the likelihood of a start-up company’s success. A large body of literature, mainly theoretical, in regional economics and economic geography (of great importance to not only urban but also science and technology planners and policymakers) has been devoted to the spatial concentration of industries. Much research in this area has focused on agglomeration externalities, and therefore analyzes the advantages an organization might gain from locating itself near other firms and important economic institutions. This literature also highlights how “knowledge spillovers” between geographically proximate firms serve to create self-reinforcing regional advantages in terms of innovative capacity. This literature includes not only classical works on location and the structure of regions (see Losch 1937 and 1954; and Isard 1956), but also more contemporary models like the ones by Solow (1994) and Romer (1994). Much recent work on industrial clusters additionally analyzes how information on new technologies and innovations diffuses within limited areas that contain many social actors working on similar problems and activities. When people with common professional interests cluster in physical space, informal social and professional networks emerge—that in turn serve to disseminate information about new technologies, promising market opportunities, or important technical answers to difficult questions (Piore and Sabel 1984; Saxenian 1994; Almeida and Kogut 1997; see Sorenson and Stuart 2001 for a review of some of this work in economic geography).

In the literature on cities and economic development, Jacobs (1961, 1969, and 1984) and Bairoch (1988) put forth the pioneering alternative proposition that diversity (not specialization) of economic actors and activities is the key factor to vitality. Glaeser, Kallal, Scheinkman, and Shleifer’s empirical study of growth in a cross-section of U.S. cities (1992) supported the claim that at the city-industry level, specialization “hurts” whereas diversity helps economic and employment growth. Subsequent studies by Henderson, Kuncoro, and Turner (1995) demonstrated that economic diversity is an important factor in explaining the creation of new
firms and the development of cities (for a survey of this literature, see Quigley 1998). In this same line of predictions, the ecological account in sociology claims that although new ventures in geographically crowded areas with specialized activities and actors benefit from proximity to technical experts, they suffer from the rivalry of nearby competitors (Freeman and Hannan 1989; Stuart and Sorensen 2003). This implies that firms in dense industrial clusters may experience more intense competition in both labor and product markets. Labor market competition occurs because firms compete for the same local labor supply; product market competition results from the strategic convergence implied by high rates of inter-firm personnel mobility and by demographic similarity.

In sum, proponents of diversity theories (both general and specific) suggest that companies in regions with higher numbers of diverse economic actors and activities might enjoy important positive economic externalities accounting for their success in the market. Consequently, some geographic areas with highly diverse economic activities and actors afford more opportunities to the success of new ventures than do others with more economic specializations. This leads to the following two testable hypotheses:

**HYPOTHESIS 1a.** Start-up companies located in areas with a higher level of employment and economic activities perform better than those located in areas with a lower level of employment and economic activities.

**HYPOTHESIS 1b.** Start-up companies located in areas with a higher level of diversity in employment and economic activities perform better than those located in areas with a lower level of diversity in employment and economic activities.

Still there is a particularly distinct but nonetheless related stream of research within this second view about the importance of geography in understanding the success of young firms. Many social scientists propose that in addition to being a critical source of capital for many start-ups, Silicon Valley’s venture capitalists and other important institutions played a central role in developing the region’s social and professional networks, especially when compared with venture capitalism’s more passive role in other regions such as Route 128 (Saxenian 1994; 10)

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1 Working with a broader definition of “diversity,” Florida (2002) argues that a region’s diversity along cultural and other human dimensions suggests a creative population. This in turn generates the “new combinations” that are the source of regional competitive advantage.
Florida and Kenney 1987; Nohria 1992). Networks of venture capitalists in Silicon Valley relied on major inflows of technical entrepreneurs, venture capitalists, management talent, and supporting services from other regions. This shared regional affiliation provided an underlying social bond for the region’s network of entrepreneurs and inventors (Nohria 1992: 255). These arguments lead to the following testable hypothesis. Even after controlling for the level of employment, economic activity and diversity in economic employment activities, young companies will still benefit from locating in the Silicon Valley area in comparison with companies located in other areas of the United States. Thus, it follows that:

**HYPOTHESIS 1c.** Start-up companies located in Silicon Valley perform better than those located in other areas within the United States.

**Syndication Networks of Venture Capital Firms**

The last set of mechanisms by which start-up companies might benefit are more sociological and emphasize the structure of relationships among the different venture capital investors. The idea is that the success of a company is facilitated by a network of investors. There is abundant evidence for the benefits that embedded exchanges provide to those actors engaged in them. Several studies, for example, find a positive relationship between position in corporate directorate interlocks and firm performance (e.g., Mizruchi 1992; Geletkanycz and Hambrick 1997), support that repeated transactions between buyers and suppliers lead to more cooperative behavior and improved performance to buyers (e.g., Heide and Miner 1992; Zaheer, McEvily, and Perrone 1998), and demonstrate a relationship between the stability of a firm’s network of strategic alliance partners and its financial performance, innovativeness and longevity (e.g., Mitchell and Singh 1996; Powell, Koput, and Smith-Doerr 1996, just to name a few). Similarly, Uzzi (1996) finds lower failure rates among garment manufacturers that interact more intensively with a limited set of exchange partners. Stuart (2000) reports that semiconductor firms in alliances with highly innovative partners benefit both in terms of their own rate of innovation and in sales growth. Ingram and Roberts (2000) show that hotels with managers who have more extensive and cohesive networks to rivals enjoy higher utilization rates, a key measure of success in the hotel industry. In the context of venture-capital-backed biotechnology firms, Stuart, Hoang, and Hybels (1999) support that young firms with inter-organizational ties go to IPO faster and earn greater valuations at IPO than young companies that lack such connections.
In this study I examine the theoretical proposition that the likelihood of start-up success and ultimate financial wealth does not depend entirely on broad economic diversity nor on specialization, but rather on densely networked interactions among social actors (such as venture capital firms) that specialize in converting innovative ideas into commercial successes. In a study of Silicon Valley social networks, Castilla, Hwang, Granovetter, and Granovetter (2000) note that dense networks within and across groups of engineers, educators, venture capitalists and angel investors, lawyers, and state and local development officials are important channels for diffusing technical and market information. This “regional ecology” of innovation is assumed to be independent of specific business models or industry sectors; it is a pure network explanation for firms’ economic performance. Castilla (2003) empirically illustrates two of the most important differences in venture investing between Silicon Valley and Route 128. First, collaboration networks among venture capital firms in Silicon Valley are denser and more dominated by connected cliques than those in Route 128; second, the number of investments and amount of money invested locally by Silicon Valley venture capital firms are much higher than corresponding numbers and amounts invested locally by Route 128 firms. Although these two differences in network structure might have shaped the allocation of resources, support, information, and legitimacy necessary for new local organizations’ development and success, there is still no empirical causal analyses to demonstrate that these networks explain the long-term development of the region.

Theoretically speaking, and in the aggregate, trust, familiarity, and other human and social dimensions of interaction emerge as part of the social capital that is a critical determinant of a firm’s success. In general, economic sociologists and organizational researchers have long highlighted how networks and network position can be beneficial to organizations. In the classical work by Granovetter (1973), we learn about the importance of a position characterized by weak, bridging ties. Burt (1992) refines this argument, decoupling the benefits of weak ties from the average strength of those ties. As Burt writes, tie weakness is a correlate rather than a cause of the value deriving from bridging ties; thus, according to Burt’s argument, the most useful type of ties are those which serve as a bridge to distinctive sources of information. In this

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2 See Castilla, Hwang, Granovetter, and Granovetter (2000] for a review of different empirical and theoretical studies in the branch of the literature that focuses on networks and the regional ecology of innovation.
paper, I explore this network argument within the venture capital industry only. Following the core contribution of a network perspective, the higher the centrality of the venture capital firms involved in the funding of any given start-up company, the greater the benefits for the start-up company’s future development and success. Thus, if this theory is correct, those firms receiving funding from highly central venture capital firms should be more likely to be profitable:

**HYPOTHESIS 2a.** Start-up companies receiving funding from highly central venture capital firms perform better than those start-up companies receiving funding from less central venture capital firms.

Burt (1992) additionally argues that structural holes yield both information and control benefits. Focusing on the information benefits only, Burt proposes that a network position with many structural holes is beneficial to a firm essentially because it can help resolve the firm’s uncertainty about any necessary market decision, such as a firm’s decision of investing in a newly created start-up company. In the inter-organizational context, the original claim is that the more structural holes that exist in a firm’s network of relations with other firms, the greater the information that the focal firms have about a wide range of market opportunities and how to fill those opportunities. Because structural holes help reduce egocentric uncertainty, firms possessing many structural holes in their network should make more successful investments. Or, stated in the form of a hypothesis:

**HYPOTHESIS 3a.** Start-up companies receiving funding from venture capital firms with more structural holes perform better than those start-up companies receiving funding from venture capital firms with fewer structural holes.

Scholars have generally highlighted two of the mechanisms explaining why social embeddedness might benefit firms. In the context of venture capital firms, the first mechanism has to do with how social ties can provide access to information regarding the quality of the investment. Thus, even if one assumes that venture capitalists have a certain ability to pick winners, those venture firms in axial positions will have access to a greater quantity and more valuable (higher quality) information which can help them make better informed selections of business ventures in which to invest in from a large pool of potential investments (this is consistent with Granovetter 1985 and Podolny 1993). A second mechanism has to do with the fact that social networks facilitate and even increase the performance of any new venture. This
revolves around the ability and willingness of these venture capital firms to help portfolio companies in recruiting managers and customers, analyzing markets and solving important strategic, production, and organization problems (Bygrave and Timmons 1992) to maximize the performance of the investment. Additionally, social networks can help to enforce contracts, either through better observation of whether the other party completed their side of the bargain, or via the applications of threats of punishment in response to non-compliance (Coleman 1990). Regardless of whether social networks reliably predict the future performance of young start-up companies or not, social networks can still produce more efficient companies even after they have been screened and funded by venture capital firms. These two mechanisms are also consistent with the economic argument that highlights the importance of incorporating the characteristics of the investors, one of them being status or centrality as proxies for the quality of these venture capital firms as investors. Economists have argued that professional service firms, for example, can certify the quality of young companies (e.g., Megginson and Weiss 1991). Lee, Lee and Pennings (2001) show that once you control for the internal capabilities of the different technology-based ventures, only the connections to venture capital firms predicted the start-up’s performance measured as sales growth. Much of the work in this area has demonstrated that firms that use prestigious investment banks are able to garner higher share prices when they first issue securities. In general, economists think that social networks are not independent of performance; therefore, social connections are important proxy variables especially when quality is not observed or is costly to measure.3

While most of the empirical past studies have tended to overemphasize the above mechanisms under which social relations benefit economic processes, there are reasons to support the idea that under certain circumstances social ties might end up in inefficient exchanges. Again in the context of venture capital firms, because venture investors prefer to

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3 For instance, the effect of investment bank prestige on underpricing, defined as the spread between the subscription price of a security and the value of the security after it is traded on the public markets for one or more days. Underpricing is costly to issuing firms because it implies that firms sell their shares at a low price relative to market value and thus garner smaller proceeds from an IPO. Economists have long argued that low-risk firms attempt to signal their risk position to the market by using high-prestige underwriters. Since investment banks must be concerned about their ability to sponsor new issues in the future, their prestige is a credible signal of the issuing firm’s quality because they have a strong incentive to preserve their status levels by avoiding low-quality securities. Under this theory, social relations are a proxy for information about the quality of the company that is difficult (and expensive) to measure (or observe).
exchange with known parties (i.e., those venture investors with whom they co-invested in the past, for instance), the propensity to avoid co-investments with new venture capital firms can ultimately result in non-profitable (or even costly) investments. This notion that over-socialization can be detrimental to social actors is indeed present (and often ignored) in the classical work in economic sociology (Granovetter 1985 and Polanyi 1944). Network ties might substitute the due-diligence behind the process of searching and evaluating information which could be gathered about the quality of the potential exchange actors and their offerings. In this sense, actors might get into economic exchanges that they would not have gotten into had they evaluated critically any information about quality of the potential exchange partner and its offerings. Another closely related mechanism has to do with the fact that social networks can sometimes increase the sense of obligation of exchange and reciprocity among the set of embedded actors (Polanyi 1944). In this sense, previous exchanges could actually increase the sense of obligation to reciprocate some time in the near future even if the quality of the common new venture is far from being perceived as efficient. In sum, in the venture capital industry this translates into venture capital firms co-investing with other prior firms —more even so when they actually are not completely sure about the quality of the start-up company in which they are co-investing. The above two mechanisms therefore suggest that if there is no objective screening of potential exchange partners or investments, networks might actually have a negative impact on the economy.

In this paper, and because I have information about different outcomes for the different start-up companies, I can investigate whether the social network position in one kind of organizational networks (e.g., venture capitalists) has a positive or a negative impact on one kind of organizational outcome (e.g., the performance of the investee company). Thus, if the alternative mechanisms apply in this setting, those companies receiving funding from highly central venture capital firms should be more likely to fail:
HYPOTHESIS 2b. Start-up companies receiving funding from highly central venture capital firms are less likely to survive than those start-up companies receiving funding from less central venture capital firms.

At the same time, a strategic firm position in terms of a high number of structural holes might be detrimental to the company as long as such position is a substitute for the due-diligence behind the process of searching and evaluating information about the quality of the potential start-up company. In this sense, certain venture capital firms might invest in certain start-up companies that they would not have invested in had they taken the time and resources to critically gather and evaluate any information about the quality of company. Or, stated in the form of a hypothesis:

HYPOTHESIS 3b. Start-up companies receiving funding from venture capital firms with more structural holes are less likely to survive than those start-up companies receiving funding from venture capital firms with fewer structural holes.

My second set of hypotheses concerns the characteristics of the network of venture capital firms providing funding to a given start-up company. Here one should explore whether the accumulated experience of the group of venture capital firms co-investing in a given company enhances the success and helps to maximize the performance of newly established companies. Consistent with the “structural holes” view of social capital (e.g., Burt 1992), this approach expects that a start-up company will be more likely to survive and to perform better when its network of venture capital firms includes numerous links to venture capital firms with different levels of expertise in the financing of high-technology companies. Thus, this argument leads to the following two testable hypotheses:

HYPOTHESIS 4a. Start-up companies receiving funding from a network of venture capital firms with higher investment experience perform better than those start-up companies receiving funding from a less experienced network of venture capital firms.

HYPOTHESIS 4b. Start-up companies receiving funding from a network of venture capital firms with higher investment experience are more likely to survive than those start-up companies receiving funding from a less experienced network of venture capital firms.

By investment/deal experience in a network of venture capital firms, I refer to variables that measure different aspects of the venture capital firms’ quality as business investors; these include the number of different companies in the venture capital’s portfolio, experience in company
investments at different stages, industries, and/or locations. I also include a variable measuring the number of successful start-up companies in the past venture capital’s portfolio (i.e., the number of IPO companies). Those start-up companies receiving funding from a network of venture capital firms with higher investment (and especially IPO “success”) experience are likely to be more triumphant than start-ups receiving funding from a less experienced network of venture capital firms. Having information about the quality of the network of venture capital firms investing in a given start-up company allows us to provide a more refined test of whether it is the centrality or the number of structural holes in the syndicate network of venture capital firms on the one hand, or whether it is the quality of the syndicate network as investors that accounts for any start-up performance differences, on the other. Such a clean test is crucial because social relations and quality can be related in complicated ways (and more importantly, they are likely to be confounded). In general, economists believe that social networks are not independent of productivity, and are, therefore, valuable proxy variables when quality or performance data is not available. In this study, I will include several direct measures of past venture capital firm performance or quality as an investor when testing the effect of venture capital firms’ network position on start-up company success.

In addition, I examine patterns indicating the physical proximity of the venture capital firms to the focal start-up company. More specifically, I study the extent to which a start-up company receiving funding from a nearby group of venture capital firms can enhance its chances of going public and performing well. Sociologists have long asserted that spatial proximity greatly facilitates relationship formation, and substantial empirical work now supports this view (Blau 1977; Sorenson and Stuart 2001). Stuart and Sorenson (2003) contend that new firms tend to concentrate in space mainly because entrepreneurs find it easier to mobilize essential resources when they reside closer to those resource-providing actors. A network-based account of start-up companies’ spatial location in relation to the venture capital firms highlights the benefits of ties between geographically proximate venture capital firms and companies, arguing that encounters between people in the venture capital firms and in the start-up companies enhances the start-up’s performance capacity. Here, there is plenty of anecdotal support for the fact that venture investors actively monitor the companies in which they invest, insisting upon close and frequent interactions with company leaders (Gompers 1995). Venture capital firms also help portfolio companies to recruit managers and customers, analyze markets, solve strategic, production, and
organizational problems, identify new investors and strategic partners, and select lawyers, consultants, accountants, and investment banks (Bygrave and Timmons 1992). Because of the depth and intensity of the relationship, venture capitalists prefer to fund ventures that are spatially proximate to at least one of the co-investors. Thus, I predict that:

**HYPOTHESIS 5a.** Start-up companies receiving funding from at least one venture capital firm closer in space to the company perform better than those start-up companies receiving funding from venture capital firms located further away.

**HYPOTHESIS 5b.** Start-up companies receiving funding from at least one venture capital firm closer in space to the company are more likely to survive than those start-up companies receiving funding from venture capital firms located further away.

The Empirical Setting: Venture Capital Firms and Their Investments

The venture capital industry has been thoroughly described by many researchers (Castilla, Hwang, Granovetter and Granovetter 2000; Podolny 2001; Sorenson and Stuart 2001; Castilla 2003). I give a very brief review here. Venture capital firms are management firms that invest capital in companies at different stages of development. The capital is provided by individual and corporate investors who contribute to the “fund.” Venture capitalists participate together in rounds of financing of companies. Some venture capitalists clearly have strong preferences for working with certain venture capital firms. Those currently investing in a young company often might be recruiting and selecting other venture capital firms for participation in subsequent rounds of financing. These processes create cliques of venture capital firms that cooperate with each other in funding similar start-ups or investee companies in other development stages (Castilla 2003). Social networks are also important sources of power and influence (see Mintz and Schwartz 1985). In Silicon Valley, for example, it has been shown that venture capitalists play more than merely conventional roles (see Castilla, Hwang, Granovetter and Granovetter 2000 for an extensive review). They are highly influential when it comes to the shaping as well as the future evolution of their client organizations. Venture capitalists provide start-ups not only with financial resources but also with management, recruiting, accounting and legal advice, and other consulting services that are just as important to the success of the new venture as is the funding. Moreover, venture capitalists have access to an informal and formal network of professionals and experts who can evaluate the long-term viability of a newly created firm, and provide in-depth knowledge of high technology industries from their portfolio of ventures.
These networks constitute a form of social capital, and are a good example of Granovetter’s embeddedness concept (Granovetter 1985). The entrepreneurial effort, as well as its financing by venture capital firms, is clearly embedded in a formal and informal network of social connections that provide support, information, status, and legitimacy to the investee company.

**Data**

The data I analyze in this paper consists of a sample of venture capital firms and their investments in start-up companies from 1995 until the first quarter of 1998. The survey was administered by PricewaterhouseCoopers. The part of the sample studied here covers a total of 7040 investment instances by 623 different venture capital firms located in the United States. The sample includes venture capital firms with investments in companies operating in different industries and at different stages. The sample also includes a wide variety of venture capital firms, ranging from those focusing on seed money to those working on more advanced and developed entrepreneurial business projects. The PricewaterhouseCoopers Money Tree Survey is a quarterly study of equity investments made by the venture capital community in the United States. Survey questionnaires are mailed. For more information about the survey, go to: http://www.pwcmoneytree.com/

For all 4,160 different investee companies that I analyze here, I collected additional information such as the current status of the company, founding date, industry, and other relevant financial information at time of IPO, such as time to go IPO, earnings per share, market capitalization, or revenue prior to IPO. This information was coded from different sources (including www.ipodata.com, www.ipo.com, and Venture Expert). Some of these data were also updated from the company’s own web page. I also collected employment and other demographic and economic information for the cities, zip codes, and states where these start-up companies are located. This information is coded from several sources; mostly, these sources include the U.S. Census Bureau, the County and City Data Book, and the Zip Code Business Patterns for the relevant historic period of time under study. The specific variables included in the analyses are described below, in the dependent and independent variables sections. More relevant to this study, I followed this sample of start-up companies through time and collected financial performance information for those that went public. My period of study goes until the end of 2002, when I closed the observation window. The main dependent variable under study is
a dichotomous variable that takes the value of 1 if the start-up company goes public (i.e., goes IPO) anytime during the period of analysis, and has a value of 0 otherwise. A set of several dependent variables provides available proxies of the company’s performance at time of IPO. These measures include variables such as time to IPO, earnings per share, market capitalization, and revenues. The measurement of organization performance (especially of created start-up companies) has often been criticized because of the lack of appropriate performance indicators for the new business ventures (Lee, Lee, and Pennings 2001). I believe that the several performance measures included in this study will help us clarify the impact of these different variables on possible new business venture outcomes. In addition to the IPO information, I have also coded information about other important start-up outcomes (such as merged or acquired, and bankrupt or defunct).

I have also examined network data from this sample of investments. For the venture capital firms in the sample I created co-investment matrices that change over time. I took several different measures of the characteristics of such syndication networks and their venture capital firms, starting with the standard centrality measure and the structural holes indicator, and then adding measures such as level of experience in funding different industries, stages, and/or locations. I also took into consideration the venture capital firms’ physical proximity to their portfolio companies. Finally, I include information about the number of IPO past successes of any given venture capitalist (e.g., IPO successes before the observation period), as probably one of the best proxies for the quality of the venture capital firm as a new business venture investor.

Data and Methodology

In this section I examine the relationship between economic, regional, and sociological factors and the performance of start-up companies, emphasizing how differences in the network cooperation among venture capital firms all over the United States from 1995 can explain differences in the success of venture-capital-backed start-up companies. In doing so, and practically speaking, this study provides important managerial implications to entrepreneurs who face a great deal of uncertainty about their business ventures. This network approach can also help social scientists and policymakers to understand the nature of the relationship between social networks of actors and regional development. Such types of network analyses are indispensable steps for understanding industrial and regional economies.
Dependent Variables

Table 2.1 contains summary statistics for the key dependent and independent variables included in this study. Following the literature, the main dependent variable measuring company performance is a dichotomous variable that takes the value of 1 if the start-up company goes public (i.e., goes IPO) anytime during the period of analysis, and has a value of 0 otherwise. A set of several dependent variables provides available proxies of the company’s performance at time of IPO. These measures include four main variables. The first variable is the logarithm of time to IPO; this variable measures the (log) number of days that the start-up took before it first sold its stock to the public. Earnings per share (logarithm) is a financial variable measuring the total earnings divided by the number of shares outstanding (i.e., the shares of a company’s stock that have been issued and are in the hands of the public, also called outstanding stock). The third variable is market capitalization or gross proceeds (logarithm), which measures the market price of an entire company, calculated by multiplying the number of shares outstanding by the price per share. Finally, the revenues (logarithm) variable measures the amount of revenues the company has generated prior to the offering (in millions of dollars). I use the logarithm of these several variables to guarantee that the dependent variable is normally distributed.

The initial public offering (IPO) is probably one of the most critical events in the lifetime of a young firm, however there are other important events often ignored in the organizational performance and social networks literature. Table 2.1. also contains summary statistics for two other important outcome variables. Merger and acquisition is a dichotomous variable that takes the value of 1 if the start-up company was acquired or merged with another company during the period of analysis (value of 0 otherwise). Bankrupt and defunct is a measure of a company’s failure and this variable takes the value of 1 if the start-up company went bankrupt or died during the period of analysis (0 otherwise).

Independent Variables

Several independent variables are included in the IPO and the other start-up performance models. Their summary statistics can also be found in Table 1. Three sets of independent variables are used. The first set includes important economic variables that could influence the process of going public for newly created small companies: the age of the company in years, the
age squared, the total amount of money received from venture capital firms during the period under study (in millions of dollars), and the number of venture investors (highly correlated with the number of investment rounds). The analyses also include a set of dummy variables to control for the major industries in the sample of start-up companies (i.e., biotechnology, communications, and software, healthcare, industrial, consumer, and business services). In addition, I included a set of dummy variables to control for the stage of the investee company by including several dummy variables signaling start-up companies in the initial/seed, first, second, third, and fourth and beyond stages (also for the bridge/mezzanine, and follow-on stages); three additional dummy variables are used to control for the first year of investment in any given company in the sample during the period of analysis. The reference year is 1995, the first year of observation in the sample. I used two additional dummy variables to identify those start-up companies located in the Silicon Valley and in the Route 128 high-technology regions in the United States. These are important control variables given the extant research since the book *Regional Advantage* was published in 1994 (Saxenian 1994).

The second set of variables includes those variables that the literature on spatial concentration and industrial clusters suggests as being important factors in accounting for newly created firms’ performance. These variables include labor market participation and diversity in the labor force where the start-up company is located. Labor force participation (LFP) is a proxy for the level of economic activity in a given location. In this paper, LFP is calculated as the ratio of employed civilian labor force to the employed and unemployed civilian labor force for each of the cities included in the sample; this measure ranges from 85 to 100 percent. The second variable, diversity in the labor force, is measured using Blau’s (1977) index of heterogeneity. This index operationalizes the probability that two randomly chosen individuals in the labor force work for different industrial sectors; Blau’s index is calculated as:

\[
1 - \sum_{i=1}^{c} (P_i)^2
\]

where \(P_i\) is the proportion of the local labor force employed in the \(i^{th}\) economic sector, and \(c\) is the number of different economic sectors. In this case, I use the different categories to represent economic diversity at the city level. The measure I use in the final analyses was computed including major economic sectors such as manufacturing, wholesale and retail trade, finance,
insurance, real state, health services, and public administration. The larger the measure, the greater the diversity in labor force employment (as a proxy for diversity of economic actors and activities). The actual scores range from .55 to .78. I also compute three other indexes of labor market diversity using categorical variables such as different population age brackets (0-5 years old, 6-10 years old, 11-18 years old, etc.), educational brackets (less than high-school, high-school, and bachelor’s or higher), and country of origin (American versus foreign born). These measures are also included in some of the performance regression models. I also try different measures of diversity used in the group and population diversity literature (Teachman 1980; O’Reilly, Williams, and Barsade 1998); very similar results were found regardless of the variable I used to represent diversity (for a review of these different measures of population heterogeneity used in organizational demography research, see Sorensen 2002).

Finally the third set of independent variables includes information about the network of venture capital firms investing in a given start-up company (i.e., the syndication network). These measures include the average and maximum values of the centrality scores for the different venture capital firms that jointly co-finance a given entrepreneurial start-up; they also include the average and maximum value for the measure of structural holes in the venture capital firms in a given syndication network. I also include the minimum distance (in driving miles) between a given start-up company and any of the venture capital firms jointly involved in the financing a given start-up company. I create such a distance variable using GIS software that determines the shortest driving route from the start-up company to their funding venture capital firms. I code the time (in hours) that it takes to drive from the company to the venture capital firm. I have also experimented with alternative options for measuring proximity to the venture capital sources such as the one illustrated by Stuart and Sorenson (2001), i.e. calculating distances according to their latitudes and longitudes (using Euclid’s formula for small distances and spherical geometry for larger distances). The results were very consistent regardless of the variable I used to represent distance.

Other variables are used to account for the experience level of the venture capital firms involved in the syndicate network. These include the maximum value of the venture capitalist’s IPO success experience, measured as the number of past investments that went IPO (in the previous 5 years, from 1990 up to 1995), the maximum value of venture capital firm investment experience in different stages, industries, and regional locations, as well as in different
companies (also from the group of venture capital firms that are jointly involved in financing a given start-up company). Again, all these measures were computed for each start-up company as the average and maximum values for the different venture capital firms included in the syndication network. To measure the centrality of the venture capital firms during the sample years, I construct a matrix based on the joint involvement of venture capitalists in financing entrepreneurial start-ups. That is, I construct a matrix R, in which cell $R_{ij}$ denotes the number of times that venture capitalist $i$ and $j$ jointly financed a start-up. Given R, I then rely on Podolny (2001) and calculate the centrality measure based on the Bonacich’s (1987) measure (also known as the “power” measure):

$$ c_i(\alpha, \beta) = \sum_{j=1}^{n} (\alpha + \beta c_j) R_{ij} $$

where $c_i$ is the centrality measure of the venture firm $i$, $\alpha$ is an arbitrary scaling coefficient, and $\beta$ weights the importance of the tie to actor $j$ for actor $i$. When $\beta$ takes a positive value the Bonacich measure indicates that actor $i$’s centrality is positively impacted by the centrality of actor $j$. That is, if venture capital firm $i$ co-invests with firm $j$, and $j$ in turn co-invests with many other firms, then positive $\beta$ suggests that $j$’s ties to those other firms redounds to $i$’s benefit. This can be an important proxy for venture capital firms’ activities such as providing management, recruiting, accounting, legal advice, and other consulting services to newly created firms. It can also be a proxy for the transference of in-depth knowledge or expertise to the founders of these companies: if venture capital firm $j$ acquires some industry insight from its association with many other venture capital firms, then $i$ is able to derive the benefit of that industry insight by co-investing with $j$. Similarly, $\beta$ can be a factor indicating how “far” out in the network $i$ is able to “reach” because of its co-investment association with venture capital firm $j$. Consistent with past research, it is recommended to select $\beta$ so that its absolute value is less than the absolute
value of the reciprocal of the largest eigenvalue of the adjacency matrix. An upper bound on the eigenvalues can be obtained by the largest row or (column) sums of the matrix (Bonacich 1987).

I used UCINET 6.0 (Borgatti, Everett, & Freeman, 2002) to manipulate the R matrix and compute the centrality status scores. Centrality scores are standardized such that the most central firm has a status of 1 (the mean value is 0). The distribution of this measure is skewed, with many more low-status (central) firms than high-status (central) firms. This skewed distribution is consistent with the distributions observed in other samples of venture capital firms (Podolny 2001) and in other industries, such as investment banking (Podolny 1993). Previous research in the topic by Podolny (2001) provides anecdotal support for the use of this particular measure for analyzing the status or centrality of venture capital firms: “Lower-status [central] venture capitalists express a strong desire to be included on deals financed primarily by higher-status firms, and higher-status venture capitalists occasionally refuse to finance a venture if that venture is receiving financing from a lower-status venture capitalist.” (Podolny 2001: p. 53).

Finally, to measure the structural holes in a venture capitalist’s network, I use Burt’s (1992) measure of autonomy. Formally, Burt (1992) defines venture capital firm i’s autonomy as follows:

$$\text{SH}_i = 1 - \sum_j \left( p_{ij} + \sum_{q} p_{iq} p_{qj} \right)^2 , i \neq j \neq q,$$

where $p_{ij}$ denotes the proportion of i’s network that is invested in the relation with j, $p_{iq}$ indicates the proportion of q’s network that is invested in its relation with j. SH$_i$ can range from 0 to 1. As firm i is connected to an infinite number of others who are themselves disconnected, SH$_i$ approaches 1. If i is connected to only one other actor, SH$_i$ = 0. For the purposes of this analysis (consistent with Podolny 2001), I identify a venture capitalist’s network from its joint involvement in financing entrepreneurial start-ups. Again, that is, when venture capitalist i

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5 The parameter $\beta$ is selected by the researcher: negative values should be selected if a VC firm's power is increased by being connected to VC firms with low power and positive values selected if an VC firm’s power is increased by being connected to vertices with high power. In any case, the maximum value that $\beta$ can take is the reciprocal of the eigenvalue of the adjacency matrix, and consistent with past research, I set $\beta$ at this value in my analyses ($\beta = .042$). The analyses were also repeated when $\beta$ was set to zero (and other values between 0 and .8). Results were very similar.

6 Burt (1992) uses A$_i$ and Podolny (2001) uses H$_i$ to represent autonomy of actor i; I use SH$_i$ to make sure it is clear that this is the indicator of the extent of holes in an actor’s network.
invests in the same start-up as venture capitalist \( j \), I code that joint participation as a tie between \( i \) and \( j \). Therefore, \( SH_i \) is a positive function of the number of different venture capitalists with which \( i \) is involved and the extent to which those other venture capitalists themselves invest in numerous, different start-up companies. Conversely, if venture capitalist \( i \) makes a small number of investments, and the other venture capitalist firms in these investments constitute a clique with identical investment patterns, then \( SH_i \) will be relatively low. For the purpose of this analysis, I weight a tie between two venture capitalist firms by the number of deals that they jointly finance.

**Models**

To test the hypotheses elaborated above, I run three different sets of regression type of analyses. The first set of regressions use whether the firm went IPO or not during the time period under study as the dependent variable. I estimate the parameters of the logistic regression models of the form:

\[
Y_i = \alpha_1 X_{i1} + \alpha_2 X_{i2} + \beta_1 C_i + \beta_2 SH_i + \gamma N_i + \varepsilon_i \quad (1)
\]

where \( Y_i \) is a dichotomous variable that takes the value of 1 if the start-up \( i \) went IPO during the time period of study (0 otherwise), \( X_i \) is a vector of covariates that contains important economic variables that could influence the success of the start-up company; these include the age of the company, the age squared, the total amount of money received, the number of funding investors, and then a set of dummy variables to control for the major industries and stages in the sample of start-up companies. The vector also includes two dummy variables to control for those start-up companies located in Silicon Valley and in Route 128 (New England). I also include several dummy variables to control for the stage of the start-up company and the first year of investment in any given company in the sample (the reference year is 1995, the first year of observation in the sample). \( X_2 \) is a vector of covariates that contain information about the local labor market where any given start-up company \( i \) is operating. Here I will include labor force participation and diversity of economic actors. \( C_i \) signifies the maximum (and average) centrality or status score for the different venture firms jointly involved in the financing of company \( i \). \( SH_i \) denotes the maximum value for the structural holes measure for the different venture capital firms in the syndication network for start-up company \( i \) (i.e., Burt (1992) measure of autonomy). \( N_i \) is a vector of covariates that contain information about the network of venture capital firms involved in the financing of the start-up company; these include minimum distance and maximum level of
experience in different industries, stages, locations, and companies (or investments). The central hypotheses in this study (H2a and H3a) are that $\beta_1 > 0$, $\beta_2 > 0$, and that $\gamma$ is a vector of significant coefficients. In other words, the higher the maximum centrality score of the venture firms in the syndication, the more likely the start-up company is to go public. The higher the number of structural holes in the syndication network of venture firms, the more likely the company is to go public. At the same time, including different network characteristics (as operationalized by $\gamma$) is hypothesized to help increase the variance in $Y_i$ explained by the model. $\varepsilon$ is the disturbance term assumed to be normally distributed and well-behaved (i.e., uncorrelated with the covariates).

In order to analyze the determinants of a start-up firm’s performance, I estimate a second set of regression models. More specifically, I estimate the parameters of the models of the form:

$$Y_i = \alpha_1 X_{1i} + \alpha_2 X_{2i} + \beta_1 C_i + \beta_2 S H_i + \gamma N_i + \varepsilon_i$$

(2)

where $Y_i$ is now any of the different performance-related variables available in this study —that includes the log of time to go public (i.e., how long the company took to go IPO), the earnings per share, the (log) revenues, and the (log) market capitalization. This performance information is only available for start-up companies that go IPO, so these performance models should not be estimated using conventional ordinarily least squares (OLS) techniques. Instead, the model is estimated correcting for selection bias (due to lack of information about start-up companies that did not go IPO during the period of study). To correct for such selection bias, I use the Heckman selection model (Gronau 1974; Lewis 1974; Heckman 1976). This model assumes an underlying regression relationship like the one described in the regression equation (3). However, the dependent variable, performance, is not observed for those companies that did not go IPO. There is a selection equation, and the start-up company went IPO (i.e., the company is therefore “selected” and included in the main performance equation) if:

$$Y'Z + \mu > 0$$

(3)

where $Z$ is a vector of covariates that affects the chances of observation of performance for a given company (i.e., going IPO), $\mu$ is normally distributed with mean 0 and standard deviation of
1. Equation 3 is identical to equation 1 above. The correlation between \( \varepsilon \) and \( \mu \) is some parameter \( \rho \); so that when \( \rho \) is different from zero, standard regression techniques applied to equation (2) yield biased results, and the Heckman selection model provides consistent, asymptotically efficient estimates for all the parameters of such models.8

Finally, I present a third set of multinomial logistic regression models to assess the effect of all the above independent variables on the probabilities of start-up companies reaching different outcomes such as going public, going bankrupt or defunct, or being acquired or merged. Thus, I extend the logit models for a dichotomous outcome such as going IPO to the case of a polytomous outcome, and I estimate a third set of multinomial logistic regression models. More specifically, I estimate the parameters of models of the form:

\[
Y_{ki} = \alpha_1 X_{1i} + \alpha_2 X_{2i} + \beta_1 C_i + \beta_2 S_{Hi} + \gamma N_i + \varepsilon_i \quad (4)
\]

where \( Y_{ki} \) is now the log odds (for company \( i \)) of reaching outcome \( k \) —which can be 1) going IPO, 2) going bankrupt or defunct, or 3) being acquired or merged— rather than the reference category which is for company \( i \) to survive or simply stay alive. This performance information is available for all start-up companies and the models are estimated by the method of maximum likelihood. In these models, and if we are to find support for H2b and H3b about the disadvantages of embeddedness resulting in the ultimate failure of the start-up company, then the set of parameters for the going bankrupt or defunct part of the multinomial logit regression should be \( \beta_1 > 0 \) and \( \beta_2 > 0 \), the positive coefficients indicate this time that the higher the maximum centrality score of the venture firms in the syndication (and the higher the number of

7 In this paper, I report the full maximum likelihood estimates for the Heckman selection model. I also obtain the Heckman's two-step consistent estimates and found similar results (available upon request). Following Stolzenberg and Relles (1997), I run several tests using different sample selection models to ensure that my results are robust, and therefore, do not change when using different selection correction specifications.

8 Recently researchers have become concerned with the precision of Heckman estimators, especially when there might be some collinearity between \( X \) and \( \rho \). The variance of \( \rho \) is determined by how effectively the probit equation predicts which observations are selected into the sample. The better the prediction, the greater the variance of \( \rho \), and the more precise the estimates will be. Collinearity between \( X \) and \( \rho \) might be determined in part by the overlap in variables between \( X \) and \( Z \). If \( X \) and \( Z \) are identical, the Heckman model is still identified (and estimable) because \( \rho \) is nonlinear (given that the results are then based on assumptions about functional form alone rather than on variation in explanatory variables). Even when statistical packages such as STATA allow researchers to estimate selection models where \( X \) is identical to \( Z \), many researchers argue that the successful use of the Heckman method should require that at least one variable in \( Z \) not be included in \( X \) (Winship and Mare 1992; Sartori 2002). In my study, the Heckman estimators were robust across these different specifications of \( Z \) and \( X \) in the two equations, and collinearity did not seem to be a problem.
structural holes in the syndication network of venture firms), the more likely the start-up company is to fail.

**Results**

Table 1 presents the descriptive statistics for both the different dependent variables and explanatory variables in the analyses. Table 2 reports bivariate correlations between the key explanatory variables. It is noteworthy that the correlations between the centrality score and the different characteristics of the venture capital firms involved in the same network syndication are low (always below .5). This suggests that the two sets of variables can be empirically distinguishable. The same applies to correlations between the measure of structural holes and the different characteristics of the venture capital investors (always below .25). Some of the different experience variables are highly correlated among each other. This clearly suggests that some of them might be measuring similar aspects of the experience and ability of the venture capital firms in both investing and diversifying their portfolios. Finally, the correlation between the two main network variables in this study is .16; while the correlation is statistically significant at the .001 level, it should be clear that the two measures are empirically distinguishable (consistent with other studies using these two measures: Podolny 2001).

[Table 2 and Table 3]

Table 3 depicts the logistic regression results predicting the likelihood of a start-up company to go public. Model 1 includes the coefficients for the main economic variables including age, age squared, number of investors, and total amount of funding as well as the two regional dummy variables for companies located in either Silicon Valley or Route 128 ($\alpha_1$). While the estimation of this model also includes several control variables such as industry and stage of the start-up company as well as year dummy variables, the coefficients are omitted from the table for presentation purposes (these estimated coefficients are available upon request). Model 2 adds the variables related to the diversity of economic activities and actors ($\alpha_2$). Models 3 and 4 present the models including variables related to the network of venture capital firms co-investing in a given start-up company. The difference between Models 3 and 4 is that Model 3 only includes the measure of centrality or power ($C_i$) and the measure of structural holes ($SH_i$); whereas Model 4 includes these two structural network variables together with the different experience measures of the different venture capital firms in the syndication network ($N_i$).
Given that some of these characteristics seem to be highly correlated with each other, in Model 6 I only include the variables measuring IPO past success experience, industry and location investment experiences of the venture capital firms in the network. Model 7 (in the last column of the table) includes the same variables as Model 6 and two of the labor market indicators, namely labor force participation and diversity in labor force employment. Finally, Model 5 presents the complete model and includes all variables in the estimation.

Looking first at Model 1, most of the economic variables are statistically significant. The coefficient for age and age squared are non-significant suggesting that the likelihood of going IPO is not related to the age of the start-up company. This is not surprising given that some of the stage of investment dummy variables (i.e., the ones controlling for early stage investments) partially capture the effect of age: The early stage investment variable is negative and statistically significant demonstrating that start-up company in early stages of venture capital funding are less likely to go IPO (these coefficients are included in the estimation but omitted from the table for presentation purposes). Also start-up firms in the biotechnology and software industries are more likely to go IPO than firms in any other industries. The start-up companies in the industrial and consumer sectors are less likely to go IPO (both significant at the .05 level). Also, when looking at the different year dummy variables, the likelihood of going IPO significantly decreases as start-up companies start receiving venture capital funding for the first time during later years in the investment sample. All of this is consistent with previous economic studies of IPOs over time (for a review see Gompers and Lerner 1999). Finally, the Silicon Valley location dummy variable is positive and very significant (at the .001 level), finding support for hypothesis H1c about the regional advantages of start-up companies located in Silicon Valley. The Route 128 location variable is never significant in any of the estimated models.

Turning to the testing of the effect of the two main economic controls of the start-up investment in this study, number of investors and total amount of funding (as signals to the market about the potential profitability of the business ventures), results are indeed inconsistent. On the one hand, the amount of venture capital invested during the period does positively impact the likelihood of going IPO. On the other, however, the number of different investors seems to have a significant negative effect, contrary to the expected sign. This finding is consistent across all different estimated logistic regressions and does not seem to be due to any collinearity.
problem between the two variables; as a matter of fact, the amount of money invested and number of different investors is low but significant (.28).

In Model 2, I include the variables related to the level of actor participation in the local economy as well as diversity in the labor market participation experience, level of education, age, and country of origin. Overall, including these variables does seem to slightly improve the fit of the IPO model (P = .0347; LR Chi-Square Test = 12.01; df = 5). The variable measuring labor force participation at the city level is positive but not significant. This finding does not support the most recent literature in economic geography (H1a), which suggests that the higher the level of economic activity in the local economy, the higher the likelihood of the start-up company to go IPO. Likewise, diversity in the type of labor force employment (at the city level too) does not seem to have any significant effect on the rate of IPOs and hypothesis H1b is therefore not supported in this study either. The measures of diversity in the level of education or age of the populations do not seem significant enough when it comes to predicting the success of the start-up companies. Only the measure of diversity in the country of origin is significant at the .05 level (one-tailed test), suggesting that immigration might play an important role in the success of start-up companies. This is in agreement with largely theoretical studies on entrepreneurship and immigration (for a review see: Saxenian 1994; Portes and Sensenbrenner 1993; and Wilson and Portes 1980). Although alternative measures of level of economic activity and diversity in economic activities were used in this study to test hypotheses H1a and H1b, I found very similar results.9 I also found very similar results when I measured labor force participation and diversity in economic activity using different levels or units of space (that is, when I measured them at both the state and the county level).

Model 3 reports the regression results when centrality scores are included in the model. The centrality measure is positive and very significant (at the .001 level). This provides support for H2a when performance is measured as the going public: Start-up companies receiving funding from highly central venture capital firms seem to be more likely to go IPO than those who

9 This is not surprising given that these alternative measures such as the number of business establishments, their estimated revenues, or taxes paid were highly correlated with the labor force participation variable used in the final analyses reported here. The same is true for alternative measures of diversity in economic activity computed using some of these measures for the different industrial sectors: such measures were highly correlated with the diversity of employment variable. Finally, results were very consistent across the different specifications of diversity used in the group and population and diversity literature (Teachman 1980; O’Reilly, Williams, and Barsade 1998).
received funding from less central venture capital firms. There is no support for H3a about the impact of structural autonomy on the likelihood of start-up IPO success. As a matter of fact, the measure of structural holes is not significant in any of the IPO models. Model 4 adds several characteristics of the venture firms involved in the syndication network to Model 3. The inclusion of these variables significantly improves the fit of the IPO model \((P = .000; \text{LR Chi-Square Test} = 132.98; df = 6)\), finding some support for hypothesis H4a. In looking carefully at these regression results, one can see that the two most significant variables are IPO past success experience and company investment experience. Thus, the higher the venture capital firm’s IPO past success experience, the higher the chance of any given start-up company to go IPO. This experience variable seems to be a very significant predictor of the likelihood of the start-up company to go IPO in all the estimated models. The investment experience in different start-up companies has a negative and significant effect on the likelihood of going IPO; this can be due to the fact that these two experience variables are highly correlated with each other: .86, significant at the .001 level. This is why Models 6 and 7 only include IPO past success experience.

Experience in investments in different locations is the only other experience variable significant at the .05 level.

A close examination of the correlation matrix in Table 2 shows that stage experience is highly correlated with variables such as investment experience and industry experience; also investment experience is highly correlated with IPO experience. For this purpose, Model 4 was re-estimated including centrality and the measure of structural holes as well as IPO past success, industry and location investment experiences as the variables measuring the maximum level of experience within the venture capital network (results are reported in Models 6 and 7 in the last two columns of Table 3). Including these four variables very significantly improves the fit of the IPO model. Model 5 is the complete model with all variables in the analyses. Although the variable centrality becomes less significant this time (significant at the .10 level), the results are still consistent with the main network hypothesis that start-up companies with highly central venture firms involved in the syndication are more likely to go IPO than companies with less central venture capital firms.

Models 4 through 7 are important because they include both the two structural social network measures and the several variables measuring the quality of the network of venture capital firms investing in a given start-up companies. To my knowledge, this provides a much more refined
test of whether it is the centrality or the number of structural holes in the syndicate network of venture capital firms or whether it is the quality of the syndicate network as investors what accounts for any differences in the likelihood of start-up companies to go IPO than any of the studies in this tradition of research has done in the past. Such clean test is crucial because social relations and quality can be related in complicated ways (and more importantly, they are likely to be confounded). In Models 4 through Model 7, I find that the level of centrality in the syndicate network of venture capital firms is always significant in predicting the success of a start-up company, even when I introduce one of the most important measures of the quality of the syndicate, the highest level of IPO past successes achieved in the past.

In none of the models do I find support for hypothesis H5a about the effect of proximity of the start-up company to any of the venture capital co-investors in the syndicate. Distance (measured in thousand of miles) does not have the hypothesized negative sign; on the contrary, the effect of distance is actually positive and significant at the .05 level. I also experimented with other measures of distance in hours that it takes to drive form the company to the venture capital firm or the one used in Stuart and Sorenson (2001). The results are very similar regardless of the variable used in the analyses to represent proximity.

[Table 4]

Table 4 reports the results for the OLS regression models with the (log) time to IPO, the (log) earnings per share, the (log) volume of revenues, and the (log) market capitalization as the dependent variables. These OLS regression models are corrected for selection bias (i.e., Heckman regression models; see models section above for an explanation). Again, the main control variables such as industry, stage, and year are included in the estimation of the models but omitted in the table. The results in this table clearly suggest that the conditions that promote new businesses’ success (i.e., IPO) differ from those that maximize the performance of the recently established companies. I find that the network factors accounting for the creation of public start-up companies do not necessarily help to maximize the performance of such recently publicly traded companies. The centrality measure alone has a positive and significant effect on market capitalization (significant at the .05 level) and has a negative and significant effect on time to IPO (significant at the .05 level, one tailed test). This suggests that public companies with highly central venture capitals firms are valued higher (and tend to go public faster) than
start-up companies backed by less central venture capital firms. The coefficients of this centrality measure on earnings per share and revenues are negative (although only significant for the revenues performance measure). The measure of structural holes is only a positive and significant predictor in the market capitalization and revenues performance models (respectively, significant at the .1 and .05 levels, one tailed tests). This suggests that public companies involved in syndication networks with venture capital investors high in the number of structural holes are valued higher and generate higher revenues prior to going IPO than start-up companies backed by venture capital investors lower in their number of structural holes.

[Table 5]

Table 5 reports the results for the multinominal regression model with IPO, merger or acquisition, and bankruptcy or defunct as the three main possible company outcomes. The reference category in the model is the start-up company staying alive. In the first two columns of Table 5, I show the coefficients for the going IPO outcome part of the model. The results are consistent with those in Table 3, where I report the estimates of the coefficients for the logistic regression models predicting the likelihood of a start-up company going public. First, although the number of different investors seems to have a significant negative coefficient, the coefficient for the amount of venture capital invested during the period of study is positive and significant as expected. As in the main IPO model, the Silicon Valley regional effect is positive and significant but none of the variables related to the level of employment activity and diversity of the location of the start-up company is significant. And finally, the centrality score has a positive and significant effect on the going IPO of the company. The experience variables such as IPO success past experience comes again as an important predictor of the IPO outcome.

In looking at the second two columns of Table 5, the results are quite consistent with the IPO outcome part of the model. Again the centrality score seem to be an important predictor of an important company outcome, merger or acquisition: The higher the centrality of the syndicate network of venture capital co-investors, the higher the odds of the company to merge with or being acquired by another company (significant at the .001 level). The structural holes measure is also positive and significant at the .05 level. This is consistent with the venture capital

10 Again the coefficients for the industry, stage, and year control variables are not reported in the table.
literature providing evidence that venture capital firms help portfolio companies identify new investors and strategic partners (Bygrave and Timmons 1992). This can be especially so in the case of venture capital firms with a high number of structural holes which can help to identify merging or selling opportunities. The Silicon Valley regional effect is not significant this time. Instead, the Route 128 location dummy variable is positive and significant at the .01 level, suggesting that start-up companies in New England have a higher propensity of merging with or being acquired by other companies when compared with other start-up companies (including the ones in Silicon Valley).

Another interesting finding is that the coefficients predicting the bankrupt or defunct company outcome part of the model as depicted in the last two columns of Table 5. I do find support for H2b: Start-up companies receiving funding from highly central venture capital firms are more likely to fail. The coefficient is positive and significant at the .05 level. This seems to suggest the alternative proposition that social networks can actually have negative consequences for the survival of the firm. There are different mechanisms that could explain why central actors will ultimately be involved in inefficient business ventures. The main mechanism has to do with the fact that network ties might substitute the due-diligence behind the process of searching and evaluating information about the quality of the new business venture. If this is the case, then venture capital firms might be investing in companies that they would not have invested had they evaluated critically any information about the quality of the potential investee company and its profitability or success possibilities. I find no support to hypothesis H3b: The structural holes measure does not seem to predict the chances of failure of a start-up company. Finally, none of the syndication network experience in investing is significant when it comes to predicting the process of bankruptcy or death for a start-up company. Interestingly enough, none of the included experience measures of the venture capital syndicate seem to be able to reduce the chances of a given portfolio company from going bankrupt or defunct, and I therefore find no support for hypothesis H4b. The variable measuring proximity does not seem to have any significant effect either in predicting failure; consequently, I find no support for hypothesis H5b.

11 In some of the analyses, I also used a dummy variable to identify those IPO companies that died during the period of analysis as a dependent variable. The variable IPO defunct takes the value of 1 if the IPO died (0 otherwise). The findings are very consistent with the findings in the model where bankruptcy and defunct is the dependent variable (analysis are available upon request).
Summary and Discussion

My empirical analyses examine a sample of start-up companies that received funding from venture capital firms from 1995 up to 1998 in the United States. I find evidence that after controlling for the most important economic factors such as amount of funding and number of investors (among many), network variables still play an important role in explaining firms’ success. Start-up companies backed by venture capital firms involved in more dense patterns of co-investments are more likely to go public (or to merge / get acquired) than start-ups funded by isolated venture capital firms. In addition, the success of a start-up company in the public market seems to be significantly enhanced when its funding comes from a syndicate group with highly central and structurally autonomous venture capital firms. Here, there are two main findings. First, public companies with highly central venture capital firms are valued higher and tend to go public faster than start-up companies backed by less central venture capital firms; second, venture capital investors high in the number of structural holes are valued higher and seem to generate higher revenues (prior to going public). Most importantly, my analyses also show that network variables can affect the survival prospects of the newly-created companies. Thus, my findings support the often ignored arguments that social ties have the potential of resulting in the funding of inefficient start-up companies. Finally, although the inclusion of variables regarding the experience of the syndication networks (especially when measured as IPO past success experience) seems to improve the fit of the model predicting start-up company success measured as going IPO or merger / acquisition, none of the experience measures of the venture capital syndicate seem to reduce the chances of a given portfolio company from going bankrupt or defunct.

I believe that my study offers three main contributions to the literature of economic sociology, sociology of the economy, and organizational performance. First, my work provides some insight into the different economic, regional, and social network arguments accounting for the performance of start-up companies. I start with the economic assumption that a rational market takes care of allocating scarce resources such as venture capital funding to the most potentially profitable business plans. Then I move toward alternative explanations in other literatures. Thus, I test the proposition, common in recent studies of economic geography, that any unit of space with a high diversity of social actors and economic activities promotes the success of newly established companies. Finally, I test a social networks perspective which
highlights how entrepreneurial efforts are more successful when embedded in a densely connected network of social actors.

Second, by examining different start-up company outcomes, this paper explores the role of social networks in explaining both the success and the failure of start-up companies. To date, there are numerous empirical studies demonstrating that embedded exchanges provide economic benefits to those actors engaged in them (for examples, see Uzzi 1996; Stuart 2000; Ingram and Roberts 2000; and Stuart, Hoang, and Hybels 1999; among many other studies). Although all these papers postulate different mechanisms explaining why embedded exchange is more efficient when embedded in networks of social actors, with this paper, I would like to “revive” the notion that alternative important mechanisms can explain the exact opposite, e.g., how social networks can actually have negative consequences on performance. In this paper, and because I have information about different measures of the performance of a start-up company (including outcomes such as going IPO or going bankrupt), I have been able to investigate whether social network position in one kind of organizational networks, the co-investment networks of venture capital firms, has any negative impact on a company’s performance over time.

Third, from a more theoretical perspective, this paper provides an opening door in linking social structure (mainly at the organizational network level) to the literature that discusses how geographic location affects not only the process of mobilization of funding to create successful start-up companies but also ultimately certain crucial organizational outcomes. In this paper, I was in a great position to test the proposition that location and its diversity of social actors and economic activities is what eventually promotes the success of newly established companies. Linking the value of a particular local network topology to the opportunity has allowed me to link relatively two distinct approaches to the study of social structure: social network theory and regional economics.

Finally, and at the more abstract level, this study supports the belief that an approach that explores the network structure among a region’s important actors can satisfactorily account for firm and ultimately regional performance advantages. In general, it has been argued that social networks matter because trust, information, action, and cooperation all operate through social relations. Developing better models that account for these crucial network factors requires that we understand how regional development is shaped by networks, which are re-shaped in turn.
Regional development, in this sense, may rely more on the structure of networks of social actors, since social actors ultimately influence the pattern of economic and organizational practices as well as the region’s institutional infrastructure. In this sense, a network theoretical perspective of regional development should operate under at least five basic premises: (1) organizations are connected to one another, and they are therefore members of regional social networks; (2) an organization’s environment consists of a network of other organizations and institutions (such as universities, venture capital firms, law firms, trade associations); (3) the actions (attitudes and behaviors) and their outcomes (performance, survival, and legitimacy) of organizations can be best explained in terms of their position in networks of relationships; (4) certain networks promote certain actions, but in turn constrain other actions; (5) networks of organizations change over time. These five premises are important to consider when comparing regions and/or industrial districts. A comparative analysis of regional development should therefore pay attention to at least a few of these network premises. Thus it is important to discover more about those kinds of regional networks which help in promoting superior economic and social development.

In addition to its theoretical importance, understanding the mechanisms underlying the funding and success of start-up companies in different industrial clusters can be informative to policymakers and planners. Urban planners have long shown interest in replicating the successes of well-established high-technology regions such as Silicon Valley. Although regional policies have been informed by a number of careful case studies of high-technology regions such as Silicon Valley and Boston’s Route 128 (e.g., Saxenian 1994), systematic analyses of carefully designed and collected data such as those I have offered here are much needed. To better understand the significance of networks of social actors, and in order to be able to distinguish among the different theoretical mechanisms affecting the development of successful and profitable business plans, I suggest that future research in this area moves toward examining these processes with detailed data collected over time.
## Table 1. Descriptive Statistics for Variables in the IPO and Performance Models.

<table>
<thead>
<tr>
<th>Dependent Variables:</th>
<th>N</th>
<th>Mean</th>
<th>SD</th>
<th>Minimum</th>
<th>Maximum</th>
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<tbody>
<tr>
<td>Going IPO (1 = Yes; O Otherwise)</td>
<td>4160</td>
<td>0.11</td>
<td>0.31</td>
<td>0.00</td>
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<tr>
<td>Time to Public Offering (in days)</td>
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<td>Earnings per Share (in dollars)</td>
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<td>Market Capitalization (in millions of dollars)</td>
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<td>66.59</td>
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<td>Revenues (prior to public offering) (in millions of dollars)</td>
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<td>Merger or Acquisition</td>
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<td>Defunct or Bankrupt</td>
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<td>IPO going Dead</td>
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<table>
<thead>
<tr>
<th>Independent Variables:</th>
<th>N</th>
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<th>Minimum</th>
<th>Maximum</th>
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<tr>
<td>Age</td>
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<td>Age, squared (in millions)</td>
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<td>Total Amount of Funding</td>
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<td>Initial/Seed Stage (1 = Yes)</td>
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<td>Year 1998 (1 = Yes)</td>
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<td>Silicon Valley Location (1 = Yes)</td>
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<td>0.21</td>
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<td>Route 128 (New England) Location (1 = Yes)</td>
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<td>0.09</td>
<td>0.29</td>
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<table>
<thead>
<tr>
<th>From the City Location of the Start-Up Company:</th>
<th>N</th>
<th>Mean</th>
<th>SD</th>
<th>Minimum</th>
<th>Maximum</th>
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<tr>
<td>Labor Force Participation</td>
<td>4079</td>
<td>93.80</td>
<td>2.53</td>
<td>80.29</td>
<td>97.98</td>
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<tr>
<td>Logarithm of Employed</td>
<td>4153</td>
<td>15.42</td>
<td>0.90</td>
<td>12.55</td>
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<td>Logarithm of Population with High-School Education</td>
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<td>14.21</td>
<td>0.93</td>
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<tr>
<td>Diversity in the Labor Force Employment</td>
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<td>0.73</td>
<td>0.03</td>
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<td>Diversity in the Level of Education</td>
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<td>Diversity in Age</td>
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<td>0.12</td>
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<table>
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<tr>
<th>From the Syndicate Network of VC Firms:</th>
<th>N</th>
<th>Mean</th>
<th>SD</th>
<th>Minimum</th>
<th>Maximum</th>
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<tr>
<td>Standardized Power Centrality</td>
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<td>1.00</td>
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<td>Structural Holes (Structural Autonomy)</td>
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<td>0.73</td>
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<td>Highest Number of IPOs Experience</td>
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<td>4.04</td>
<td>5.03</td>
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<td>19.00</td>
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<tr>
<td>Lowest Geographic Distance (in miles)</td>
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<td>655.13</td>
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<td>4160</td>
<td>7.65</td>
<td>5.63</td>
<td>1.00</td>
<td>24.00</td>
</tr>
<tr>
<td>Highest Company Investment Experience</td>
<td>4160</td>
<td>25.92</td>
<td>21.98</td>
<td>1.00</td>
<td>91.00</td>
</tr>
</tbody>
</table>
Table 2. Correlation Matrix among Dependent and Key Independent Variables in the IPO/Performance Models.

<table>
<thead>
<tr>
<th>Dependent Variables:</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
<th>8</th>
<th>9</th>
<th>10</th>
<th>11</th>
<th>12</th>
<th>13</th>
</tr>
</thead>
<tbody>
<tr>
<td>Going IPO (1 = Yes; 0 Otherwise)</td>
<td>1.00</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Time to Public Offering (in days)</td>
<td>1.00</td>
<td>1.00</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Earnings per Share (in dollars)</td>
<td>0.04</td>
<td>-0.20 ***</td>
<td>1.00</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Market Capitalization</td>
<td>0.03</td>
<td>0.05</td>
<td>-0.28 ***</td>
<td>1.00</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Revenues (prior to public offering) (in millions of dollars)</td>
<td>0.06</td>
<td>0.17 **</td>
<td>-0.01</td>
<td>-0.04</td>
<td>1.00</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Merger or Acquisition</td>
<td>-0.14 ***</td>
<td>-0.02</td>
<td>-0.02</td>
<td>-0.04</td>
<td>1.00</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Defunct or Bankrupt</td>
<td>-0.05 ***</td>
<td>0.01</td>
<td>-0.02</td>
<td>-0.06 ***</td>
<td>1.00</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Independent Variables:</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
<th>8</th>
<th>9</th>
<th>10</th>
<th>11</th>
<th>12</th>
<th>13</th>
</tr>
</thead>
<tbody>
<tr>
<td>8 Age</td>
<td>0.00</td>
<td>0.96 ***</td>
<td>-0.11 *</td>
<td>0.01</td>
<td>0.14</td>
<td>0.00</td>
<td>0.01</td>
<td>1.00</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>9 Age, squared</td>
<td>0.00</td>
<td>0.88 ***</td>
<td>-0.27 ***</td>
<td>0.10 *</td>
<td>0.14</td>
<td>0.00</td>
<td>0.01</td>
<td>0.88 ***</td>
<td>1.00</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>10 Number of Investors</td>
<td>0.06 ***</td>
<td>-0.07</td>
<td>-0.02</td>
<td>-0.04</td>
<td>-0.11 **</td>
<td>0.05 **</td>
<td>0.05 ***</td>
<td>-0.03 ***</td>
<td>-0.04 **</td>
<td>1.00</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>11 Total Amount of Funding</td>
<td>0.20 ***</td>
<td>0.08</td>
<td>-0.07</td>
<td>-0.11</td>
<td>0.09 *</td>
<td>0.05 **</td>
<td>0.03 **</td>
<td>0.05 **</td>
<td>0.05 ***</td>
<td>0.28 ***</td>
<td>1.00</td>
<td></td>
<td></td>
</tr>
<tr>
<td>12 Silicon Valley Location (1=Yes)</td>
<td>0.11 ***</td>
<td>-0.13</td>
<td>0.00</td>
<td>-0.06</td>
<td>-0.09 *</td>
<td>0.04 **</td>
<td>0.02</td>
<td>-0.09 ***</td>
<td>-0.06 ***</td>
<td>0.04 **</td>
<td>0.04 *</td>
<td>1.00</td>
<td></td>
</tr>
<tr>
<td>13 Route 128 (New England) Location (1=Yes)</td>
<td>0.00</td>
<td>0.03</td>
<td>0.02</td>
<td>-0.02</td>
<td>-0.05</td>
<td>0.07 ***</td>
<td>0.02</td>
<td>-0.01</td>
<td>-0.01</td>
<td>0.06 ***</td>
<td>-0.02</td>
<td>-0.17 ***</td>
<td>1.00</td>
</tr>
<tr>
<td>14 Labor Force Participation</td>
<td>-0.02</td>
<td>0.00</td>
<td>0.03</td>
<td>0.02</td>
<td>0.04</td>
<td>-0.03</td>
<td>-0.03</td>
<td>0.02</td>
<td>0.01</td>
<td>0.02</td>
<td>-0.01</td>
<td>-0.23 ***</td>
<td>-0.17</td>
</tr>
<tr>
<td>15 Diversity in the Labor Force Employment</td>
<td>0.01</td>
<td>0.04</td>
<td>0.00</td>
<td>0.02</td>
<td>0.04</td>
<td>-0.02</td>
<td>-0.03</td>
<td>0.04 **</td>
<td>0.04 **</td>
<td>-0.02</td>
<td>0.03 *</td>
<td>0.22 ***</td>
<td>-0.18</td>
</tr>
<tr>
<td>16 Diversity in the Level of Education</td>
<td>0.03</td>
<td>-0.06</td>
<td>0.02</td>
<td>-0.02</td>
<td>-0.07</td>
<td>0.05 **</td>
<td>0.02</td>
<td>-0.06 ***</td>
<td>-0.05 **</td>
<td>0.00</td>
<td>0.08 **</td>
<td>0.29 ***</td>
<td>0.14</td>
</tr>
<tr>
<td>17 Diversity in Age</td>
<td>-0.05 ***</td>
<td>0.08</td>
<td>0.02</td>
<td>0.06</td>
<td>0.06</td>
<td>-0.01</td>
<td>-0.01</td>
<td>0.05 **</td>
<td>0.05 **</td>
<td>-0.02</td>
<td>-0.03 *</td>
<td>-0.34 ***</td>
<td>0.36</td>
</tr>
<tr>
<td>18 Diversity in Country of Origin</td>
<td>0.11 ***</td>
<td>-0.11</td>
<td>0.01</td>
<td>-0.1172</td>
<td>-0.10 *</td>
<td>0.04 *</td>
<td>0.03</td>
<td>-0.07 ***</td>
<td>-0.06 ***</td>
<td>0.04 **</td>
<td>0.06 **</td>
<td>0.66 ***</td>
<td>-0.05</td>
</tr>
</tbody>
</table>

Notes: (a) * p < .05; ** p <.01; *** p < .001 (Two-tailed Tests).
Table 3. Logistic Regression Models Predicting the Likelihood of a Start-Up Company Going Public.

<table>
<thead>
<tr>
<th>Independent Variables (b):</th>
<th>Model 1</th>
<th>Model 2</th>
<th>Model 3</th>
<th>Model 4</th>
<th>Model 5</th>
<th>Model 6</th>
<th>Model 7</th>
</tr>
</thead>
<tbody>
<tr>
<td>Constant</td>
<td>-2.16 ***</td>
<td>0.22</td>
<td>-0.03</td>
<td>6.34</td>
<td>-2.03 ***</td>
<td>0.28</td>
<td>-2.03 ***</td>
</tr>
<tr>
<td>Age</td>
<td>-0.01</td>
<td>0.02</td>
<td>-0.01</td>
<td>0.02</td>
<td>-0.01</td>
<td>0.02</td>
<td>-0.01</td>
</tr>
<tr>
<td>Age, squared</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
</tr>
<tr>
<td>Number of Investors</td>
<td>-0.11 *</td>
<td>0.05</td>
<td>-0.11 *</td>
<td>0.05</td>
<td>-0.20 ***</td>
<td>0.05</td>
<td>-0.17 **</td>
</tr>
<tr>
<td>Total Amount of Funding</td>
<td>0.04 ***</td>
<td>0.00</td>
<td>0.04 ***</td>
<td>0.00</td>
<td>0.04 ***</td>
<td>0.00</td>
<td>0.03 ***</td>
</tr>
<tr>
<td>Silicon Valley Location (1= Yes)</td>
<td>0.65 ***</td>
<td>0.12</td>
<td>0.35 *</td>
<td>0.15</td>
<td>0.53 ***</td>
<td>0.12</td>
<td>0.38 **</td>
</tr>
<tr>
<td>Route 128 (New England) Location (1= Yes)</td>
<td>0.04</td>
<td>0.19</td>
<td>-0.07</td>
<td>0.20</td>
<td>-0.03</td>
<td>0.19</td>
<td>0.15</td>
</tr>
</tbody>
</table>

From the City Location of the Start-Up Company:

| Labor Force Participation | 0.02 | 0.03 | -0.01 | 0.03 | 0.00 | 0.03 | 0.00 | 0.03 |
| Diversity in the Labor Force Employment | -2.15 | 1.73 | -2.36 | 1.82 | -2.93 | 1.75 |
| Diversity in the Level of Education | -1.94 | 1.59 | -1.19 | 1.65 | |
| Diversity in Age | -1.99 | 5.59 | -1.36 | 6.14 | |
| Diversity in Country of Origin | 1.24 * | 0.58 | 0.30 | 0.61 | |

From the Syndicate Network of VC Firms:

| Standardized Power Centrality | 0.28 *** | 0.06 | 0.17 ** | 0.07 | 0.16 * | 0.07 | 0.18 ** | 0.07 | 0.16 ** | 0.07 |
| Structural Holes (Structural Autonomy) | 0.03 | 0.21 | -0.11 | 0.22 | -0.11 | 0.22 | -0.41 | 0.22 | -0.40 | 0.22 |
| Highest Number of IPOs Experience | 0.24 *** | 0.02 | 0.23 *** | 0.02 | 0.12 *** | 0.01 | 0.12 *** | 0.01 | 0.12 *** | 0.01 |
| Lowest Geographic Distance (in thousand miles) | 0.14 ** | 0.05 | 0.14 ** | 0.05 | 0.17 ** | 0.05 | 0.17 ** | 0.05 | 0.17 ** | 0.05 |
| Highest Stage Investment Experience | -0.07 | 0.04 | -0.07 | 0.04 | |
| Highest Industry Investment Experience | 0.02 | 0.03 | 0.02 | 0.03 | -0.05 * | 0.03 | -0.05 * | 0.03 | 0.03 | 0.03 |
| Highest Location Investment Experience | 0.04 * | 0.02 | 0.04 * | 0.02 | -0.01 | 0.01 | -0.01 | 0.01 |
| Highest Company Investment Experience | -0.04 *** | 0.01 | -0.04 *** | 0.01 | |

LR Chi-Square Statistic: 270.52 270.67 291.41 435.09 426.59 392.94 386.17
Degrees of Freedom: 16 21 18 29 22 24 24
p > Chi² 0.000 0.000 0.000 0.000 0.000 0.000 0.000
Pseudo R Square: 0.094 0.096 0.102 0.152 0.151 0.138 0.137

Notes: (a) † p < .1; * p < .05; ** p <.01; *** p < .001; (b) Coefficients for the industry, stage, and year control variables are not shown in the table (although they are included in the estimation).
Table 4. Models of Different Performance Measures (OLS Regression correcting for Sample Selection).

<table>
<thead>
<tr>
<th>Main Model:</th>
<th>Logarithm of Time to Public Offering</th>
<th>Logarithm of Earnings per Share</th>
<th>Logarithm of Market Capitalization</th>
<th>Logarithm of Revenues</th>
<th>Heckman Selection Model</th>
</tr>
</thead>
<tbody>
<tr>
<td>Constant</td>
<td>8.15 ***</td>
<td>1.30</td>
<td>2.19</td>
<td>18.80</td>
<td>4.87 *</td>
</tr>
<tr>
<td>Age</td>
<td>0.15 ***</td>
<td>0.01</td>
<td>-0.09</td>
<td>0.62</td>
<td>-0.06 ***</td>
</tr>
<tr>
<td>Age, squared</td>
<td>0.00 ***</td>
<td>0.00</td>
<td>0.00</td>
<td>0.01</td>
<td>0.00 ***</td>
</tr>
<tr>
<td>Number of Investors</td>
<td>0.13 ***</td>
<td>0.02</td>
<td>1.30</td>
<td>2.78</td>
<td>-0.03</td>
</tr>
<tr>
<td>Total Amount of Funding</td>
<td>-0.01 ***</td>
<td>0.00</td>
<td>-0.04</td>
<td>0.18</td>
<td>0.01 *</td>
</tr>
<tr>
<td>Silicon Valley Location (1= Yes)</td>
<td>-0.11 *</td>
<td>0.06</td>
<td>-0.77</td>
<td>0.72</td>
<td>-0.01</td>
</tr>
<tr>
<td>Route 128 (New England) Location (1= Yes)</td>
<td>-0.06</td>
<td>0.08</td>
<td>-1.09</td>
<td>1.32</td>
<td>0.05</td>
</tr>
<tr>
<td>From the city location of the Start-Up Company:</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Labor Force Participation</td>
<td>-0.01</td>
<td>0.01</td>
<td>0.08</td>
<td>0.35</td>
<td>-0.01</td>
</tr>
<tr>
<td>Diversity of Labor Force Employment</td>
<td>0.14</td>
<td>0.76</td>
<td>-0.32</td>
<td>10.61</td>
<td>-0.19</td>
</tr>
<tr>
<td>From the group of VC Firms in the Syndicate:</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Standardized Power Centrality</td>
<td>-0.05 *</td>
<td>0.03</td>
<td>0.03</td>
<td>0.29</td>
<td>0.54 ***</td>
</tr>
<tr>
<td>Structural Holes (Structural Autonomy)</td>
<td>0.07</td>
<td>0.10</td>
<td>-2.12</td>
<td>3.33</td>
<td>0.07 †</td>
</tr>
<tr>
<td>Highest Number of IPOs Experience</td>
<td>-0.03 ***</td>
<td>0.01</td>
<td>-0.10</td>
<td>0.34</td>
<td>-0.02</td>
</tr>
<tr>
<td>Lowest Geographic Distance (in thousand miles)</td>
<td>-0.03</td>
<td>0.02</td>
<td>-0.26</td>
<td>0.74</td>
<td>-0.06</td>
</tr>
<tr>
<td>Highest Industry Investment Experience</td>
<td>0.01</td>
<td>0.01</td>
<td>0.05</td>
<td>0.19</td>
<td>-0.04 *</td>
</tr>
<tr>
<td>Highest Location Investment Experience</td>
<td>-0.01</td>
<td>0.01</td>
<td>-0.09</td>
<td>0.25</td>
<td>0.02 **</td>
</tr>
</tbody>
</table>

Chi-Square Statistic: 561.86, 99.11, 240.80, 173.05
p > Chi² 0.00, 0.00, 0.00, 0.00
Rho -0.98, -1.00, -0.30, -0.95
Test of Independence of Equations: 105.10, 0.42, 26.57
p > Chi² (1) 0.00, 0.52, 0.00

Number of Start-Up Companies: 4070, 4070, 4070, 4070
Public Companies (selected cases): 397, 100, 437, 4070

Notes: (a) † p < .1; * p < .05; ** p < .01; *** p < .001; (b) Coefficients for the industry, stage, and year control variables are not shown in the table (although they are included in the estimation).
Table 5. Multinomial Logistic Regression Predicting Different Company Outcomes (Omitted Category: Company is alive).

<table>
<thead>
<tr>
<th>Main Model:</th>
<th>Going IPO</th>
<th>Merger or Acquisition</th>
<th>Bankrupt or Defunct</th>
</tr>
</thead>
<tbody>
<tr>
<td>Constant</td>
<td>1.71</td>
<td>3.23</td>
<td>0.34</td>
</tr>
<tr>
<td>Age</td>
<td>0.01</td>
<td>0.02</td>
<td>0.04 *</td>
</tr>
<tr>
<td>Age, squared</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00 *</td>
</tr>
<tr>
<td>Number of Investors</td>
<td>-0.33 ***</td>
<td>0.06</td>
<td>-0.12 *</td>
</tr>
<tr>
<td>Total Amount of Funding</td>
<td>0.06 ***</td>
<td>0.01</td>
<td>0.04 ***</td>
</tr>
<tr>
<td>Silicon Valley Location (1= Yes)</td>
<td>0.29 *</td>
<td>0.16</td>
<td>0.05</td>
</tr>
<tr>
<td>Route 128 (New England) Location (1= Yes)</td>
<td>0.15</td>
<td>0.21</td>
<td>0.44 **</td>
</tr>
</tbody>
</table>

From the city location of the Start-Up Company:
| Labor Force Participation | 0.00      | 0.03                  | 0.01                | 0.02      | 0.07        | 0.05      |
| Diversity of Labor Force Employment | -2.10 | 1.91             | -1.69               | 1.59      | -4.26       | 3.08      |

From the group of VC Firms in the Syndicate:
| Standardized Power Centrality | 0.20 ** | 0.07                  | 0.20 ***             | 0.06      | 0.29 *      | 0.12      |
| Structural Holes (Structural Autonomy) | -0.39 | 0.43         | 0.34 *               | 0.21      | -0.35       | 0.40      |
| Highest number of IPOs Experience | 0.14 *** | 0.02              | 0.05 **              | 0.02      | -0.01       | 0.03      |
| Lowest Geographic Distance (in thousand miles) | 0.20 ** | 0.06             | 0.09                | 0.05      | -0.02       | 0.12      |
| Highest Industry Investment Experience | -0.06 * | 0.03            | 0.00                | 0.02      | 0.05        | 0.05      |
| Highest Location Investment Experience | -0.03 † | 0.02         | -0.04 *             | 0.01      | -0.02       | 0.03      |

Chi-Square Statistic: 641.2
p > Chi^2 0.000
Pseudo R-Square: 0.109

Number of Start-Up Companies: 4160

Notes: (a) † p < .1; * p < .05; ** p < .01; *** p < .001; (b) Coefficients for the industry, stage, and year control variables are not shown in the table (although they are included in the estimation).
References


Losch, August. 1954. The Economics of Location. Yale University Press.


