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The Downside of Repeated Ties:

Syndicated Venture Capital Investments

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The Downside of Repeated Ties: Syndicated Venture Capital Investments

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The Downside of Repeated Ties: Syndicated Venture Capital Investments

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Abstract

My dissertation develops a conceptual framework to study the largely unrecognized negative side effects or social costs of repeated ties with the same partners and partners' social characteristics. Drawing on insights from the literatures on social networks, prestige and endorsements, learning, expertise and small groups, I suggest that the costs of repeated ties with the same partners are manifest by a bias in partner search, evaluation and selection; inadequate monitoring of familiar partners; and the adoption of suboptimal, insufficiently adapted routines developed during prior exchanges. I ultimately argue that these costs can be high enough to outweigh the benefits of repeated ties partially or even completely. I further argue that the level of cohesion in the network in which the actors and their partners are embedded, and the degree of similarity between them will moderate these costs. I also explore the effects of highly sought after partner characteristics such as their prestige/status and prior experience, on the likelihood of success of the partnership. I test the predictions of my theory on a longitudinal dataset consisting of the population of nearly 1,300 startups that received first round investments from syndicates of venture capital (VC) firms during the period 1997 to 2001.

As predicted, I find that the likelihood of a syndicate's success is related to the number of prior ties between syndicate members in an inverted U-shaped manner and that the costs associated with repeated ties are accentuated by partner homogeneity. I also find that the likelihood of the syndicate's success decreases with an increase in the level of cohesion in the syndicate and the prior experience of the members. Finally, I find that the likelihood of success increases at a decreasing rate as syndicate members' prestige increases. These findings make a number of contributions to research on strategy and organizational theory, primary among which is to further understanding of the negative effects of social networks. The study highlights the importance of considering the costs of prior ties in addition to their benefits when making partner selection decisions, particularly in contexts characterized by high levels of reciprocity between partners.

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CHAPTER 1: INTRODUCTION

In this dissertation, I consider the costs of repeated ties with the same partners. I argue that the very reasons that lead actors to prefer prior partners may also lead them to make sub-optimal decisions with regard to the selection and subsequent monitoring of those partners. Actors are also less likely to question the appropriateness of the routines established during their prior exchanges with those partners. I suggest that together these factors are likely to have negative performance consequences. I also explore the effects of certain other factors such as partner prestige, partner experience and network cohesion, many of which are often considered universally beneficial, on the outcomes of partnerships.

MOTIVATION FOR THE STUDY

Research on social networks has established that firms have a predisposition to enter into exchange relationships with their prior partners or their partners' partners (e.g., Eccles and Crane, 1988; Gulati, 1995). Doing so is thought to provide several advantages such as lower costs of partner search and governance, lower uncertainty regarding partner quality and behavior and greater trust, communication and coordination with them (Axelrod, 1984; Granovetter, 1985). The costs of engaging in repeated ties with the same partners have however, received only limited research attention, as have the costs of entering into exchange relations with prior partners' partners, particularly in the literature on inter-organizational alliances.

The research question that motivates my dissertation is: What are the negative side effects, or social costs, of repeatedly interacting with the same partners? Drawing on key insights from the vast literatures social networks, prestige and endorsements, learning, expertise and small groups, I develop a theoretical framework that suggests that the costs of repeated ties with the same partners are manifest by: (a) a bias in the search for, evaluation of, and selection of partners; (b) sub-optimal monitoring of familiar partners; and (c) a reliance on prior routines that are insufficiently adapted to the focal situation. I ultimately argue that these costs can be high enough to outweigh the benefits of repeated ties. I also argue that the costs of repeated ties will be intensified by the level of cohesion in the network in which the partners are embedded and the degree of similarity between the focal actors and their partners. Finally, I also consider the effects of partner characteristics including their status/prestige and their prior experience, and group characteristics including the number of members and their homogeneity on the outcome of the focal partnership.

I develop and test specific hypotheses regarding the social costs of repeated ties and the other factors mentioned above on a longitudinal dataset of US-based new organizations or "startups" that received funding from a syndicate[1] of US-based professional venture capital (VC) firms for the first time during the period 1997 to 2001. The empirical results of the study are largely supportive of my theory. These findings, along with the contribution they make to research on strategy and organizational theory, are summarized in this section.

Findings and Contribution of the Study

The core contribution of this dissertation is to the literature on social networks, particularly to understanding of their detrimental effects, which until recently, have received

[1] A syndicate of venture capital firms refers to two or more venture capital firms investing jointly in a startup.

little systematic consideration in social network theory. The negative effects of social networks have been especially under-appreciated in the literature on inter-organizational relationships (Salancik, 1995). Most prior research on social networks has assumed that social ties are beneficial for network members. Although there has been a growing recognition among researchers in recent years that this may not always be true, the focus of this stream of literature has largely been on identifying the contingencies under which social ties are more or less beneficial (e.g., Ahuja, 2000), and the types of ties and network structures that have the most detrimental effects (Uzzi, 1996; 1997). Moreover, barring a few exceptions (e.g., Ahuja, 2000), research on the contingent value of ties has largely focused on the interpersonal (e.g., Burt, 1992; Podolny and Baron, 1997), rather than the firm level. Similarly, the potential firm-level negative effects of networks have also not been explored (although, see Uzzi, 1996; 1997). While the cost, in terms of time and effort, of developing and maintaining social ties, in terms of time and effort, has been discussed occasionally (Nahapiet and Ghoshal, 1998), the negative effects of entering into repeated exchanges with the same partners have largely been neglected. The importance of obtaining a better understanding of the effects of social networks is underscored by the fact that many outcomes associated with them have been shown to ultimately affect firms' survival rates and financial performance (D' Aveni, 1990; Baum and Oliver, 1991; Uzzi, 1996; Pfeffer, 1997; Stuart, Hoang and Hybels, 1999; Higgins and Gulati, 2003).

The primary finding of this study is that the number of prior ties between members of the focal syndicate has an inverted U-shaped relationship with the syndicate's likelihood of success. This finding demonstrates that while prior ties provide fast and relatively economical access to important information, enabling firms to form partnerships when required, they also impose considerable costs which increase at a greater rate than the benefits, eventually outweighing them completely. Thus, this study suggests that when selecting partners, firms should consider the potential costs of entering into repeated exchanges with prior partners along with the costs because failure to do so may lead to unexpected outcomes, some of which may become apparent only in the long term. The theoretical arguments developed in this study are especially relevant to other contexts such as investment banking syndicates characterized by high levels of reciprocity because of the importance of maintaining on-going relationships with other network members. Similarly, in contexts where the existence of prior ties between service or resource providers is generally viewed as an advantage, prior partners are considered highly desirable future partners. However, this study shows that such reliance on prior ties may also impose significant costs which need to be taken into account while selecting partners.

The second key contribution of this study is to suggest that rather than being universally beneficial as is generally believed (although recent studies such as Uzzi, 1996, have suggested otherwise), high degrees of network cohesion may impose certain constraints on the focal actors themselves, and discourage them from engaging in behaviors that would be beneficial to them as well as to the collective interests of network members. In general, network cohesion is thought to curb opportunism and other non-normative behaviors that may be detrimental to the individual or collective interests of network members by creating the threat of sanctions and disseminating reputational information about violators throughout the network. However, the theory developed in this study as well as its empirical findings suggest that because cohesion promotes two-way transparency in the network, the threat of sanctions or reputational consequences is equally applicable to all network members and not just the focal actors' potential partners. Thus, cohesion may constrain the behavior of not only potential partners, but also the focal firm itself.

Moreover, cohesion may also suppress behaviors that might be beneficial to the individual or collective interests of network members. For example, monitoring of partners is likely to be beneficial to the collective interests of network members in contexts such as the present where the task to be performed by the partnership is delegated to one partner (known as the Lead VC firm), the quantity and quality of effort exerted by that partner is non-contractible, and that partner's individual interests are in conflict with the collective interests of the partnership. In such situations, ongoing monitoring of the "Lead" partner's efforts may be the remaining partners' only means of timely detection of emerging problems. However, since monitoring is psychologically aversive to actors who are subjected to it and moreover, is seen as a sign of distrust, it is discouraged in cohesive networks. Thus, actors may be reluctant to monitor partners with whom they are cohesive because of the fear of negative reputational consequences. Because the speed of transmission of information throughout the network increase and thus the reputational costs, with network density, higher degrees of cohesion may increase actors' reluctance to engage in monitoring. By preventing the timely detection of problems resulting from inadequate effort by the "Lead" partner however, such suppression may be detrimental to their collective interests.

The third contribution of this study is to the literature on prestige and endorsements, which has largely focused on the beneficial consequences of association with prestigious actors (Podolny, 1994; Podolny, Stuart and Baron, 1996). This study suggests that in addition to these positive consequences, interaction with high status or prestigious actors also imposes significant costs. Not only are prestigious partners difficult to monitor, high status/prestige also intensifies actors' concerns about protecting their existing relationships with such partners, thereby making them more reluctant to challenge or monitor those partners.

Finally, this study also contributes to research on the venture capital industry in which syndication is a common practice. Prior strategy research on VC syndication has tended to assume that syndication has positive effects including increasing each individual firm's geographical and industry reach (Sorenson and Stuart, 2001). Finance-oriented research on VC syndication has also largely focused on its benefits such as risk reduction (see, for example, Coyle, 2000; Lerner, 1994). In reality however, as this study suggests, syndication may increase the overall level of risk faced by firms, particularly when they syndicate repeatedly with the same other firms, because the quality of such familiar firms may be over-estimated while the need for monitoring them may be under-estimated. This bias resulting from the familiarity of syndication partners may reduce the likelihood of the funded startup being successful rather than increasing it, thereby increasing the risk faced by the syndicate. Similarly, syndicating with cohesive partners may increase VC firms' reluctance to monitor or challenge those partners. In addition, VC firm characteristics such as status/prestige, prior experience and similarity to the focal firm, all of which are generally considered beneficial, may also contribute to a reduction in the likelihood of the syndicate's success.

STRUCTURE OF THE REMAINING DOCUMENT

The remainder of this document is divided into five chapters. Chapter 2 provides a review of the extant literature on social networks, with a specific focus on the research on repeated ties and cohesive networks. I develop the theory and hypotheses in chapter 3, and elaborate on aspects of the data and statistical analyses I use to test the hypotheses, in chapter 4. Next, I present the results of the empirical analyses in chapter 5. Finally, in chapter 6, I discuss the contributions of this study and the implications of its findings for future research.

CHAPTER 2: LITERATURE REVIEW

There is a vast body of research on the benefits of social networks. A considerable portion of this research has focused specifically on the benefits of cohesive networks and on the benefits of repeated ties with prior partners. On the other hand, the costs, or negative effects, of social networks in general and of cohesive ties and repeated ties in particular, on the other hand, have received only limited research attention, especially in the literature on inter-organizational alliances. This is the gap I seek to address in this dissertation. In line with this objective, I review below the extant theoretical and empirical research on the benefits and negative effects of social networks, with a specific focus on research on repeated ties with the same partners and cohesive networks.

RESEARCH ON SOCIAL NETWORKS

Entering into exchange relationships with unknown actors is fraught with risk and uncertainty because of the imperfect availability of information about the potential partners' capabilities, reliability and motives (Williamson, 1975; Pfeffer and Salancik, 1978; Kogut, 1988). At the same time, the notion that instead of being driven solely by profit maximization considerations of individual, atomistic actors, economic action takes place within the context of relationships which develop between economic actors over time, has been well accepted in research for several years now. Granovetter (1985) argued that firms' economic actions are embedded in social networks, where embeddedness refers to the extent to which actions are informed, influenced and enabled by the network of accumulated stable and preferential social relations. Indeed, research on social networks has provided evidence that actors' social ties help to overcome some of the risks associated with entering into exchange relationships with previously unknown actors, by providing reputational information about their past behavior (Burt and Knez, 1995), as well as referrals (Granovetter, 1974). In addition, their own prior experience with other actors helps build trust between them, thereby reducing the risk associated with future interactions with those actors. Not surprisingly then, actors demonstrate a marked preference for interaction with their prior partners (Podolny, 1994; Gulati, 1995), or their partners' partners (Baker, 1990; Uzzi, 1996). While uncertainty with respect to the former is minimized because of the actors' own prior direct experience which enables trust-building, in the case of the latter, the reduction in uncertainty results from the experience of others whom they trust.

Benefits of Social Networks

Research has explored a wide range of benefits thought to accrue from social networks both at the inter-personal and the inter-organizational levels. The benefits individuals derive from social networks include getting a job (Granovetter, 1974), intra-organizational mobility (Burt, 1992; Ibarra, 1995) and superior job performance (Mizruchi and Stearns, 2001). At the firm level, among the many beneficial effects of networks are greater survival rates, improved financial performance and innovation (Shan, Walker and Kogut, 1994; Powell, Koput and Smith-Doerr, 1996; Baum and Oliver, 1991; Pfeffer, 1997; Stuart, Hoang and Hybels, 1999; Ahuja, 2000; Higgins and Gulati, 2003).

At both levels, perhaps the most studied benefit of social networks is members' ability to access information. In general, social networks are thought of as a relatively efficient and inexpensive channel through which actors can access required information (Burt, 1992; Nahapiet and Ghoshal, 1998). In addition, social network also often provide members access to information that is not available elsewhere. Among the types of information social networks provide are information about job opportunities and expected salaries (Granovetter, 1974; 1982; Fernandez and Weinberg, 1997; Seidel, Polzer and Stewart, 2000), collaborative opportunities (Gulati, 1999), technological developments (Powell, Koput, and Smith-Doerr, 1996) and novel practices such as the M-form organization (Fligstein, 1985) and TQM (Westphal, Gulati and Shortell, 1997).

In addition to information, members are also able to access opinions and advice through their social networks (Constant, Sproull, and Kiesler, 1996; Westphal, Seidel and Stewart, 2001). Moreover, information accessed from social networks is frequently accompanied by referrals or reputational endorsements, which facilitate the evaluation of potential business partners. The evidence suggests that firms regularly rely on referrals from existing employees when hiring new employees (Granovetter, 1995; Bian and Ang, 1997; Fernandez and Weinberg, 1997). Firms are thought to be unwilling to form ties with unknown firms if they lack at least an indirect network connection to those firms (Gulati and Gargiulo, 1999; Powell, Koput and Smith-Doerr, 1996). Network members are also frequently able to use the influence of their direct and indirect ties to co-opt actors on whom they depend (Garguilo, 1993).

Another important beneficial outcome of network membership is that it provides legitimacy to its members, where legitimacy is defined as "a generalized perception or assumption that the actions of an entity are desirable, proper, or appropriate within some socially constructed system of norms, values, beliefs, and definitions" (Suchman, 1995: 574). Legitimacy enables actors to access required resources from their environment (Podolny, Stuart and Hannan, 1996; Zuckerman, 1999), which in turn affects both their performance and survival.

Further, membership in social networks bestows differential status or prestige on actors in accordance with their location in the network as well as the status/prestige of the actors to whom they are connected (Podolny, 1993). Thus, perceptions of an actor's quality are influenced considerably by its pattern of relationships, especially when quality cannot be measured objectively (Stuart, 2000). Research suggests that a firm's current and prior affiliations are frequently taken into consideration when it is being evaluated as a potential exchange partner (Kogut, Shan and Walker, 1992; Powell, Koput and Smith-Doerr, 1996; Nahapiet and Ghoshal, 1998; Gulati and Garguilo, 1999) and the identity of an actor's network partners has considerable influence on the actor's status/prestige (Podolny, 2001).

Ties to prestigious actors are seen as particularly powerful indicators of an actor's quality because prestigious actors are thought to have the ability to discern quality and, at the same time, be discriminating in their choice of partners in order to guard against the potential loss of their own status from association with a poor quality actor (Blau, 1964; Baum and Oliver, 1991; Podolny, 1994; Stuart, 1998; 1999). Like legitimacy, status/prestige also enables actors to access required resources from their environment (e.g., Larson, 1992; Podolny, 1994; Podolny, Stuart and Hannan, 1996; Zuckerman, 1999). Research on the likelihood of success of new ventures has also provided evidence that supports this view. Studies have shown that indicators of new venture success such as receiving funding from a prestigious VC firm, making an Initial Public Offering (IPO), and having a leading investment banker manage the IPO, are all associated with the presence of prestigious individuals on the new venture's top management teams (Bygrave and Timmons, 1992; Stuart, Hoang and Hybels, 1999; Gulati and Higgins, 2003). Moreover, status is implicitly transferred across ties, and thus, an actor's status or prestige is increased by relationships with prestigious partners (Baum and Oliver, 1991; Podolny, 1993; 1994; Stuart, 1998).

Repeated Ties

Research suggests that interacting with weak ties and with actors to whom a firm has no prior ties can be beneficial because it provides access to non-redundant information, or brokerage opportunities including innovation (Burt, 1992; Ahuja, 2000; Rowley, Berhens and Krackhardt, 2000). Paradoxically though, research on partner selection suggests that actors consistently exhibit a relatively high propensity for repeatedly choosing their past partners, and their partners' partners for future interactions (Eccles and Crane, 1988; Levinthal and Fichman, 1988; Gulati and Gargiulo, 1999; Li and Rowley, 2002; Rowley, Greve, Rao, Baum and Shipilov, 2005; Gulati, 1995). Among the reasons for this preference may be the increase in mutual understanding and learning about each other's abilities and motives for entering into interorganizational relationships that accompanies working together (Gulati, 1995; Uzzi, 1996; Gulati and Gargiulo, 1999; Li and Rowley, 2002). This familiarity makes actors more comfortable with each other since it facilitates trust-building, and the establishment of exchange norms based on an expectation of future interaction (Axelrod, 1984; Larson, 1992;

Gulati, 1995; Chung, Singh and Lee, 2000). Repeated interaction also facilitates the development of a common language and routines that make subsequent interaction more efficient (Mohr and Spekman, 1996; Simonin, 1997; Inkpen and Dinur, 1998; Zollo, Reuer and Singh, 2002).

Research on partner selection has proposed two models to explain this preference for interaction with prior partners: the evaluation model and the inertial model. The evaluation model suggests that interacting with prior partners helps to reduce the considerable risk and uncertainty that are inherent in entering into exchange relationships with unfamiliar partners (Podolny, 1994; Gulati, 1995) because of the limited availability of information about other potential partners' capabilities and reliability (Pfeffer and Salancik, 1978; Williamson, 1975; Kogut, 1988; Oxley, 1997). This perspective suggests that the reason for the preference for interacting with prior partners or partners' partners is that their local networks are able to provide them reputational information that helps them in discerning the capabilities and reliability of potential partners (Gulati and Gargiulo, 1999). Interacting with prior partners therefore enables actors to circumvent adverse selection and moral hazard problems associated with new partners (Hitt, Dacin, Levitas, Arregle and Borza, 2000). For the same reason, when exchange with prior partners is not possible, actors prefer to enter into exchange relationships with their partners' partners.

In contrast, the inertial model suggests that the preference results from the path dependent routines that develop over time (March and Simon, 1958; Hannan and Freeman, 1984; Amburgey and Miner, 1992). In general, inertial models of behavior are based on the notion that in uncertain situations, firms rely on historical experience (March, 1988), and thus, past solutions to problems become the starting point for new searches (Nelson and Winter, 1982). Results of past search become the starting points for future searches because boundedly rational actors rely on established routines to drive the search for knowledge and moreover, routines are relatively stable and greatly influenced by experience and history of the firms and the individuals therein (Nelson and Winter, 1982; Baum, Li and Usher, 2000).

A consequence of this preference for embedded ties is that the networks surrounding the actors increase in density and cohesiveness, becoming relatively stable over time (Baum, Rowley, Shiplov and Chuang, 2005). In turn, the greater density of these networks makes them effective informal governance mechanisms that prevent opportunism and facilitate the development of trust and reciprocity between members (Granovetter, 1985; 1992; Bourdieu, 1986; Coleman, 1988; Portes and Sensenbrenner, 1993; Portes, 1998).

Repeated ties and trust between partners tend to be mutually reinforcing. The level of mutual trust between partners increases with repeated interaction. In turn, the increased trust frequently leads to a decline in the level of monitoring and the use of formal controls because the familiar partners are deemed to be trustworthy and thus expected to refrain from being opportunistic as well as competent in their abilities to complete the objectives of the partnership (e.g., Argyris, 1952; Das and Teng, 1998; Zaheer, McEvily and Perrone, 1998; Sorenson and Stuart, 2001). A display of trusting behavior, through a decrease in the level of formal controls, for example, is thought to lead to an increase in the level of cooperation between partners (Ring and Van de Ven, 1992; Child and Faulkner, 1998;

Zaheer, McEvily and Perrone, 1998) as well as the degree of reciprocal trust, which refers to an actor reciprocating in kind when in response to feeling trusted by a partner (Zand, 1981; Gambetta, 1988; Bradach and Eccles, 1989).

Network Cohesion

Cohesion refers to the existence of mutual partners between two actors who are tied to each other, or the degree of density in an ego network[2], where ego density is the extent to which an actor's partners are connected to each other. Cohesive networks have a number of beneficial effects. Cohesion facilitates the diffusion of information about members' prior exchanges throughout the network and the speed at which information diffuses through networks increases with their density (Burt and Knez, 1995). Thus, dense networks tend to become repositories of considerable information about their members' reputations and past behavior (Walker, Kogut and Shan, 1997; Gulati and Gargiulo, 1999). In such networks, actors are thus able to develop relatively accurate and reliable expectations regarding potential future partners (Granovetter, 1985; Raub and Weesie, 1990; DiMaggio and Louch, 1998; Gulati and Garguilo, 1999).

Consequently, cohesive networks facilitate the development of greater trust and reciprocity between actors (Coleman, Katz and Menzel, 1966; Rogers and Kincaid, 1981; Baker, 1984; Granovetter, 1985, 1992; Coleman, 1988; Grief, 1989; Burt, 1992; Ingram and Roberts, 2000). The level of cooperation is also generally greater in dense networks (Granovetter, 1992; 2002; Reagans, Zuckerman and McEvily, 2004). The increased trust, in

[2] An ego network consists of ego i.e., the focal actor from whose perspective the relationships are examined, the alters i.e., actors to whom ego is connected and the ties between ego's alters.

turn, helps to reduce partner search costs, the perceived uncertainty regarding partner quality and behavior, as well as the perceived need for monitoring those partners (Granovetter, 1985; Coleman, 1990). By promoting the belief that partners will not pursue their own self-interests, or take advantage of their vulnerabilities, trust in turn, facilitates the exchange of information that is complex or tacit between partners (Ring and Van de ven, 1992; Uzzi, 1997).

The greater density of ties increases the likelihood that a member engaging in non-normative behavior, such as opportunism, will be observed by another member (Merry, 1984), and gossip about the violation will spread through the network, damaging the violators' reputation (Granovetter, 1985; Coleman, 1988; Raub and Weesie, 1990; Burt and Knez, 1995). Density also increases the probability of the violator being subjected to sanctions by other network members (Coleman, 1990). To the extent such reputational damage and sanctions lead to a loss of existing ties or the inability to form new ties in the future (Macaulay, 1963; Granovetter, 1985; Maitland, Bryson and Van de Ven, 1985; Garguilo and Benassi, 2000), network cohesion can create significant dis-incentives for network members to engage in violating the norms of behavior (Mayhew, 1968; Burt, 1992; Brass, Butterfield and Skaggs, 1998). Therefore, cohesive networks function as informal governance mechanisms that control members' behavior.

Negative Effects of Social Networks

Barring some recent exceptions (e.g., Uzzi, 1996; Garguilo and Benassi, 2000; Mizruchi and Stearns, 2001), most research on social networks in general and repeated ties with the same actors in particular, has been based on the largely tacit assumption that the benefits from social ties exceed their costs. Over time however, research has gradually begun to acknowledge that while networks serve as sources of opportunities, they can also impose significant constraints on their members (Burt, 1992; Baker and Faulkner, 1993; Powell, Koput and Smith-Doerr, 1996; Uzzi, 1996, 1997; Gulati, 1998; Labianca, Brass and Gray, 1998; Galaskiewicz and Zaheer, 1999; Garguilo and Benassi, 2000; Mizruchi and Stearns, 2001).

Moreover, social ties, especially strong ties, require a considerable amount of time and effort to develop and maintain, and thus, trying to maintain too many ties could well result in a dilution of the actor's focus on key activities required for the business. A large number of ties can place a strain on the actor's absorptive capacity (Ahuja, 2000) or provide the actor excessive amounts of information, determining the relevance of which consumes precious cognitive resources (Feldman and March, 1981). Such cognitive overload can prevent the actor from processing even the relevant information effectively.

Cohesion/Over-embeddedness

There has also been some recognition of the detrimental effects of an over-reliance on embedded ties. Research suggests that over-embeddedness in a network can curtail the amount of external information members receive, which can lead to a decline in their performance and even threaten survival (Burt, 1992; Uzzi, 1996; Beckman, Haunschild and Phillips, 2004). Being embedded in dense networks can also reduce a firm's ability to innovate and develop new competencies (McEvily and Zaheer, 1999; Ahuja, 2000), or reduce actors' autonomy, increasing their dependence on partners (Burt, 1992; Kogut, 2000). The redundancy of ties in cohesive networks can also lead to a decline in the potential for brokerage opportunities (Ibarra, 1993). Firms embedded in dense networks can also become inertial, which can lead to a decline in the rate of radical inventions they generate (Abrahamson and Fombrun, 1994).

By insulating the member organizations from the external environment, such networks can also lead to the members entirely miss new technological developments. Moreover, such networks can also cause individual actors to become dependent on each other in such a way that uncertainty brought by environmental changes can affect all the interdependent organizations in unpredictable ways (Pfeffer and Salancik, 1978; Provan and Milward, 1995). Sudden changes in the environment, or the departure of a core member can then prove detrimental to individual members or even the entire network (Uzzi, 1996). When resources reside in a network instead of a single firm, member firms can lose their competitive advantage when a technological change renders obsolete the capabilities of their co-opetitors, that is, suppliers, customers, and complementors (Afuah, 2000). A high level of cohesiveness can also lead to rigidity in the network, which in turn can hinder cooperation (Garguilo and Benassi, 2000). Over-embeddedness can also make organizations rigid and slow to adapt to changing environments, ultimately having detrimental effects on the individual actors as well as the network itself (Galaskeiwicz and Zaheer, 1999).

In addition, networks can also exert social pressures that lock firms into unproductive relationships or preclude their partnering with other viable firms (Gulati, Nohria and Zaheer, 2000). Similarly, the social obligations that develop within particular personal relationships have been argued to force actors to undertake actions that may be against their own interests (Nahapiet and Ghoshal, 1998). In a study of ethnic entrepreneurs, Portes and Sensenbrenner (1993) showed the same cohesive social ties that initially provide the entrepreneurs crucial support and access to essential resources can eventually become a source of constraints, imposing particularistic demands on the entrepreneurs, and preventing them from pursuing new opportunities. As the level of cohesion in the focal actor's network increases, there is a corresponding increase in collective pressure on the focal actor to continue working with those partners (Gargiulo and Benassi, 2000; Baum, Rowley, Shipilov and Chuang, 2005).

SUMMARY OF LITERATURE REVIEW

To sum up, the social networks literature reviewed in this section suggests that the focus of prior research has primarily been on their positive effects. These beneficial effects have been linked to a variety of important positive outcomes including firm profitability and survival. Understanding of the costs and the side effects of social networks, on the other hand, is relatively limited. Clearly, recognizing the benefits but not the costs or side effects can lead to unexpected outcomes. The importance of the positive outcomes associated with social networks underscores the need for a more holistic picture of the effects of networks. This is the area to which I seek to make a contribution in this dissertation.

CHAPTER 3: THEORY AND HYPOTHESES DEVELOPMENT

In this chapter, I develop specific hypotheses regarding the social costs of repeated ties with the same partners. Before I launch into developing the theory and hypotheses however, it will be useful to briefly discuss the research setting namely, the syndication of investments by venture capitalists (VCs), where I test these hypotheses.

EMPIRICAL SETTING: VENTURE CAPITAL SYNDICATION

Entrepreneurial organizations are inherently risky because they are subject to, amongst other threats, the liabilities of newness and smallness (Stinchcombe, 1965). This high level of susceptibility to failure results from the new organizations' lack of established internal and external work relationships, their limited access to resources, and low levels of legitimacy (Stinchcombe, 1965; Aldrich and Fiol, 1994; Baum, Calabrese and Silverman, 2000). In addition, organizations that are set up specifically for the purpose of developing new technologies or products face even greater risks because the rewards of innovation are uncertain.

Most entrepreneurial initiatives require substantial funding and returns on such funding are not only uncertain, but also distant in time. In the bio-technology industry, for example, it can take 7-10 years for a firm to advance from basic R&D to clinical trials and ultimately to FDA approval process (Deeds, DeCarolis and Combs, 1997). Since traditional sources of finance are not available for projects of this nature, entrepreneurs rely mainly on firms of venture capitalists (VCs), who specialize in funding risky projects with high turnaround times. VC firms are typically set up as partnerships that invest funds they have raised from investors called Limited Partners (LPs), who may be wealthy individuals, pension funds, etc. The money raised from LPs is placed in "funds" which have pre-determined life as well as stated risk preferences. A VC firm may manage multiple funds at the same time. Over the last few decades, VCs have become a very important vehicle for promoting innovation and bringing entrepreneurial ideas to fruition.

When investing in a startup, VCs take the risk that they will not provide an adequate return, or, in the worst case, any return, within the desired time period (Ferrary, 2003). The risk associated with their investments stems from three sources: the environment, the project, and the entrepreneur (or the entrepreneurial team). VCs tend to manage environmental uncertainty by restricting their investments to certain industries based on the expertise their firms possess, as well as their risk preferences and those of their limited partners.

Project uncertainty revolves around the extent to which the new venture seeking funding already has a developed product. The National Venture Capital Association (NVCA) groups venture capital investment into four categories or stages namely seed, early, expansion and later stage. Early stage investments are defined as investments in companies for product development and initial marketing, manufacturing and sales activities. Late stage investments on the other hand, are defined as financing provided for the expansion of a company which is producing, shipping and increasing its sales volume. Clearly, the level of uncertainty attached to a project decreases as it moves through subsequent stages of development. Again, based on their risk preferences and expertise, VCs restrict investments to early or late stage projects. In addition, they subject the new venture to a detailed due diligence in order to make an assessment of the market potential for the product, as well as the technical feasibility of developing the product and bringing it to market.

VCs conduct their own due diligence instead of relying on the information about the project they receive from the entrepreneur for a number of reasons. First, the entrepreneurs have inside information about the projects, which creates informational asymmetries between them and the VCs. Second, entrepreneurs also tend to overstate the project attractiveness, in order to secure funding (Cable and Shane, 1997; Sorenson and Stuart, 2001) or simply be overconfident about the likely success of their projects. Third, due to concerns about maintaining the confidentially of their ideas and/or technology, entrepreneurs frequently limit the amount of information they are willing to share with VCs prior to approval of funding. Thus, VCs rely on their industry knowledge and specialization to make this assessment. However, conducting due diligence on a proposal takes considerable time and effort. In an effort to minimize the time they spend in identifying potential startups for funding, as well as to manage their risk, VCs often resort to syndicating, that is, making joint investments along with one or more other VC firms, a proportion of their total investments (Wilson, 1968; Coyle, 2000).[3]

Finally, uncertainty relating to the entrepreneur, or the entrepreneurial team, arises from the fact that often the individual or team's capabilities with respect to successfully setting up and managing a startup are unknown since they do not have prior experience with

[3] VCs may also enter into syndicates for several other reasons such as maximizing their deal flow, increasing their prestige and so on, as is explained later in this section.

similar activities. VCs tend to manage this type of uncertainty based on their own observation of the individuals, supplemented by information they obtain by conducting extensive reference checks from the individuals' prior employers, colleagues, etc.

Syndication is a very common practice in the VC industry (Sorenson and Stuart, 2001; Wright and Lockett, 2003) and VCs are repeatedly involved in selecting partners to syndicate specific investments with (Fenn, Liang and Prowse, 1997; Gompers and Lerner, 2000b). However, as discussed in detail later in this section, if the partners selected for syndication are inappropriate for the startup to which the syndicate provides funding, the syndicate's likelihood of success may decline. Therefore, the setting offers the opportunity to test predictions about the effects of repeated ties with the same partners. Moreover, investments made by a VC firm involve considerable opportunity costs and involve high levels of potential risk as well as returns, both in financial and reputational terms (Dixit and Pindyck, 1994). Given that a significant portion of VC firms' overall investment is made in syndicates, syndication can have a significant impact on a VC firm's performance. Thus, VC syndication is also strategic and interesting to study in its own right.

THEORY DEVELOPMENT

I now turn to developing the theory and developing specific hypotheses in the context of VC syndication. In developing these hypotheses, I draw on insights from the literatures on social networks, prestige and endorsements, learning, expertise and small groups. I ultimately suggest that repeated ties with the same partners can lead to certain social costs such as a bias in partner selection, inadequate monitoring of familiar partners and the use of routines insufficiently adapted to the focal context, and that these costs can be significant enough to offset the benefits of repeated ties. Next, I develop hypotheses about the effects of factors such as the level of cohesion in the network in which such actors are embedded, the level of partner prestige/status and experience, the number of members in the focal partnership and the degree of homogeneity between them on the outcome of the partnership. Finally, I also explore the moderating effects of network cohesion and partner homogeneity on the detrimental effects of prior ties. The hypotheses developed in this chapter are summarized in Figure 1.

Social Costs of Repeated Ties

Research on social networks has established that firms have a predisposition to enter into exchange relationships with their prior partners (e.g., Eccles and Crane, 1988). Doing so is thought to provide several advantages such as lower search costs, lower uncertainty regarding quality and behavior, greater trust and communication and easier coordination (Axelrod, 1984; Granovetter, 1985). However, the social costs of engaging in repeated ties with the same partners have received only limited research attention. In this study I focus on three types of costs of social ties namely, a bias in the search for and evaluation and selection of partners, inadequate monitoring of familiar partners and the use of ossified routines that are insufficiently adapted to the focal context. Each of these costs is discussed in the paragraphs that follow.

Bias in Partner Search, Evaluation and Selection: The first type of cost of repeated ties I focus on is a bias in partner search, evaluation, and selection. March and

Simon (1958) proposed that rather than making fully informed decisions, people satisfice, that is, they terminate the search for further information as soon as they believe they have an acceptable solution (Borgatti and Cross 2003). Further, the extent to which people satisfice, is a function of the ease with which solutions are located; as solutions become harder to find, standards of search fall (Cohen, March and Olsen, 1972). Accordingly, I argue that by providing easily accessible and acceptable solutions, prior partners can cause firms to conduct biased or less expansive searches, that is, to "satisfice" in their search for suitable partners (Simon, 1947).

Both practitioner accounts and academic research suggest that in addition to providing funds, VC firms add value to the funded startups in a number of ways (Sorenson and Stuart, 2001; Baum and Silverman, 2004; Kaplan and Stromberg, 2004). This value-addition can occur in the form of either: (a) management interventions such as replacing the founder following poor performance; or (b) support activities (Botazzi, Da Rin and Hellman, 2005) such as addressing weaknesses in the startup's business model or entrepreneurial team (Kaplan and Stromberg, 2004), providing advice on strategic matters (Jain and Kini, 2000), assisting with hiring professional managers and acquiring other resources (Jain and Kini, 2000; Hellman and Puri, 2000; 2002), and providing access to their own resources which may enable the startup to reach potential customers, suppliers and/or strategic alliance partners (Lindsey, 2002).

The extent to which a VC firm is able to add value to a startup depends on a number of factors including its network resources and its ability to anticipate and understand the strategic and management issues facing the startup. In turn, a VC firm's ability to anticipate and understand the needs of a new organization is a function, at least in part, of the nature of its prior investment experience as well as the prior industry and direct entrepreneurial experience of its partners (Bygrave and Timmons, 1992; Sorenson and Stuart, 2001). At the same time, startups too can differ considerably from each other in terms of their strategic and organizational requirements because of differences in their opportunities, technology, product offerings, the experience and skills of the entrepreneurial team, and so on. Therefore, the degree to which a particular VC firm is a "good match" for two different startups can vary significantly. Stated differently, a VC firm that was an appropriate partner for a particular startup funded in the past may not be optimal for the focal startup.

Further, research suggests that actors frequently overestimate the quality of their prior partners because the familiarity and positive affect created by prior exchange relations may lead them to: (a) recall their prior exchanges favorably; (b) give greater benefit of the doubt when interpreting ambiguous information about their quality; (c) over-simplify the causes of past successes; and (d) over-attribute those successes to their partnership, although the causes of success are often difficult to ascertain (Zajonc, 1980; Johnson and Tversky, 1983; Coleman, 1990; Lawler, 1992; Li and Rowley, 2002; Slovic, Finucane, Peters and McGregor, 2002). Together with the limited search for potential partners, this over-estimation of partner quality can result in a misleading reduction in uncertainty, and a reduction in the perceived need to conduct an expansive search for appropriate partners, leading firms to make sub-optimal partner choices in terms of both quality and appropriateness for the focal context. Thus, while prior partners may enable better coordination, this coordination may occur with partners that are sub-optimal for the focal startup. The ultimate effect of this biased partner search, evaluation and selection may be to reduce the funded startup's likelihood of success.[4]

Inadequate Monitoring of Prior Partners: The second type of cost of repeated ties I focus on is inadequate monitoring of familiar partners because of an under-estimation of the need for monitoring them, and a reluctance to challenge them. A history of exchange leads to a presumption, possibly erroneous, of trustworthy future behavior, which in turn can lead actors to under-estimate the need for monitoring familiar partners (Granovetter, 1985; Coleman, 1990) or even deem it altogether unnecessary (Lewicki and Bunker, 1996). Further, the cognitive comfort and perception of reliability that accompany trust in a partner have the effect of reducing the search for information and attention to detail on the part of the trusting partner (Langfred, 2004). In effect, familiarity with partners may lead actors to under-estimate the need for monitoring them.

Moreover, even if they believe it to be necessary, actors may be reluctant to monitor or challenge partners with whom they have prior ties. Research on social networks suggests that the fear of loss of ties or loss of network membership, which would render them unable to continue to derive benefits from the network, often forces actors to behave in ways that are acceptable to other network members (Burt, 1992; Brass, Butterfield and Skaggs, 1998). Similarly, social relationships between group members are also thought to create a reluctance to challenge fellow members and have been shown to significantly reduce, even eliminate

[4] The economic objective of VCs, whether investing in startups alone or as part of a syndicate, is financial gain from those investments by liquidating their stake in the startup either when it is acquired by another company or when it goes public. The extent to which the funded startup is successful largely determines the VC investors' ultimate financial gain. Therefore, for the purpose of this study, I treat the startup's success as a proxy for the syndicate's success.

debate, which is thought to have adverse effects on the quality of decisions made by the group (Nelson, 1989). This reluctance to monitor may stem from the common belief that monitoring of trusted members is both unnecessary and a violation of their mutual trust (Lewicki and Bunker, 1996), and thus, may have a detrimental effect on the existing relationship between the "monitoring" and the "monitored" partner (Feldman, 1984).

Formal controls between partners are thought to signal that the monitored partner is not trusted to be competent in completing the objectives of the partnership or to refrain from being opportunistic (e.g., Argyris, 1952; Das and Teng, 1998; Zaheer, McEvily and Perrone, 1998). The resulting environment of distrust can lead to a reduction in cooperation between partners (Ring and Van de Ven, 1992; Child and Faulkner, 1998; Zaheer, McEvily and Perrone, 1998), or even the demise of the relationship itself (Smith, Carroll and Ashford, 1995). These detrimental effects are particularly strong when the monitoring is perceived as being intrusive or as curtailing the "monitored" actor's decision autonomy (Ouchi and Maguire, 1975; Das and Teng, 1998; 2001).

In general, actors are more likely to cooperate if they believe that their partners trust them to do so (Berg, Dickhaut and McCabe, 1995; McCabe, Rigdon and Smith, 2003). Conversely, an actor who feels mistrusted by a partner is less likely to cooperate with that partner in the future (Johnson, Cullen, Tomoaki and Takanouchi, 1996; Serva, Fuller and Mayer, 2005). Thus, even if a relationship survives monitoring by one of the partners, their "reciprocal trust," which refers to an actor reciprocating in kind when he feels trusted by a partner, may nevertheless be eliminated (Zand, 1981; Gambetta, 1988; Bradach and Eccles, 1989), and this may, in turn, lead to a deterioration in the quality of their relationship.

In the present context, typically when VC firms co-invest as a syndicate, to avoid duplication of effort, the task of interacting with the startup is delegated to one firm, known as the Lead firm (Botazzi, Da Rin and Hellman, 2005). Consequently, as compared to other syndicate members, Lead VCs are far more involved with conducting the pre-investment evaluation as well as with subsequent activities related to the ongoing monitoring[5] of funded startups, and may spend up to ten times as much time as other syndicate members in their interaction with the funded startups (Gorman and Sahlman, 1989). Lead VCs typically hold a seat on the startup's board, which gives them the opportunity to interact frequently with the entrepreneurial team, advise them on strategic issues, provide access to their network and other resources, and so on (Fenn, Liang and Prowse, 1999). The high level of trust non-Lead VC firms place in the Lead VCs' due diligence and post-investment monitoring capabilities enables them to substantially limit their involvement with these activities (Sorenson and Stuart, 2001). Moreover, this involvement declines further with repeated interaction, as the mutual trust between the firms increases (Sorenson and Stuart, 2001; Wright and Lockett, 2003).

However, it is also acknowledged that there is considerable variance among VC firms in terms of the extent to which they actually get involved with monitoring and supporting the startups they fund (Botazzi, Da Rin and Hellman, 2005). Monitoring and support

[5] Monitoring here refers to the ongoing monitoring of the performance of the funded startup, as against monitoring of partners (or syndicate members) which is discussed throughout this document.

activities can take substantial amounts of time and effort (Gorman and Sahlman, 1989; Kaplan and Stromberg, 2004) and VC firms exercise considerable discretion as to how involved they get with monitoring and supporting any particular startup (Botazzi, Da Rin and Hellman, 2005). At any given point in time, each VC firm typically has several startups in its portfolio, each of which requires monitoring as well as support. In addition, they also need to spend considerable time on identifying and evaluating new investment opportunities as well as on raising money for future investments. Thus, their time has a non-trivial opportunity cost and the time spent on monitoring or supporting one startup takes away from similar involvement in another startup or from one or more other important activities. This implies that depending on how well or poorly the other startups in its portfolio are performing, the Lead VC may be distracted away from the focal startup and devote sub-optimal time or effort to it, reducing its likelihood of success.

Given their passive involvement and the non-contractibility of the degree of the Lead VC's involvement in monitoring and supporting the startup (Botazzi, Da Rin and Hellman, 2005) the non-Lead VCs in the focal syndicate are likely to have incomplete information about how well the Lead VC is performing its role. While more complete information may be obtained by closer monitoring such as by asking the Lead firm to report on the frequency with which it interacts with the startup, or the degree of its involvement with recruiting the management team or assembling the board of directors (Botazzi, Da Rin and Hellman, 2005), such monitoring is likely to be perceived as both intrusive and curtailing the Lead VC's decision making autonomy. However, as prior theoretical discussion suggests, a firm that is seen to display a lack of trust by questioning the Lead VC or interfering with the manner in which it performs its role runs the risk of damaging its relationship with that firm. At the very least, by engaging in monitoring or challenging, the firm runs the risk of being subjected to similar scrutiny by the partner if it takes on the role of Lead in a future syndicate of which the partner is a member, a prospect that is psychologically aversive. In addition, other non-Lead members of the syndicate are also likely to discourage the monitoring of one firm by another because it can result in strained relations between the two firms, disrupting the working of the focal syndicate as well as other existing and potential future syndicates involving the same firms.

Finally, I suggest that concerns about protecting their existing relationships will be especially salient to actors in contexts characterized by high levels of reciprocity such as VC syndicates and investment banking syndicates. In the context of VC firms, reciprocity is evident in the role their relationships with other VC firms play in maintaining their deal flow, that is, the number of proposals a VC firm receives for funding. These relationships are a valuable source of deal flow, and can considerably reduce the time and effort each individual VC firm needs to expend in order to identify appropriate startups for funding. Moreover, deals referred by other VC firms are often accompanied by invitations to participate in funding syndicates, which allows VC firms to diversify their portfolio, broaden their sources of funds, and manage their exposure to specific startups and industries, while at the same time enabling them to expand their geographical and industry reach (Lerner, 1994; Sorenson and Stuart, 2001).

In sum, prior relationships with partners are likely to prompt sub-optimal levels of monitoring either because the need for monitoring is under-estimated or because concerns for protecting the relationships outweigh the motivation for monitoring. Such concerns arise from the belief that not only is monitoring unnecessary in trusting relationships, but it also violates trust, with the potential to significantly reduce cooperation, or even destroy the relationship. Thus, even if actors correctly estimate the need for monitoring familiar partners, they are likely to avoid it, particularly when the reciprocity between partners is crucial for their business.

Use of Sub-optimal, Ossified Routines: Finally, the third type of cost of repeated ties I consider is the use of suboptimal, ossified routines, this is, routines developed during previous exchanges insufficiently adapted to the differences in conditions. One of the benefits of repeated exchange with the same partners is that over time, routines specific to the relationship are established and these enhance coordination, enabling the partners to work together more efficiently in the future (Bryman, Bresnen, Beardsworth, Ford and Keil, 1987; Zollo, Reuer and Singh, 2002). At the same time however, insights from learning theory suggest that routines are often transferred between contexts even if they are not appropriate (Cohen and Bacdayan, 1994; Kogut and Zander, 1996), or are transferred without being sufficiently adapted to differences in conditions. This literature further suggests that once transferred, inappropriate routines tend to persist because they are sub-optimal, but not incorrect (Singley and Anderson, 1989). Moreover, such inappropriate transfer and persistence are often compounded by the absence of explicit evaluation because established routines are simply taken for granted.

Drawing on these insights, I argue that as partners become more accustomed to working together because of repeated interaction, their routines will become more established, and this will lead to an increase in the likelihood that they will (i) transfer those routines to subsequent exchanges; and (ii) fail to adapt those routines to the differences in conditions surrounding the subsequent exchanges because of a disproportionate focus on the coordination benefits of the routines and an under-estimation of the differences in the two sets of conditions. In the context of syndicated investments by VCs, as noted earlier, startups can differ from each other considerably in terms of their strategic and organizational requirements, increasing the likelihood that routines developed during prior investment interactions will be inappropriate for the focal investment. Thus, the use of such inappropriate or ossified routines, such as the routines used to determine the extent of involvement of a non-Lead syndicate member with appointing the board of directors, hiring the management team or establishing contact with potential customers, can lead a VC syndicate to make sub-optimal decisions which can have a detrimental effect on the startup's likelihood of success.

To summarize the discussion thus far, the costs of prior ties include (a) a bias in partner search, evaluation and selection, which will promote (i) a less expansive search for potential partners due to the tendency to satisfice and to over-estimate the quality of familiar partners, and (ii) failure to update partner selection criteria in the absence of an accurate assessment of the differences between the prior and the focal situation, which together will result in the selection of sub-optimal partners for the focal situation; (b) inadequate monitoring of familiar partners because of (i) an under-estimation of the need to monitor them, and (ii) a reluctance to monitor and challenge them, arising from the fear of damage to the relationship; and (c) the use of sub-optimal routines, that is, routines developed during prior exchanges and insufficiently adapted to the focal situation. I suggest that each of these costs will increase with the number of prior ties.

The benefits of repeated ties, on the other hand, are unlikely to increase in the same manner as the number of prior ties increases. Among the key benefits of prior ties identified by prior research, is mutual trust, which is thought to enhance partners' ability to transfer complex and tacit information. However, neither the complexity, nor the tacit-ness of information to be exchanged between partners in VC syndicates is particularly high. Thus, in the present context, the greater trust resulting from repeated ties only provides limited benefits. Repeated interaction with the same partners also leads to the establishment of routines and a common language, which in turn increases the efficiency, reliability, and effectiveness in communication and coordination. While these outcomes can be highly beneficial in contexts with small differences across situations where partners are engaged in activities that rely on routines and require frequent communication and coordination, in contexts such as the present where the conditions surrounding each interaction differ considerably, routines provide only limited benefits. Thus, in the present context, the overall benefits from repeated interaction are likely to increase at a diminishing rate with an increase in the number of prior ties.

Taken together, the above discussion suggests that while repeated interaction with the same partners will be beneficial initially, as the number of prior ties increases beyond a point, the costs will begin to outweigh the benefits. Therefore, as the number of prior ties between syndicate members increases, the likelihood that the startup funded by the focal syndicate will be successful will first increase and then decrease. More formally,

Hypothesis 1: The likelihood that the startup funded by the focal VC syndicate will be successful will have an <u>inverted U-shaped</u> relationship with the number of prior ties between the VC firms in the syndicate.

<u>Cohesion</u>

Cohesion, or the existence of mutual partners, facilitates exchange in networks by enabling the diffusion of information about members' reputations and thereby controlling their behavior (Mayhew, 1968; Burt, 1992). Information about members' prior exchanges with other network members thus becomes available to potential future partners, enabling them to develop more accurate and reliable expectations regarding the partners' behavior (Granovetter, 1985; Raub and Weesie, 1990; DiMaggio and Louch, 1998; Gulati and Garguilo, 1999). Consequently, trust develops more easily between actors embedded in cohesive networks (Baker, 1984; Coleman, 1988; Grief, 1989; Ingram and Roberts, 2000). Moreover, the level of trust and reciprocity increases with the cohesiveness of the network (Granovetter, 1985, 1992; Coleman, 1988) because the speed at which information flows through a network increases with density (Burt and Knez, 1995).

Cohesion also facilitates the establishment of norms as well as social control of actors who violate those norms. High levels of network closure increase the likelihood that violators will be observed by network members (Merry, 1984). Normative violations then prompt negative gossip about the violators, which damages their reputation and reduces their ability to continue existing relationships and form new ones with other network members (Burt and Knez, 1995). Moreover, violators are frequently sanctioned by network members (Coleman, 1990), leading to the loss of repeat business and other points of interaction with existing partners (Macaulay, 1963; Granovetter, 1985; Maitland, Bryson and Van de Ven, 1985), further diminishing violators' ability to continue to enjoy the benefits of network membership (Garguilo and Benassi, 2000). By enabling a greater number of actors to coordinate their actions, cohesiveness also increases the effectiveness, and therefore the costs, of sanctions (Coleman, 1990). Thus, cohesion increases not only the likelihood that actors who violate norms will face sanctions, but also the expected cost of those sanctions.

As noted earlier, in comparison to the Lead VC, non-Lead VC firms' direct involvement with monitoring and supporting funded startups is very limited (Sorenson and Stuart, 2001; Wright and Lockett, 2003). Because the degree of involvement by the Lead VC firm is non-contractible and almost entirely within it's discretion (Botazzi, Da Rin and Hellman, 2005), even if a non-Lead firm suspects that the Lead firm is spending inadequate time and effort on the focal startup, the only way for it to actually ascertain if this is true is to closely monitor the Lead firm. However, such monitoring is likely to be perceived as a sign of distrust, particularly when the VC firms are embedded in a cohesive network. Monitoring or challenging of the Lead by a non-Lead syndicate member is also likely to be discouraged, or even sanctioned, by the other syndicate members, in part because by allowing such monitoring or challenging, they would legitimize it, creating the psychologically aversive possibility that they themselves will be subjected to similar scrutiny in future syndicates they lead.

Therefore, non-Lead VCs engaging in monitoring or challenging their fellow partners are likely to face the threat of reputational damage resulting from negative gossip. They also run the risk of being sanctioned collectively by the Lead firm and their mutual partners. Both the likelihood and the effectiveness of such sanctions is likely to increase with the extent to which the partners are embedded in a cohesive network, that is, have mutual partners.

Sanctions in this context can be in the form of other firms not inviting the sanctioned firm to participate in syndicates or declining invitations to participate in syndicates initiated by the sanctioned firm. As noted earlier, such sanctions can considerably limit the sanctioned firm's ability to diversify its portfolio and maximize its deal flow. Thus, such sanctions are likely to serve as a considerable disincentive for a non-Lead firm embedded in a cohesive network with the Lead firm to engage in monitoring.

The extant theory on social control would predict that a Lead VC firm embedded in a cohesive network with one or more non-Lead firms would perform its role of monitoring / advising the funded startup effectively in an effort to protect its reputation and avoid sanctions from network partners. However, the above discussion suggests that, contrary to the predictions of social control theory, in the current context, cohesion may actually prevent the non-Lead firms from monitoring the Lead firm. Said differently, rather than promoting behaviors that are beneficial to the collective interests of all members, social control facilitated by cohesive networks may actually suppress such behaviors.

In addition to the potential costs of cohesion just discussed, high levels of cohesion may also have a detrimental impact on the quality of information received by network members. Research on social networks has suggested that diverse networks enable actors to gather non-redundant information, which in turn promotes better decisions (Beckman and Haunschild, 2002; Moran, 2005). However, in general, members of cohesive networks tend to be homogeneous, which in turn, limits the diversity of information available to them. Moreover, the likelihood of novel information flowing into highly cohesive networks is relatively low because such networks tend to become isolated from the environment (Uzzi 1997). Finally, cohesive networks may also promote “satisficing” information search and exchange behavior by members, in which sources are searched until a "satisfactory" solution is found (Simon, 1955; 1956), because the redundancy in available information may lead them to prematurely conclude that the solution they have found is “satisfactory” (Beckman, Haunschild and Phillips, 2004). Consequently, the quality of startups selected for funding may be sub-optimal.

To sum up the above discussion I argue that VC firms that are embedded in networks of multiple mutual partners will be reluctant to monitor the Lead firm in syndicates of which they are members, even if they believe that the Lead is not providing adequate support to the funded startup because of the potential reputational costs and the threat of sanctions. Moreover, the greater the level of cohesiveness in the focal syndicate, the greater will be the potential reputational damage and the cost of sanctions to the member that engages in monitoring the Lead firm and thus the greater will be the member's reluctance to monitor the Lead VC. Finally, the quality of startups funded by actors embedded in cohesive networks may be sub-optimal due to the limited amount of novel information flowing into the network as a whole, as well as the tendency towards "satisficing" information search behavior by individual members. Therefore, greater cohesiveness between members of a syndicate will ultimately lead to a lower likelihood of the startup's success. More formally,

Hypothesis 2: **The likelihood that the startup funded by the focal VC syndicate will be successful will be <u>negatively</u> related to the degree of cohesion between VC firms in the syndicate.**

Next, I suggest that in addition to the effects discussed above, cohesion between syndicate members will also moderate the effects of prior ties between them such that the interaction between prior ties and cohesion will be negatively related to the likelihood of success of the funded startup. As I argue above, monitoring a familiar partner is seen as a violation of trust, which gives rise to negative affect in the monitored actor. Since trust increases with the number of prior ties, it follows that a greater number of prior ties between the actors will promote a more intense negative affect. In turn, this greater negative affect will increase the likelihood of the actor initiating negative gossip about the actor engaging in monitoring. Thus, as the extent to which the monitoring partner's cohesiveness with the monitored partner increases, so will the potential reputational damage and the likelihood and effectiveness, that is, the costs of sanctions.

Therefore, I suggest that cohesion will heighten actors' reluctance to engage in monitoring to the extent they have prior ties with the monitored partner. The resulting inadequacy of monitoring will have detrimental effects on the quality and quantity of effort the Lead VC spends on the focal startup. The reason for this lowering of inputs is that the amount of time and effort the Lead VC spends on monitoring and supporting activities is discretionary, and may be affected by other demands on the firm's time, potentially compromising the quality of support provided to the startup. Monitoring of the Lead VC by the other VCs could provide "early warning", based on which corrective measures could be implemented in time. Thus, I suggest that cohesion will increase actors' reluctance to engage in monitoring their partners, which may lower the quality of VC contributions to the startup, and thus decrease the likelihood of the startup's success. More formally,

Hypothesis 3: **The likelihood that the startup funded by the focal VC syndicate will be successful will be <u>negatively</u> related to the interaction of the number of prior ties and the degree of cohesion between VC firms in the syndicate.**

<u>Syndicate Member Status/Prestige</u>

Actors' status/prestige, conceptualized here as network centrality[6], provides a number of benefits, such as legitimacy, which in turn, enables them to access required

[6] I use the terms status and prestige inter-changeably in this discussion. For the purpose of this study, I am interested in network driven status/prestige, which is best represented by network centrality and has been used as an indicator of VC firms' status/prestige in syndication networks in prior research (Podolny, 1993; Stuart, 1998; Sorenson and Stuart, 2001). Several researchers have noted that terms such as status, reputation, prestige and prominence are difficult to disentangle theoretically and that they have been used synonymously in prior

resources from their environment (Podolny, Stuart and Hannan, 1996; Zuckerman, 1999). Social network theory and research suggests that network membership bestows differential status or prestige on actors in accordance with both their location in the network and the status or prestige of the actors to whom they are connected (Podolny, 1993).

Perceptions of an actor's quality are influenced considerably by its pattern of relationships, especially when quality cannot be measured objectively (Stuart, 2000). Status is implicitly transferred across ties, and thus, an actor's own status or prestige is increased by relationships with prestigious partners (Baum and Oliver, 1991; Podolny, 1993; 1994; Stuart, 1998). Ties to prestigious actors are especially beneficial because of the high level of trust placed in their ability to discern quality and the common presumption that in order to guard against the potential loss of status from association with a poor quality actor, they perform a thorough evaluation before entering into a relationship (Blau, 1964; Baum and Oliver, 1991; Podolny, 1994; Stuart, 1998; 1999). By definition, prestigious partners are highly influential members of the networks, with ties to a large number of actors and/or a few prestigious actors. Thus, a positive reference from a prestigious firm can be highly beneficial to the focal actor while a negative referral can be highly damaging (Stuart, 1999). Status is also thought to provide access to better quality resources (Stuart, 2000). In the present context as well, high status VC firms are believed to have access to both a larger number and better quality proposals from entrepreneurs seeking funding, which on average, is likely to lead to the funding of better quality projects. Thus, relationships with prestigious firms are generally

research (Sine, Shane and DiGregario, 2003; Washington and Zajac, 2005; Sullivan, Haunschild and Page, 2007).

believed to provide access to deals that are superior in quality, in addition to helping them maintain their deal flow.

Considerable empirical evidence suggests that ties to prestigious actors signal an actor's legitimacy, which again benefits them in various ways including enhancing their access to resources from the environment (Wood and Bandura, 1989; Starks, 1996; Stuart, 2000), performance (Stuart, Hoang and Hybels, 1999), and survival (Baum and Oliver, 1992). Research on new organizations has also provided evidence consistent with this view. Having prestigious individuals as members of its top management teams has been shown to increase the likelihood that a new venture will be funded by a prestigious VC firm and make an Initial Public Offering (IPO), and further that a leading investment banker will manage its IPO (Bygrave and Timmons, 1992; Stuart, Hoang and Hybels, 1999; Gulati and Higgins, 2003).

At the same time however, as the level of prestige increases, certain costs of having a prestigious partner begin to accumulate. One type of cost relevant to this context is inadequate monitoring of partners. In general, prestigious actors are believed to be more competent. As noted earlier, greater trust in a partner's competence in completing the objectives of the partnership suggests a lower need for monitoring them (e.g., Argyris, 1952; Das and Teng, 1998; Zaheer, McEvily and Perrone, 1998). Therefore, in general, actors are likely to believe that the greater their partners' prestige, the lower the need to monitor them. Moreover, even if a prestigious partner engages in behavior that suggests lower competence, a lack of effort, or opportunism, actors are less likely to believe that they require monitoring because, contrary to their general tendencies, people tend to make situational rather than personal attributions for less desirable actions of high status actors (Giordano, 1983; D'Aveni, 1990). Therefore, behaviors that would prompt them into concluding that there is a need to monitor a lower status partner are less likely to lead to similar conclusions when the partner is prestigious. In the present context, a prestigious VC would need to provide far greater evidence of incompetence or of providing inadequate monitoring or support in comparison to a less prestigious VC to the funded startup in order to prompt monitoring or challenging by a partner. This suggests that the reluctance to monitor partners is likely to increase with the partner's prestige.

Finally, even if they do believe that there is a need to monitor or challenge a prestigious partner, actors are likely to be highly reluctant to do so because damaging a relationship with a prestigious partner is costly because of the loss of all abovementioned benefits they receive from such relationships. As noted above, ties to prestigious partners not only help VC firms to maintain their deal flow, but also improve the quality of deals they have access to. At the same time, because prestigious actors are accustomed to deference from their partners, they are likely to react more negatively to being monitored (Coleman, 1990), and therefore, the likelihood of the relationship being damaged is particularly high.

Taken together, the above arguments suggest that as partner prestige increases, benefits such as legitimacy and access to resources, will increase as well. However, beyond a point, further increases in partner prestige will also give rise to certain costs such as an under-estimation of the need to monitor prestigious partners and a reluctance to monitor or challenge them, which will, at least in part, offset the benefits. This suggests that the likelihood of success of the startup funded by the focal syndicate being successful will increase at a decreasing rate as syndicate members' status/prestige increases. More formally,

Hypothesis 4: **The likelihood that the startup funded by the focal VC syndicate will be successful will <u>increase at a decreasing rate</u> as the status/prestige of VC firms in the syndicate increases.**

<u>Syndicate Member Prior Experience</u>

In general, people's performance at tasks improves as they gain experience and familiarity at those tasks. The learning-by-doing model for the prediction of performance in the psychological literature on expertise suggests that performance improves with practice, that is, through trial and error learning (Anderson, 1987; Seifert, Patalano, Hammond and Converse, 1997). As decision makers gain experience, they learn to focus attention on dimensions that contribute the most variance to decision outcomes (Chase and Simon, 1973; Weber, 1980; Choo and Trotman, 1991). Experience also facilitates the codification of individuals' knowledge into categories based on strong links between concepts (Chi and Koeske, 1983; Gobbo and Chi, 1986; Fredrerick, 1991). This codification enables experts to see more patterns and connections between individual elements of knowledge instead of disparate issues in comparison to novices (Kirschenbaum, 1992; Chattopadhyay, Glick, Miller and Huber, 1999). Therefore experts are able to utilize their knowledge more effectively. Prior research has provided considerable evidence of the significant beneficial effects of experience on outcomes such as manufacturing plant productivity (e.g., Argote, Beckman and Epple, 1990), service timelines (Argote and Darr, 2000) and hotel survival (Baum and Ingram, 1998).

It is generally presumed that individuals' expertise in a particular domain continues to increase with their level of experience in that domain. However, the literature on learning asserts that while knowledge does increase with experience, this increase occurs at a diminishing rate (e.g., March, Sproull and Tamuz, 1991). Psychological research on the effects of experience has also noted that while experience generally improves performance, there is reason to believe that as experience accumulates, the incremental benefits from such additional experience start to decline. Both streams of research suggest that one of the main reasons for the declining marginal benefits is that beyond a point, additional experience provides knowledge that is redundant with knowledge already gained, and is therefore unlikely to add to the individual's expertise in the relevant domain.

Further, psychological theory and research on expertise also argues that as individuals' experience exceeds a certain level, they become trapped in certain ways of thinking. As the rigidity in their thinking increases (Nisbett and Ross, 1980), highly experienced individuals become unable to perform well at new tasks or situations that deviate significantly from what they normally see (Frensch and Sterberg, 1989; Koonce and Mercer, 2002). As noted earlier, initially, experience enables the codification of an individual's knowledge into categories. Subsequent experience then increases their familiarity with these codified knowledge structures. At the same time, this additional experience also increases their perceived familiarity with the range of likely situations and outcomes, which in turn, diminishes their ability to imagine outcomes other than the ones they have seen in the past. As a result, highly experienced individuals become increasingly less likely to engage in counterfactual thinking or make judgments based on step-by-step processing (Roese, 1997; Baron, 1998; 2000). Instead, they become increasingly more likely to make memory-based or associative/analogy-based judgments. This adds further to their inability to recognize differences between current and past situations, and thus to modify decision making processes accordingly (Feltovich, Spiro and Coulson, 1997). The effects of this rigidity in individuals' thinking are especially strong because it functions outside their awareness, due to which they are not even aware of its cognitive consequences (Wiersema and Bantel, 1992).

These arguments have received empirical support from research on a variety of subjects including executives. Executives with long industry tenures tend to exhibit a greater commitment to the status quo in large part because increasing experience promotes greater reliance on "industry recipes," that is, common ways of thinking which form powerful constraints on their thinking (Spender, 1989; Hambrick, Geletkanycz and Fredrickson, 1993). Prior research further suggests that even if experts were to recognize the need for modification in their decision making processes, over time, it becomes harder for them to do so because of the increasing rigidity in their thinking. Therefore, together with the decrease in incremental benefits of experience, this increase in costs may result in overall negative effects of high levels of experience (see Einhorn, 1974; Camerer and Johnson, 1997).

Extending the above arguments to the context of VC syndication, I suggest that initially, experience with funding startups will lead to learning and therefore, an improvement in VC firms' performance. As experience begins to accumulate however, the incremental learning will decline, and thus further improvement in performance will occur at a decreasing rate. At the same time, with additional experience, the rigidity in VCs' thinking will increase, preventing them from recognizing and accommodating the often significant differences in the organizational and strategic requirements of startups. In turn, this will lead to an over-reliance on partner selection criteria they used in the past and a failure to adjust such criteria to the particular needs of the funded startup. Thus, their ability to select the optimal (or the most appropriate) syndicate partners based on the needs of the funded startup will diminish as their level of experience increases.

This loss of flexibility in their thinking will also have a detrimental effect on their ability to provide appropriate advice and resources to the startup after making the investment. In addition, as noted earlier, expertise increases at a declining rate at best with additional experience beyond a point. However, greater experience in a particular domain is generally presumed to increase individuals' expertise in that domain. Thus, partners of highly experienced actors will under-estimate the need for monitoring them to a greater extent.

Moreover, as argued earlier, even if they correctly estimate the need for monitoring, syndicate members will be reluctant to engage in optimal levels of monitoring in the interest of protecting their dyadic relationship with the highly experienced Lead VC as well as protecting their network reputation against negative gossip initiated by such a partner. Additionally, as in the case of prestigious VCs, the likelihood that monitoring will damage their relationship with highly experienced VCs is also relatively high because they are also likely to be accustomed to other VCs deferring to their judgment and thus react more negatively to being monitored or challenged. Again, because experience is presumed to be correlated with expertise (Li and Rowley, 2002), monitoring of highly experienced partners is also likely to be considered non-normative and thus be discouraged or even sanctioned by the other members of the focal syndicate. Consequently, syndicate partners are less likely to engage in monitoring of highly experienced partners. This reluctance to monitor or challenge a highly experienced partner will at least partially offset the benefits of greater experience, and may even outweigh them completely.

It may be argued that the negative effects of this increasing cognitive rigidity may be offset, at least in part, by the presence of group members with varying levels of experience or other types of diversity. However, the reversal of these effects requires a considerable amount of task related debate so that the alternative points of view can be expressed and the group is forced to thoroughly discuss them and choose the best. Such open debate may not occur in the presence of highly experienced partners because as in the case of prestigious partners, such debate may be seen as challenging the experienced partner, creating a risk of damaging the relationship with them.

To summarize, while additional experience increases knowledge, the increase occurs at a declining rate since a greater portion of the knowledge gained from additional experience is redundant with the knowledge already acquired. Thus, the benefits of experience will also increase at a declining rate. At the same time, the costs of experience such as an increased rigidity in thinking and increased inability to recognize and adjust for difference between the current and past situations continue to increase. The costs in this case are an increased likelihood of selection of less than optimal syndicate partners to fund the funded startup, which will in turn decrease the likelihood of its success. In addition, partners' reluctance to engage in monitoring highly experienced actors will continue to increase. Therefore, I expect the costs to offset at least part of the benefits of additional experience and hypothesize that the likelihood that the funded startup will be successful will increase at a decreasing rate with the syndicate members' prior investment experience. More formally,

Hypothesis 5: The likelihood that the startup funded by the focal VC syndicate will be successful will <u>increase at a decreasing rate</u> as the prior investment experience of VC firms in the syndicate increases.

<u>Syndicate Characteristics</u>

Groups possess more knowledge, expertise and cognitive resources than any individual member. Nevertheless considerable social psychological research on small groups suggests that groups do not always make better decisions than individuals because they are susceptible to decision-making failures including groupthink. Groups also suffer from process and motivation losses which prevent them from harnessing the available resources in an optimal manner. While each of these problems can result from a number of factors, I focus here on the impact of two factors, namely, member homogeneity and group size, both of which are relevant in the context of VC syndication.

Syndicate Member Homogeneity: Homogeneity implies that group members are similar on important characteristics and therefore share similar experiences, vocabularies and paradigms. The more similar actors are, the greater their mutual attraction (Kanter, 1977; Pfeffer, 1983; Rogers, 1995), or homophily bias (McPherson and Smith-Lovin, 1987). One other outcome of homogeneity is cohesiveness (Pfeffer, 1983), which is thought to promote agreement. At the same time, cohesive networks tend to include actors that are similar to each other (see McPherson, Smith-Lovin and Cook, 2001 for a summary of this research). Among the benefits of member homogeneity are more efficient communication, easier transmission of tacit knowledge (Cross, Borgatti and Parker, 2001), simplification of coordination (O'Reilly, Caldwell and Barnett, 1989; Ancona and Caldwell, 1992) and avoidance of conflict (Pfeffer, 1983; Pelled, Eisenhardt and Xin, 1999). Therefore, homogeneity among members is likely to have positive effects on group performance.

However, as homogeneity increases, the redundancy in group members' knowledge and expertise is likely to increase as well. Further, due to the similarity of members' views, very high levels of homogeneity or cohesiveness are thought to cause groupthink, which is a syndrome of ineffective decision making by groups, leading to biased decisions (Janis, 1972; McCauley, 1989; Hart, 1991; Kroon, Hart and van Kreveld, 1991; Guzzo and Shea, 1992; Turner and Pratkanis, 1994; Moorehead and Neck, 1995; also see Esser, 1998 and Turner and Pratkanis, 1998 for comprehensive reviews of groupthink research). Groupthink is characterized by limited information search, misperception of data and premature consensus-seeking without adequate consideration of alternatives. Often, even if heterogeneous opinions do exist, they are not expressed during discussion (Stanley, 1981) because of barriers to communication and conformity pressures exerted by the group. Barriers to communication, such as the dismissal of information that could incite internal conflict, may prevent divergent opinions from being voiced even at the cost of compromising task performance (Janis, 1982; Baron and Greenberg, 1990; Gruenfeld, Mannix, Williams and Neale, 1996). Similarly, conformity pressures such as ostracism of members expressing dissenting opinions may also have the same effect (Janis, 1982; Baron, Vandello and Brunsman, 1996; Langfred, 2004). Research suggests that such conformity pressures occur more frequently in cohesive groups, particularly when cohesion results from prior network ties or demographic homogeneity (Schachter, 1951; Cartwright, 1968; Scott, 1976; Coleman, 1994). Moreover, pressures for conformity are thought to increase with the degree of cohesion in the group (Lott and Lott, 1965; Hackman, 1976).

Diversity among members, on the other hand, enhances the breadth of knowledge, expertise and cognitive resources available to the group (Hoffman and Maier, 1961), which if utilized properly, can positively affect performance since it promotes task-related conflict and more comprehensive analysis (Jehn, Northcraft and Neale, 1999). At the same time, prior research also suggests that diversity among group members, which implies differences in their values and paradigms, is not without cost either. The negative emotions created by task conflict reduce members' mutual attraction (Nemeth and Staw, 1989). High levels of diversity have also been shown to reduce cohesiveness (Lott and Lott, 1965) which makes information exchange more difficult (Ancona and Caldwell, 1992), decreases communication frequency (Stasser, 1993), and increases personal conflict (Nemeth and Staw, 1989) and the costs of coordination (Pfeffer, 1983). Many of these problems arise because diversity promotes "us-versus-them" thinking which is found when members categorize other members as "in-group" or "out-group," and are biased towards members who they consider as in-group (Krackhardt and Stern, 1988).

To summarize the above arguments, as the homogeneity of members increases, they become more trusting of each other and the level of cohesiveness in the group increases. This reduces conflict, and facilitates communication and coordination between them. However, at some level, the costs of homogeneity, such as the redundancy of available information and expertise and the suppression of divergent opinions, begin to outweigh the benefits. Similarly, at the other extreme, the costs of very high levels of diversity will also outweigh the benefits. As diversity increases, so does the difficulty of communication by members who don't share the same values or a common vocabulary. However, given their cognitive limitations, members are unlikely to take note of the differences until they become considerably high. Thus, the level of diversity would need to be considerably high before such "us-versus-them" thinking is prompted and the attendant in-group and out-group biases are felt. This may be particularly likely in the context of VC syndication, given the prevalence of continued partnering with the same other firms as well as the considerable movement of executives between firms. The familiarity created by such repeated interaction and movement of executives across organizations may increase the tolerance for differences between partners.

Taken together, this discussion suggests that while a minimum level of similarity may be essential for a group to be able to take advantage of the available resources (Lott and Lott, 1965), too much similarity may lead to a different set of problems which interfere equally with group functioning. Therefore, I hypothesize that the extent of homogeneity among VC firms in a syndicate will have an inverted U-shaped relationship with the likelihood of startup success. More formally,

Hypothesis 6: **The likelihood that the startup funded by the focal VC syndicate will be successful will have an <u>inverted U-shaped</u> relationship with the degree of homogeneity among VC firms in the syndicate.**

Actors enter into social relations with others who are similar to them because similarity is a crucial determinant of attraction, and thus, members with pre-existing relationships are likely to have more knowledge and beliefs in common (Newcomb, 1961; Ancona and Caldwell, 1992). Moreover, people who have social ties to each other also tend to develop shared understandings of the issues they face, and thus, social ties increase the homogeneity of beliefs and attitudes (Friedkin and Johnsen, 1999). Therefore, as prior ties between members increase, so will the extent of cohesion in the group. At the same time, by increasing their exposure to each other, prior ties will also increase members' mutual attraction and the similarity of their ideas. Thus, groups consisting of members with a greater number of prior ties will tend to be more susceptible to the costs of similarity discussed above.

Member diversity, on the other hand, will mitigate the negative effects of prior ties. Diversity among members prompts task-related debate and disagreement, which forces the group to consider alternative points of views and arrive at better, more thought out decisions. In addition, disagreement and cognitive conflict also reduce mutual attraction between members. Therefore, I expect diversity to counter the negative effects of prior ties. Stated differently, the greater the diversity between members of a group, the greater will be the number of prior ties required to bring about a relatively high level of attitudinal similarity between partners. Therefore, I hypothesize that high levels of member diversity will mitigate the negative effects of prior ties between syndicate members on the likelihood of the funded startup being successful. More formally,

Hypothesis 7: The likelihood that the startup funded by the focal VC syndicate will be successful will be negatively related to the interaction of the number of prior ties and the degree of homogeneity among VC firms in the syndicate.

Syndicate Size: As noted above, groups have greater expertise as well as cognitive and other resources than individual members. Therefore, it may seem reasonable to expect that larger groups will always perform better than smaller ones. However, prior research has argued and provided empirical evidence that this does not necessarily happen. As group size increases, groups begin to experience process and motivation losses, which result in a decline in group performance

Process losses refer to coordination or interaction difficulties due to which groups are unable to optimally utilize the available resources (Steiner, 1972; Tindale and Davis, 1983; Stasser and Titus, 1985; Schulz-Hardt, Jochims and Frey, 2002; see Williams, Harkins and Karau, 2003 for a review). Research has provided considerable evidence that such problems increase with group size. Studies have demonstrated that as group size increases, it becomes increasingly difficult to build inter-personal relationships that further cohesion (Latane, Williams and Harkins, 1979; Wagner, 1995) and thus cohesiveness, cooperation and consensus decline (Shull, Delbecq and Cummings, 1970; Wagner, 1995). At the same time, coordination and communication difficulties increase (Blau, 1970; Shaw and Harkey, 1976).

One of the outcomes of motivation losses is a phenomenon called social loafing, which refers to reduced effort by individual members (Steiner, 1972; Latane, Williams and Harkins, 1979). The loss of motivation is thought to promote social loafing because of the difficulty in evaluating individual members' input into the collective output of the group (Harkins, 1987; 2000; Szymanski and Harkins, 1993). This difficulty becomes especially acute as groups become larger (Herold, 1979; Gladstein, 1984). Evidence of social loafing has been provided in a variety of settings, using both laboratory and field studies involving evaluative tasks such as rating advertisements and resumes (e.g., Williams and Burmont, 1981; Erez and Somech, 1996), cognitive tasks such as remembering information relevant to a mock trial and looking for the appearance of specific signals on a computer (e.g., Harkins and Szymanski, 1988; 1989), physical tasks such as rowing and pumping air through a handheld device (e.g., Kerr and Bruun, 1983; Anshel, 1995), and work related tasks such as completing an in-basket managerial exercise and selling products (e.g., Earley, 1989; George, 1995; see

Williams, Harkins and Karau, 2003 for a comprehensive review of the empirical evidence relating to social loafing; also see Karau and Williams, 1993 for a meta-analysis of 78 studies on social loafing).

Thus, individual members' contribution tends to decline, that is, they tend to contribute less than they might, as group size increases. In addition, larger groups are also faced with greater process losses which prevent them from harnessing available resources. However, considerable research on groups suggests that size is unlikely to have simple linear effects on performance. Rather, while performance may improve initially with an increase in the number of members because of the availability of greater resources, beyond a certain threshold, further increases in size can lead to dysfunctional member behavior, and therefore, to a decline in overall performance (Steiner, 1972; Hackman, 1987). The threshold or optimal group size tends to vary by the type of task the group is required to perform. For problem solving tasks that have at least one "correct" solution, this threshold may be relatively high at around 4-5 members. However, when the task involves making decisions under conditions of uncertainty, as it does in the present context, and one "correct" solution does not exist, the threshold may be considerably lower. Accordingly, I expect the number of syndicate members to be related to the performance of VC syndicates (and consequently, to the likelihood that the startup will be successful) in an inverted U-shaped manner. More formally,

Hypothesis 8: The likelihood that the startup funded by the focal VC syndicate will be successful will be related to the number of VC firms in the syndicate in an inverted U-shaped manner.

Stage of Development of Funded Startup

Entrepreneurial organizations suffer from the liability of newness which leads to high mortality rates during the initial years of their existence (Stinchcombe, 1965), although this liability decreases as the organizations move through successive stages of development. Startups funded by VCs tend to experience even higher rates of failure than other new organizations in part because they are typically engaged in developing new products or technologies and the rewards of innovation are uncertain. The National Venture Capital Association (NVCA) categorizes VC funding provided to startups into the following stages based on their stage of (idea/product) development: **(a) Seed stage:** financing before there is a real product or company organized; **(b) Early stage:** financing a company in its first or second stages of development, when it has exhausted its initial capital and needs funds to initiate commercial manufacturing and sales; **(c) Expansion:** financing to help a company grow beyond a critical mass to become more successful, when it needs working capital for producing and shipping its products; and **(d) Later stage:** financing to help the company grow to a critical mass to attract public financing through a stock offering, or to attract a merger or acquisition with another company by providing liquidity. Given that the liability of newness declines as new organizations successfully go through successive stages of development (Stinchcombe, 1965), I expect that, all else equal, startups at later stages will be more likely to survive.

As noted earlier, in addition to providing funds, VC firms add value to the startups they fund in a number of ways. This value addition can include addressing weaknesses in the startup's business model or its entrepreneurial team (Kaplan and Stromberg, 2004), providing advice on strategic matters, helping them to hire professional managers (Hellman and Puri, 2000; 2002) and providing access to their own networks which may enable the startup to reach potential customers and suppliers or form strategic alliances (Lindsey, 2002). However, as I also argued earlier, VC firms can select partners that are sub-optimal for the particular organizational and strategic requirements of the focal startup because they are biased in favor of their prior partners. Moreover, they may select partners without adjusting their selection criteria because they underestimate the differences in the needs of the focal startup from those of a prior startup in which they co-invested with the same firm, but for which that VC firm was more appropriate.

Syndicates composed of sub-optimal VC firms may therefore not possess the skills and resources required by the focal startup. However, since a startup's dependence on its investors for value addition decreases as it grows through successive stages of development, this match between the VC firms' skills and resources and the startup's needs should be less critical at later stages than it is at earlier stages. Therefore, it seems reasonable to argue that startups that receive VC funding for the first time at later stages of development will be more capable of withstanding the negative effects of receiving funding from VC syndicates that include inappropriate, or less than optimal, VC firms.

Thus, I hypothesize that startups at later stages of development will be more likely to survive and be successful as compared to startups at earlier stages. Further, startups at later stages of development will be more likely to be successful despite receiving suboptimal strategic and/or organizational support from their investors. More formally,

Hypothesis 9: The earlier the stage at which the startup funded by the focal VC syndicate receives VC funding for the first time, the lower will be its likelihood of success (that is, the likelihood of success will be the least for seed/early stage startups and the greatest for later stage startups).

Hypothesis 10: The likelihood that the startup funded by the focal VC syndicate will be successful will be negatively related to the interaction of the number of prior ties between the VC firms in the syndicate and the stage at which it receives VC funding for the first time (that is, the earlier the stage, the greater will be the negative effect of prior ties).

CHAPTER 4: METHODS

This chapter discusses the methodological issues relating to the study. The chapter begins with a description of the sample used and the data sources. Next, all the independent and control variables required to test the hypothesized effects proposed in chapter 3 are defined and their operationalization described. Table 1 summarizes the operationalization of each independent construct. Finally, the details of the statistical methods to be used in the testing of these hypotheses are also discussed.

PRELIMINARY IN-DEPTH INTERVIEWS

Prior to the commencement of the study, in-depth interviews were conducted with 18 respondents. These respondents included seven senior partners from VC firms, five entrepreneurs, three industry experts and three professors. The industry experts included senior officials involved with the VC related practice at PriceWaterhouse Coopers (PWC) and Thomson Financial Venture Economics. The professors teach graduate level private equity and entrepreneurship courses in addition to conducting research in these areas at a leading business school. Consequently, they have a considerable amount of interaction with VCs and entrepreneurs. Most of these interviews were conducted in person, although some were also conducted telephonically, with pre-arranged appointments. Each interview lasted 30-90 minutes, depending on the respondents' availability.

The purpose of these interviews was to obtain the perceptions of practitioners about why VC firms syndicate investments with other firms, how they select firms to syndicate with, how they select startups for funding and so on. Detailed checklists of questions, developed in advance, were used to guide these interviews, although the discussions themselves were unstructured. As part of the discussions, respondents were asked to comment on the proposed study hypotheses in order to ensure their reasonableness and face validity. Some respondents were interviewed more than once in order to clarify and/or validate information provided by them or by other respondents. The study hypotheses were modified as appropriate on the basis of these interviews.

SAMPLE AND DATA

The sampling frame for the study was U.S. based startups which received equity financing from a syndicate of U.S. based, professional VC firms for the first time during the period 1997 to 2001[7]. This time frame is appropriate for this study because it covers first-round fundings in the period prior to the burst of the "dot-com" bubble as well as at the time of the burst (mid-2000 to mid-2001) and a few months subsequently. I focus on the first time a startup receives funding from a syndicate of professional VC firms because the level of uncertainty regarding the likelihood of success of the startup is the greatest at this point, and therefore, social ties play an important role. Such a focus is also appropriate because research on VC syndication suggests that, in subsequent rounds, the motivations for syndication as well as for the selection of syndicate partners are entirely different from those in the first round (Admati and Pfleiderer, 1994). For example, the informational asymmetries that arise between first-round and subsequent-round investors may play a significant role in partner-selection decisions in subsequent rounds. Moreover, sometimes VC firms participate

[7] According to information provided by VX, a total of approximately 800-1,000 startups received funding every year during the period 1997-2001.

in syndicates in later rounds in order to "window dress" (that is, overstate) their performance to potential investors in funds they plan to raise in the future, as is done by pension funds (Lakonishok, Shleifer, Thaler and Vishny, 1991; Lerner, 1994; Sorenson and Stuart, 2001).

The primary source of archival data for the study was a database called VentureXpert, which is maintained by Thomson Financial VentureXpert (VX).[8] VX obtains information about venture funding and related activities in the US through a quarterly survey (called MoneyTree™) of venture funded startups and VC firms it conducts jointly with the National Venture Capital Association (NVCA) and PriceWaterhouse Cooper (PWC). Accounting for an estimated 90% of all VC investments in the US, this database is the leading provider of VC investments, and has been used extensively in VC related academic research (Megginson and Weiss, 1991; Gompers and Lerner, 2000a; 2001; Stuart, Hoang and Hybels, 2001; Shane 2002).

According to information available from VX, a total of 1,341 US-based startups received their first round of funding from a syndicate of US-based VC firms. Given the high mortality rates among new organizations, this entire population of startups was included in the initial sample in order to ensure that the number of successful events (defined below) would be adequate to enable analysis of the data. However, 57 startups had to be eliminated from the sample because of inconsistencies in the available information (discussed below), resulting in a final sample of 1,284 startups.

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[8] Two other sources of information regarding VC firm age, size, focus areas, general partners, etc., that were used to supplement the information available from VX were Pratt's Guide to VC Sources and Galente's Handbook of Information on VC firms.

As mentioned above, VX obtains information about venture funding from surveys of VC firms and startups. This information is compiled by VX and reported on a deal-by-deal (that is, round-by-round) basis. Since the information comes from both startups and VC firms, variations in the names of the startups and VC firms were observed frequently across rounds. Such variations include mis-spelling, the inclusion or exclusion of terms (e.g., Limited, Company), abbreviations (e.g., "Ltd" vs. "Limited", or "Co." vs. "Company"), punctuation marks (e.g., Co vs. Co.), or even variation in the use of upper-case and lower-case letters, all of which made it difficult for the names to be matched electronically. I created appropriate rules to reconcile such differences. Another frequently occurring difference across observations referring to the same company which was resolved electronically was legal changes in names, particularly the startups' names. In cases where the differences in names were not straightforward, I manually looked up the company profiles (provided separately by VX) and tried to match information such as the office address, founding date, name of founder industry, and so on, in order to assess whether the two records referred to the same startup.

In a number of cases however, adequate information was not available to enable me to unambiguously conclude that two observations clearly referred to the same startup or to different startups. In such cases, I searched multiple sources of information including web pages of the VC firms and startups which contain company profiles. VC firm web pages also frequently contain a list of the startups in their portfolio, while web pages of startups list the VC firms from which they have received funding. I also searched archival sources such as newspapers, newsletters and journals (including sources that are solely devoted to venture funding activity such as Venture Capital Journal, Private Asset Management, Crains and Mercury News for Silicon Valley[9]) with the help of search engines such as Dow Jones Interactive, Factiva, Infotrack, Infotext and Lexis-Nexus. In addition, I searched websites such as Findarticles.com, Vcbuzz.com, Bizjournals.com, Techdealmaker.com, and Epraire.com which are focused on VC activity, and specialized databases such as Hoover's. Finally, information regarding startups that have already issued IPOs is also available in EDGAR archives, since it contains the information required to be submitted to the SEC by companies intending to go to IPO. Similarly, the Mergers and Acquisitions Database maintained by Securities Data Corporation (SDC) contains data on mergers and acquisitions. Therefore, I also searched these sources as necessary.

VARIABLE DEFINITIONS AND OPERATIONALIZATION

In order to test the hypotheses developed in the previous chapter, I used a longitudinal research design, and thus, constructed a longitudinal dataset from the above database. I tracked all 1,284 startups in my sample, that is, startups that received funding from a syndicate of VC firms for the first time during the period 1997-2001. The observation window continued until June, 30, 2004. I updated all variables annually, and the final dataset consisted of 5,225 firm-years. Startups entered the risk set during the year in which they received the first round of funding from a VC syndicate. Thus, no startups were left-censored. Once a startup receives early funding, in every subsequent time period it is at risk of experiencing one of the following events: (a) follow-on VC funding; (b) an initial

[9] Such sources tend to report a large portion of all funding deals, and provide basic information about the VC firms and startups involved (Rogers and Larson, 1984; Saxenian 1994).

public offering (IPO); (c) an acquisition by another company; or (d) death (that is, dissolution or disbanding for reasons other than an acquisition, such as bankruptcy). Thus, startups were removed from the risk set when they either died or experienced an exit, that is, an IPO or an acquisition. As explained in detail further below, exit (that is, an IPO or an acquisition) is commonly used in research as an indicator of startup success, particularly when the VCs' perspective is being considered, since it enables the VCs to liquidate their investments (Freeman, 1999; Gompers and Lerner, 2000a; Stuart and Sorenson, 2003). Startups that were still alive at the end of the observation window, that is, June 30, 2004 and had not experienced either an exit or death, were right censored on that date. I discuss below the operationalization of each variable used in this research.

Dependent Variable

The hypotheses developed in the previous chapter identify the dependent construct as the success of the startup funded by the focal syndicate of VC firms which, as I note in that chapter, I treat as a proxy for the syndicate's success for the purpose of this study. This is appropriate because VCs' economic objective, whether investing in startups alone or as part of a syndicate, is financial gain from their investments, which they attain by liquidating their stake in the startup either when it is acquired by another company or when it goes public; and the extent to which the funded startup is successful largely determines the VC investors' ultimate financial gain.

Measuring the performance of a new venture is difficult since many of the traditional, accounting measures such as profits, sales, revenues, etc., may be neither relevant nor readily available for such organizations. For instance, some new ventures, especially in the bio-technology industry, take several years to even start producing a product since product development requires a significant amount of R&D. Depending on the research question, prior research has used a variety of measures of new venture performance including, to name a few, survival, success in recruiting human capital (annual increase in the number of dedicated R&D employees), investment in innovation and innovative capabilities (annual increase in R&D spending), level of innovation (number of patent applications filed and/or number of patents obtained), reaching milestones such as obtaining VC funding, making an initial public offering (IPO), likelihood and success of IPO and likelihood of a merger or acquisition at a favorable price (Welbourne and Andrews, 1996; Freeman, 1999; Stuart, Hoang and Hybels, 1999; Welbourne and Cyr, 1999; Gompers and Lerner, 2000b; Certo, Covin, Daily and Dalton, 2001; Hannan, Baron, Hsu and Kocak, 2001; Burton, Sorenson and Beckman, 2002; Higgins and Gulati, 2003; Stuart and Sorenson, 2003).

In the context of this study, it is reasonable to assume that all startups are striving for an IPO or an acquisition at a favorable price because this enables them to obtain funding, often substantial, for expansion (Beckman, Burton and O'Reilly, 2002). Since IPOs and acquisitions allow VCs to cash their investments, they are called "liquidity or exit events" and are critical milestones for startups, commonly used as indicators of performance (Freeman, 1999; Stuart and Sorenson, 2003). Research has shown that IPOs tend to provide the highest returns to VCs, and hence are the most preferred exit route (Gompers and Lerner, 2000b), although in some industries such as biotech, acquisition are the most common form of exit. On average, IPOs and acquisitions occur within a period of 5-7 years from receipt of initial venture funding. However, being fragile, not all startups survive long enough to experience either of these events. Thus, IPOs and acquisitions are both considered significant achievements, since they are indicative of the market's confidence in the organization's future performance. The likelihood of the occurrence of each of these is contingent on investors being willing to pay a certain price for ownership of the company (Stuart, Hoang and Hybels, 1999). Moreover, according to SEC rules, in order to be able to go to IPO, firms are required to be of a certain minimum size. Experiencing an IPO or acquisition therefore implies that the organization has, at least to some extent, overcome the liabilities of newness and smallness and is used as a measure of success. Thus, a successful exit (that is, either an IPO or an acquisition) is used as the dependent variable for this study, and exits due to bankruptcy, dissolution, etc., will be excluded from this variable.

The variable "exit" was coded as 1 in the year in which a startup experienced either an IPO or an acquisition, and 0 in all years previous to that year. Once the startup experienced a successful exit, it dropped out of the observation set. Startups which died also dropped out of the dataset in the year following the year in which they died. Finally, as mentioned above, startups that did not experience an exit event during the time frame of the study were right censored on the last day of the time window.

It is worth noting here that explicit information about a startup's death is seldom recorded. Once a VC firm invests in a startup however, it is reasonable to assume that it will not continue to hold its investment for an unlimited period of time, particularly given that VC funds have limited lives and the investments made from a fund must be liquidated and any profits distributed to the limited partners who invested in the fund at the time the fund's life ends. Therefore, even if a startup is not performing well and is thus unlikely to go public or be acquired at a profitable price, the VC investors do need to liquidate their holdings. Thus, if a VC firm does not report disbursing a further round of funding to a startup in its portfolio for a certain period of time, it is reasonable to assume that the firm has liquidated its holding in the startup, and the startup has undergone dissolution. Following prior research, startups that have neither experienced an exit event, nor received follow-on VC funding during the preceding 535 days (that is, the average time between the last round of funding and exit or death in my dataset), were assumed to have died (Guler, 2002). Startups which received the last round of funding less than 535 days before the last day of the time-window (that is, 1997-2001) were right censored.

Independent Variables

Research suggests that ties in one year may not provide an adequate picture of the relationships between actors because it takes time to build relationships (Sorenson and Stuart, 2001). In the case of VC syndication as well, actual investment in a startup occurs after months of negotiation and due diligence, so ties in one year may not accurately reflect the relationships. Moreover, once formed, syndicates last for several years, until the startup receives the next round of funding, exits or is dissolved. The effects of these relationships also tend to outlast the formal relationships. Therefore, following prior research, I used a period of 5 years to calculate the prior ties between VC firms, which then formed the basis of calculation of all other network measures namely, the number of prior direct ties, cohesion and network driven status/prestige, which are descried further below.

The first step in calculating these variables was to create annual adjacency matrices based on information on all VC co-investment activity during the year. Thus, the value of cell (i,j) in the matrices was equal to the number of times firm i and firm j invested together in the same round in a startup during the respective year. I then aggregated the annual adjacency matrices to form matrices representing each 5-year period, thereby creating counts of the number of times each dyad of VC firms co-invested in a startup during each period of 5-years starting from 1992. Thus, I created adjacency matrices for 5-year moving windows starting from 1992-96 till 1996-2000. Next, I imported the 5-year matrices into the network analytic package UCINET 6 (Borgatti, Evertt and Freeman, 2002), and ran the appropriate routines in the package to create the required variables.

Most of the variables described below were first calculated at the level of the individual VC firm or dyad of VC firms, and then aggregated to arrive at the relevant value for the focal syndicate. The method used to aggregate to the syndicate varied across variables, and the specific method used for each variable is discussed below.

<u>Number of prior ties between syndicate partners</u>: I operationalized prior ties between VC firms as a count of their prior co-investment or syndication relationships, that is, investment in the same startup in the same round during the 5 years preceding the focal investment. Thus, the count of prior ties generated based on the co-investments made by the syndicate partners during the period 1992-96 was used for the focal investments made in 1997, the count for the period 1993-97 was used for focal investments made in 1998 and so on. Dyads which had not worked together during a 5 year period were assigned a value of 0 for prior ties. The measure of prior ties for each syndicate was calculated by averaging the number of prior ties across all dyads in the syndicate.

<u>Cohesion between syndicate partners</u>: Several different measures of cohesion have been proposed by social network researchers (e.g., Burt, 1992). I operationalized the level of cohesion between syndicate members in three alternative ways. The first of these measures was Burt's (1992) **dyadic constraint** which refers to the extent to which each ego is constrained by alter (see Burt, 1992, equation 2.4, page 55). Ego is constrained by alter j if: (a) j represents a large proportion of ego's relational investment; and (b) if ego is heavily invested in other people who are in turn heavily invested in j. Thus, an alter j constrains ego if ego is heavily invested in j directly and indirectly. Dyadic constraint was calculated for each dyad of each syndicate and aggregated to the syndicate by averaging the values across all dyads.

The second measure was **Simmelian/embedded tie strength** Simmel's (1950). Two actors are said to have a Simmelian tie to each another if they are reciprocally and strongly tied to each other and to at least one common actor (Krackhardt, 1999). According to Simmelian tie theory, such ties strengthen the bond between actors. However, this strengthening occurs at the cost of making the actors subject to the norms of the cliques within which they are embedded. A greater number of Simmelian ties only marginally strengthen actors' bonds. However, the more cliques an actor has Simmelian ties to, the more restrictions there are on the actors' behavior. This measure of constraint resembles Burt's (1992) measure of dyadic constraint. Yet, as Krackhardt (1999) argues, these measures differ in terms of the degree of constraint on ego in triads of differing structures; while Burt (1992) emphasizes the connection between an actor's ties (that is, the constraint on an actor is the greatest if all of his/her ties are connected to each other), according to Simmelian theory, the constraint on an actor is the greatest when the actor is embedded in multiple maximally connected cliques (see Figure 2). Thus, while both theories would predict the same degree of constraint when an actor is a member of only one clique, Simmelian theory predicts a far higher degree of constraint than structural holes theory, when the actor is a member of multiple cliques. Simmelian/ embedded ties were calculated for each dyad in the syndicate, and the value for the syndicate was arrived at by averaging across all dyads.

Finally, the third measure was **ego network density,**[10] which refers to the extent to which ego's alters are connected to each other (Kadushin, 1968; Blau, 1977; Alba and Moore, 1982; Burt, 1983). As discussed in chapter 3, the speed at which information flows through the network varies with network density (Coleman, Katz and Menzel, 1966; Granovetter, 1982; Rogers and Kincaid, 1981; Burt, 1992). Therefore, information about actors' behavior and reputation is likely to spread faster in dense networks, which is likely to intensify actors' concerns about their reputation. Ego network density is calculated as the number of ties between all the members of the ego network, excluding ties to ego, divided by the total number of pairs in the ego network.

[10] Networks consist of ego, that is, the focal actor from whose perspective relationships are examined, and alters, that is, actors to whom ego is connected. An ego network consists of a focal node (called ego) and the nodes to which the ego is directly connected (called alters), and the ties between ego's alters. Thus, by definition, ego is connected to all the other members (i.e., alters) in an ego network.

Syndicate members' prior prestige: VC firm status/prestige was measured as the firm's centrality in the VC syndication network (Podolny, 1993; Stuart, 1998; Sorenson and Stuart, 2001; Sullivan, Haunschild and Page, 2007). Centrality was calculated using Bonacich's (1972) eigenvector centrality measure which takes into account not only an actor's own direct ties, but also the centrality of those to whom the actor is tied. This measure was based on each firm's syndication ties with other VC firms during the 5 years preceding the focal investment. Status/prestige for the syndicate as a whole was calculated by taking the average across all syndicate members.

Syndicate member prior experience: Three different aspects of VC firms' prior startup investment experience were measured. The first measure was a count of the total number of startups each VC firm had invested in prior to the focal funding, to represent the VC firm's **total experience**. The second measure was a count of each firm's prior investments in the focal startup's industry to represent **experience in the focal startup's industry**. Finally, the third measure was a count of each firm's prior investments in startups at the same stage as the focal startup to represent **experience at the focal stage**. Each of these measures was aggregated to the syndicate by taking the average across all members. Further, since hypothesis 4 predicted an inverted U-shaped relationship, each of the measures was squared to test for such a relationship.

Homogeneity of syndicate members: The **degree of homogeneity** among firms can be assessed along a number of different characteristics such as age, experience, prestige and so on. Research on the prestige/status of group members suggests that members frequently categorize other members into in-group and out-group members on the basis of their relative status/prestige (Krackhardt and Stern, 1988). At the same time, prior research also suggests that similar organizations receive comparable market information, pursue overlapping strategies, react to environmental conditions in like fashion, and thus have deeper insight into each other's situations and behaviors (Haveman, 1993; Davis & Greve, 1997). Firms with similar amounts of experience, or of similar vintage, tend to face similar strategic challenges, and develop similar perspectives for dealing with those issues. It follows that VC firms that have been making investments in startups within the same industry or at the same stage, would be likely to go through similar experiences and develop similar perspectives.

Moreover, the extent of diversity, in terms of the proportion of investments in specific industries or at specific stages, is also likely to have a significant impact on their perspectives. As discussed in chapter 3, as they gain experience, individuals tend to increasingly rely on "industry recipes," which are common ways of thinking, and have been argued to constrain their thinking (Spender, 1989; Hambrick, Geletkanycz and Fredrickson, 1993). Therefore, high levels of experience are associated with an increasing rigidity in thinking. However, one factor that might mitigate the rigidity-causing effects of experience is diversity of that experience. In the case of VCs, such diversity may take the form of investments in different industries, for example. By exposing the individual to varied conditions, such diversity may help them maintain greater flexibility in their thinking, thereby slowing the onset of rigidity in thinking. Thus, groups consisting of members with similar levels of diversity in their prior experience may have greater insights into each others' thinking.

Since there was no theoretical reason ex-ante to believe that the degree of homogeneity along any particular characteristic would be more meaningful, I used a number of alternative measures. Specifically, I calculated the degree of homogeneity of syndicate members along the following characteristics: (a) prestige; (b) age; (c) prior total experience; (d) diversity of prior industry experience; and (e) diversity of prior stage experience.

The calculation of the basic measures of prestige, age and experience has already been described earlier in this section. I calculated the degree of homogeneity among members of each syndicate as 1 minus the coefficient of variation (that is, the standard deviation divided by the mean) among the members along each of these three characteristics. In order to calculate the diversity of prior industry and stage experience, I used an entropy-based index which is typically used in the treatment of categorical variables (Palepu, 1985; Ancona and Caldwell, 1992). The standardized index, which ranges from 0 to 1, was calculated as follows:

$$\sum_{i=1}^{n} P_i \ln(1/P_i)$$

where n is the number of industries or stages the VC firm has invested in prior to the focal investment and P_i is the proportion of investments in industry or stage i.

The measure accounts for both the number of categories and the relative importance of each category (Palepu, 1985). If a VC had no prior experience in a particular industry or stage, the value assigned to that industry or stage for that VC was 0. I then calculated the coefficient of variation for the entropy index for prior industry or stage experience as described above and inverted it by subtracting it from 1. Thus, the resulting measure of homogeneity of the diversity of syndicate members' prior industry and stage experience is an indicator of the level of similarity in the extent to which their prior experience was diverse. For example, a syndicate including two members with very diverse experience, and two members with experience in only one industry segment each, would score low on the homogeneity measure as compared to another syndicate in which all four members have diverse experience.

Syndicate size: The size of the syndicate was simply the number of syndicate members, that is, the number of VC firms that invested in the focal startup in the first round. To test hypothesis 8 which predicted an inverted U-shaped relationship, I calculated the square of the number of syndicate members.

Startup stage at initial funding: New organizations suffer from the liability of newness which lead to high mortality rates during the initial stages/years of their existence (Stinchcombe, 1965), and this liability decreases as the organizations move through successive stages of development and/or grow older. As noted earlier, the NVCA categorizes VC funding provided to startups into the following stages based on their stage of idea/product development: (a) **seed stage:** financing before there is a real product or company organized; (b) **early stage:** financing a company in its first or second stages of development, when it has exhausted its initial capital and needs funds to initiate commercial manufacturing and sales; (c) **expansion:** financing to help a company grow beyond a critical mass to become more successful, when it needs working capital for producing and shipping its products; and (d) **later stage:** financing to help the company grow to a critical mass to attract public financing through a stock offering, or to attract a merger or acquisition with another company by providing liquidity. Accordingly, at the time of initial funding, startups were categorized into one of four stages. Since the vulnerability of startups at the seed and early stages is the greatest, I combined these together into one category called Seed/Early stage. The two remaining stages, that is, expansion and later stages were combined into a second category called Expansion/Later stage. I then created a dummy variable which was coded as 1 if the startup was at Seed or Early stage when it received VC funding for the first time, 0 otherwise.

<u>Control Variables</u>

The analysis controlled for a number of factors which have been shown by prior research to be influential in determining startup performance. These factors included characteristics of the VC firms in the syndicate (e.g., age and prior success rate) as well as characteristics of the focal startup (e.g., industry, total number of rounds of funding received, amount of funding received at the first and each subsequent funding round, and prestige of the VC firm(s) providing the subsequent rounds). Other than variables like startup industry which remained constant, most of these variables were updated each year. When a startup did not receive a round of funding during a year, the values of certain variables did not change. On the other hand, when a startup received more than one funding round in a year, the variables were averaged across the rounds.

Startup industry: The performance of startups in different industries may be affected by industry specific factors such as the rate of technological change, market size and growth rate etc. Some industries have access to larger markets and faster growth opportunities and therefore, show higher propensities for successful exit. They may also vary in terms of milestones they need to achieve before exit, the number of rounds of funding they typically receive, and the time they take to exit (Gompers and Lerner, 2000a). As noted earlier, an example is startups in the biotech industry, which frequently go to IPO even before they have a product, while in most other industries, startups tend to go to IPO only after they begin commercial production. Thus, a series of dummy variables indicating the industry in which the startup conducts, or proposes to conduct, most of its business, were created to control for industry specific differences in speed of development, commercialization, etc. (Powell and Brantley, 1992), and each dummy was coded as 1 if the startup was in that industry, 0 otherwise. The industry classification used was borrowed from VX, which has established a proprietary set of industry codes, analogous to 4-digit SIC codes. VX assigns each portfolio company to the industry that accounts for the majority of actual or prospective sales, based on information supplied by the startups and the VC firms. Startups were divided into 10 industry segments which include communications and media; computers and hardware; computer software; internet and online related; other electronics related; biotechnology and pharmacology; medical/health related; consumer related; industrial products and; other services and manufacturing.

Age: The age of the startup was included to ensure that any significant effects of the independent variable stage were not simply the spurious result of aging-related processes, which can be either positive because of the liability of newness (Stinchcombe, 1965; Hannan and Freeman, 1977) or negative because of the liability of senescence (Ranger-Moore, 1997). In fact, research has also argued for the liability of adolescence (Bruderl and Schussler, 1990). Moreover, other researchers have suggested that the effects of age may be contingent upon factors such as the strategy followed by the organization (Henderson, 1999). In calculating a startup's age, the earliest of the year of incorporation, year of hiring of first employee, and year of start of "normal business operations" was considered as the founding date (Beckman, Burton and O'Reilly, 2002). Generally, these dates are within a few months of each other, although there was considerable variation in the order in which they occurred. I also tested for an inverted U-shaped effect of age by including age squared.

Funding amount: The amount of financial resources available to a new organization can significantly affect its likelihood of survival and success (Pfeffer and Salancik, 1978). At the same time, recent research has argued that a lack of resources can make new firms more innovative in certain environments (Katila and Shane, 2005). In either case, the total amount of VC funding received by a startup could ultimately affect its likelihood of success. Thus, the amount of VC funding received in the first round was included in the analysis as a control variable. Further, the cumulative amount of funding received by the startup, updated on receipt of each subsequent round of funding, was also included. Both these variables were logged to account for the heteroscedasticity resulting from the wide range of values.

Syndicate members' prior success: Prior performance may influence a VC firm's risk tolerance, as well as the quality of decisions it makes. Research has shown that performance below aspiration level increases risk tolerance and vice versa (Greve, 1999). Past research has controlled for the VC firms' prior success (see, for example, Barnes, 1983). Therefore, I also included the average rate of prior success experienced by syndicate members in the analysis.

Number of financing rounds: VC firms typically disburse funds in stages, known as rounds, to be able to better manage their risk. Research has shown that a firm's likelihood of going public first increases and then decreases as the total number of rounds of financing it receives increase (Guler, 2002). Thus, the square of the total number of rounds received by the startup was controlled for. However, sometimes VC firms disburse the amount agreed for a certain round in multiple installments for various reasons such as availability of funds, separate checks being sent by the different VCs participating in the funding round. Although these installments are part of the same round, VX often shows the receipts as separate funding round, thereby overstating the number of rounds the startup received. The norm in the VC industry is that the "term sheet," that is, the terms of any funding provided, are valid for a period of 90 days. Consequently, I followed the recommendation provided by Lerner (1994) that multiple rounds received by a startup within 90 days be aggregated into one round.

Number of VC firms in each follow-on funding round: As in the case of the first round, having multiple co-investors in follow-on funding rounds might also affect the startup's likelihood of success by providing access to a greater amount of resources and signaling positive expectations to the market. Thus, the number of co-investors at each follow-on funding round was included as a control variable.

Prior ties between VC firms providing each follow-on funding round: For follow-on funding rounds involving more than one VC firm, the number of prior ties between the firms was included as a control. As with the first round syndicate, the number of prior ties between members of subsequent-round syndicates was also operationalized as a count of the number of co-investments the VC firms had made during the 5 years preceding the year of the follow-on round.

Prestige of VC firms in each follow-on funding round: The status/prestige of the VC firm(s) providing the follow-on funding round was included to control for the effects of the status/prestige on the startup's success likelihood.

IPO market conditions: How favorable or unfavorable the market is for equity offerings is a critical aspect of uncertainty for investors, and research has shown that the favorability of equity markets fluctuates significantly and affects the preferred timing of IPO (Lerner, 1994). Further, prior research has argued that since IPOs and acquisition are complementary outcomes from the VCs' perspective, equity market conditions may also affect both the likelihood and timing of acquisitions. Thus, IPO market conditions during each year of the observation period for the study was controlled for by including the number of IPOs issued during the year.

<u>Time since first round</u>: The time elapsed since the startup received the first round of funding was also controlled for.

<u>ANALYSIS</u>

I estimated the instantaneous hazard rate of an exit by a startup funded by a syndicate of VC firms using a continuous-time event history analysis (Allison, 1984) using a Cox Proportional Hazards model. The model was estimated using the STCOX procedure in STATA with the ROBUST option. The basic model is given by the equation:

$$h(t) = h_0(t)\exp[\beta X(t)]$$

where $h_0(t)$ is the baseline hazard function and $X(t)$ is the vector of covariates.

This model assumes that the hazard rate is fixed within each period of time, although it can vary across time periods. A Cox model was appropriate because it does not require any assumptions about the intrinsic shape of the hazard function. Moreover, Cox models are particularly suited to handle time-varying covariates and right-censored observations. The latter avoids biases arising from either dropping the right-censored observations altogether or assuming those organizations to be dead at the end of the observation window (Tuma and Hannan, 1984).

CHAPTER 5: RESULTS

This chapter provides the results of the empirical analyses conducted to test the hypotheses proposed in chapter 3. The chapter begins with a description of the data and goes on to present the results.

DESCRIPTIVE STATISTICS

A total of 1284 startups funded by VC syndicates during the period 1997 to 2001 are included in the analyses. These startups were observed until June 30, 2004 and the data pertaining to each startup was updated annually. This provided 4,975 observations and 287 events. Following prior research (e.g., Freeman, 1999; Stuart and Sorenson, 2003; Gompers and Lerner, 2000b; Stuart, Hoang and Hybels, 1999), an event was defined as a startup experiencing a liquidity event, that is, a successful exit, through either an acquisition or an Initial Public Offering (IPO) between January 1, 1997 and June 30, 2004[11].

Table 2 provides the descriptive statistics for all the variables used in the analyses. The average startup was approximately 17 months old at the time it received VC funding for the first time and received a total of $28.33 million in VC funding during the observation period. This funding was disbursed over 2.57 distinct rounds on average, with the average startup receiving one round of funding approximately every 16 months.

The average syndicate that provided first round funding to the sample startups consisted of 2.39 VC firms, while some syndicates consisted of as many as 7 members. It is

[11] A total of 704 startups died (i.e., went defunct or bankrupt) during the observation period. As noted in chapter 4, these startups were dropped from the dataset in the year following the year in which they died; however, in accordance with the definition of the dependent variable, these cases were not treated as events.

worth noting here that nearly 70% of the syndicates in the sample consisted of only two members each, while another 24% consisted of three members each. Thus, only 6% of the observations involved syndicates of more than three members each. The number of VC firms in syndicates that provided subsequent rounds of funding to startups in the sample was somewhat higher at 3.28, with the largest of these syndicates consisting of 18 members.

The average number of prior ties between syndicate members[12] was 2.09, although this number was as high as 52 in some cases. One reason the average number of prior ties is relatively low at 2.09 is that members of nearly 55% the VC syndicates did not have any prior ties at all. The average number of prior ties between VC firms that had worked together in the past was 4.54, which is more than twice the abovementioned average. Prior to funding the focal startup, syndicate members had, on average, funded approximately 50 startups each. Approximately 22% of these startups had been successful, that is, had exited via either an IPO or an acquisition.

Table 3 shows that correlations between all the variables used in the analysis. As the table shows, correlations between some theoretical variables are relatively high, as are those between some theoretical variables and some control variables. For example, the prestige of first round VCs is correlated to the prestige of round j[13] VCs (r-value = .74) as well as to their prior experience (r-value = .86) and prior success rate (r-value = .52); and prior

[12] As specified in chapter 4, the average number of prior ties between members of a syndicate is measured as the number of times each dyad of VC firms had co-invested in a startup during the 5-year period preceding their participation in the focal syndicate, averaged across all dyads in the syndicate.

[13] Round j refers to the latest round received by the startup during the window year. When a startup received more than one round in a year, the values of all variables for the window year were arrived at by averaging across the rounds during the year.

experience is correlated with both prior success rate (r-value = .58) and prestige of round j VCs (r-value = .64). Similarly, prior ties between round 1 VCs are correlated with prior ties between round j VCs (r-value = .52); and Simmelian ties are correlated with prior ties (r-value = .64) and prior experience (r-value = .55). These correlations are not unexpected given prior research discussed previously in chapter 2 and the prevalence of syndication in the VC industry.

Nevertheless, taken together with the various squared and interaction terms included in the models for hypotheses testing, these correlations do raise the threat of multicollinearity, which can inflate standard errors and result in less precise coefficient estimates. In order to guard against these problems, I took two steps. First, in accordance with the approach recommended by Jaccard, Turrisi & Wan (1990), I centered each independent variable at its mean prior to creating the squared and interaction terms required to test my hypotheses. Centering has the effect of reducing the correlations between the variables in question and any interaction or squared terms involving those variables. Second, I conducted diagnostic tests for multicollinearity. Specifically, I computed the variance inflation factors (VIF) for each model. The threshold level for maximum VIF recommended in the literature is 10 (Belsley, Kuh and Welsch, 1980). The highest average VIF across the models I ran was 3.35 ~~3.32~~ (model 6). The highest VIF for any individual variable across these models was 10.96 (model 9), which slightly exceeds the recommended threshold. However, it is worth noting here that these models are the ones that include several square and interaction terms. Moreover, the estimated coefficients and standard errors were relatively stable across the models, including the models with high VIFs. This suggests that multicollinearity is not a serious problem in the models.

Because I had multiple cases where a VC firm was a member of more than one syndicate that financed the startups in the sample, I estimated robust standard errors using the Huber/White sandwich estimator (White, 1980). This method allows the assumption of independence of observations to be relaxed and yields estimates that are asymptotically consistent, even when errors are heteroscedastic.

DETAILED RESULTS

As mentioned in chapter 4, a Cox proportional hazards model was used to estimate the likelihood of exit by startups funded by syndicates of VC firms between 1997 and 2001. Table 4 provides a summary of the results of this analysis. More detailed results, including the estimated coefficients and the associated standard errors, are provided in tables 5 to 10. Significant positive coefficients in these tables imply that an increase in the level of the respective variable increases the focal syndicate's likelihood of success (that is, the focal startup's likelihood of exit). Significant negative coefficients, on the other hand, imply that a decrease in the level of the respective variable decreases the focal syndicate's likelihood of success (that is, the focal startup's likelihood of exit). Further, table 11 presents the hazard ratios for the key independent variables and the control variables that emerged as significant in model 9. Hazard ratios are obtained by taking the exponential on the coefficients estimated by the model. Hazard ratios of greater than one imply that an increase in the respective variable is associated with an increase the focal syndicate's likelihood of success over the baseline hazard rate, while hazard ratios of less than one imply that an increase in the respective variable is associated with a decrease in the syndicate's likelihood of success.

Table 5 presents the primary set of results obtained from the analyses (models 1 to 9). Model 1 is the baseline model, that is, it contains only the control variables. Model 2 adds all the predicted main effects. In this model, cohesion is measured as dyadic Simmelian ties, experience is measured as total prior experience and homogeneity is measured as the homogeneity of prior industry experience. Both prestige and experience are entered in this model in their logarithmic forms. A significant positive coefficient on a logarithmic variable would suggest that, as the level of the variable increases, the focal syndicate's likelihood of success increases at a decreasing rate. On the other hand, a significant negative coefficient would suggest that, as the level of the variable increases, the focal syndicate's likelihood of success decreases at a decreasing rate. Next, models 3, 4 and 5 include one interaction term each, relating to hypotheses 3, 7 and 10, respectively. All other variables in these models are the same as those in model 2. Further, models 6, 7 and 8 include two interaction terms each. Finally, model 9 is the complete model, that is, it includes all the hypothesized effects.

Models 10, 11 and 12 (table 6) were run in order to determine whether it would be more appropriate to use the logarithmic or the untransformed form of the variable prestige in the models i.e. whether the hypothesized relationship between prestige and the dependent variable is logarithmic or inverted-U shaped. Specifically, model 10 excludes prestige altogether, model 11 includes the untransformed variable, and model 12 includes the untransformed variable as well as its square. The objective was to identify the form of the variable that provided the best model fit, and thereby assess the shape of the function, by comparing each of these models to model 2, which includes the logarithmic form of the variable. With a similar objective, models 13, 14 and 15 were run including corresponding forms of the variable prior experience.

Models 16 to 22 present the results obtained from models using some of the alternative operationalizations of the independent variables discussed in chapter 4. Specifically, models 16 and 17 in table 8 present the results obtained when cohesion is operationalized as ego network density instead of dyadic Simmelian ties. All other variables are the same as those included in models 2 and 9, respectively. In models 18 to 20 in table 9, experience in the industry of the focal startup was used in place of total experience. While model 18 includes the logarithmic form of experience in the focal industry, models 19 and 20 replicate models 14 to 15 i.e. include the untransformed variable and its square. Finally, models 21 and 22 in table 10 present the results obtained when homogeneity is operationalized as the homogeneity of prior total experience instead of homogeneity of prior industry experience.

In addition to presenting the models, tables 5 to 10 also compare fit statistics, that is, the likelihood ratio, across all the models presented. The likelihood ratio is a chi square distribution and comparing it across models tests the global (null) hypothesis that all beta coefficients in a model are equal to zero. A significant result indicates that the null hypothesis is rejected.

Below I interpret the full model, that is, model 9, and note any differences in the other models. The results obtained from models with other alternative measures of cohesion, experience and homogeneity not presented here are also noted where they are qualitatively different.

Hypotheses Tests

Hypothesis 1 predicted an inverted U-shaped relationship between the number of prior ties between VC firms in the focal syndicate, that is, the syndicate that provided funding to the focal startup and the likelihood of the syndicate's success. Briefly, the argument was that while prior ties have beneficial effects, as the number of prior ties increases beyond a point, the costs associated with them also increase such that they at least partially offset the benefits. As model 9 shows, the coefficient on prior ties is positive and significant ($\beta = 0.118$; $p < .01$), while the coefficient on prior ties squared is negative and significant ($\beta = -0.004$; $p < .10$). This suggests that initially, prior ties are beneficial. However, as the number of prior ties increases beyond a point, the costs associated with them also increase, eventually overwhelming the benefits completely. Together, these two coefficients constitute support for the hypothesis that the number of prior ties has an inverted U-shaped relationship with the focal syndicate's likelihood of success. Further, using the coefficients on prior ties and prior ties square, the point at which the marginal effect of prior ties turns negative, that is, the point of inflexion, is estimated at approximately 14.5 ties.

I ran several additional models in order to check the robustness of the results of the analyses with respect to prior ties. First, it could be argued that the skewness in the variable prior ties may be driving the results obtained. Therefore, as a robustness check, I ran a selection model with the second stage including only syndicates with non-zero prior ties. The inverse Mills ratio obtained from this model was not significant, suggesting that the inclusion of syndicates with no prior ties does not lead to a bias in the analysis. Moreover, the second stage still provided evidence of an inverted U-shaped relationship between prior ties and the dependent variable, that is, while prior ties was positive and significant, prior ties square was negative and significant. Many of the other hypothesized results did not hold in this model, which is not surprising since the number of observations as well as events in this model were reduced significantly due to the elimination of nearly 55% of the observations in which syndicate members had no prior ties.

I also ran additional models in order to rule out the alternative explanation that the results are an artifact of the relatively lower stringency exercised by VC firms in evaluating startups for funding during the dotcom boom years. In these models, I included the interaction of prior ties with a dummy variable (Round1_BoomYr) that took the value of 1 if the focal startup received its first round of funding from a VC syndicate during the boom years (i.e. 1997, 1998 or 1999) and 0 otherwise. I then interacted this variable with prior ties and added both the dummy variable as well as the interaction term to the full model (model 9). The interaction term was not significant, implying that the results obtained are not an artifact of the effects of the dotcom boom.

Hypothesis 2 argued that syndicates embedded in highly cohesive networks incur additional costs resulting from inadequate monitoring of partners and "satisficing" information search behavior, and therefore, startups funded by such syndicates would be less likely to experience successful exits. Further, hypothesis 3 argued that the interaction of network cohesiveness with prior ties between syndicate members would further intensify the negative side effects of prior ties. Cohesion was negative and significant when it was measured as dyadic Simmelian ties, as is shown in models 2 and 9 ($\beta = -0.007$; $p < .10$ and $\beta = -0.008$; $p < .10$, respectively). However, the interaction of cohesion and prior ties was not significant. In model 16 where cohesion was operationalized as ego network density instead of dyadic Simmelian ties, the main effect of cohesion remains negative and significant ($\beta = -0.008$; $p < .10$). The interaction of prior ties with cohesion was again not significant (model 17). Moreover, when the interaction of prior ties with cohesion was added into the model, the main effect of cohesion also became insignificant. Finally, the third operationalization of cohesion, that is, dyadic constraint was used in models not shown here. Neither the main effect nor the interaction was significant in these models. Thus, hypothesis 2 was supported when cohesion was operationalized as dyadic Simmelian ties and ego network density, but not when operationalized as dyadic constraint. Hypothesis 3 was not supported using any of the alternative operationalizations of cohesion.

Hypothesis 4 suggested that high status/prestige of partners would make firms reluctant to monitor or challenge those partners because of reputational concerns as well as the desire to continue their relationship with those prestigious partners. I argued that not only is having a prestigious partner considered beneficial, the consequences of losing such partners are also worse than the consequences of losing less prestigious partners; and therefore, the likelihood that a partner would be monitored or challenged would be inversely related to that partner's prestige. In other words, while partner prestige would be beneficial, as the level of prestige increased, the costs associated with it would also increase such that they would offset the benefits at least partially. Accordingly, I hypothesized that as partner prestige increased beyond a point, the likelihood that a startup would experience a successful exit would increase at a decreasing rate. In order to test this hypothesis, I ran models without the variable prestige (model 10), with the logarithmic form of the variable (model 2), with the untransformed variable (model 11), and with the untransformed variable as well as its square (model 12). As table 6 shows, neither prestige (untransformed) nor its square were significant in models 11 and 12, while the log of prestige was positive and significant ($\beta = 0.201$; $p < .01$) in model 2. Moreover, while the logarithmic form of the variable resulted in a significantly better model fit (Δ log likelihood= 9.94; $p < .01$) over model 10, the untransformed variable (model 11) as well as the untransformed variable and its square (model 12) did not. This suggests that the logarithmic form of the variable is the most appropriate form of the variable to include in the models. This also suggests that partner prestige has a positive relationship with the syndicate's likelihood of success. However, as prestige increases beyond a certain level, the incremental benefits from additional prestige begin to decline, although they remain positive. Thus, hypothesis 4 is supported.

Hypothesis 5 predicted that the effect of syndicate members' prior experience would follow a pattern similar to that described above for prestige, that is, while it would be beneficial, as the level of experience increased, the costs associated with it would also increase such that they would offset the benefits at least partially. In order to test this hypothesis, I ran models without experience (model 13), with the logarithmic form of experience (model 2), with the untransformed variable (model 14) and with the linear and square terms of the untransformed variable (model 15). As model 2 shows, the log of prior experience was negative and significant ($\beta = -0.374$; $p < .01$), suggesting that the total costs of experience always exceed the total benefits. This result is even stronger than I hypothesized. In model 14, total prior experience (untransformed) was also negative and significant ($\beta = -0.007$; $p < .05$), although its square was not significant (model 15). The negative coefficient on the untransformed term also suggests a stronger negative relationship than I hypothesized. However, including the logarithmic form of total experience resulted in a better model fit (Δ log likelihood = 8.58; $p < .01$) as compared to the untransformed variable (Δ log likelihood = 6.00; $p < .05$), suggesting that the logarithmic form of the variable is the more appropriate form to include in the models.

In addition to total experience (discussed above), I also measured two other aspects of prior experience namely, experience in the industry of the focal startup and experience at the stage of the focal startup. Models 18 to 20 presented in table 9 include experience in the industry of the focal startup instead of total experience. Model 18 includes the logarithmic form of this experience variable, while models 19 and 20 include the untransformed variable and its square. The logarithmic term relating to experience was not significant (model 18), nor were the untransformed term and its square when they were included together (model 20). However, when the untransformed term was included alone, that is, without its square (model 19), it was negative and significant ($\beta = -0.013$; $p < .05$), which is a stronger effect than was hypothesized. Finally, in models not reported here, I included experience measured as prior experience at the stage of the focal startup. The variable was not significant in any of these models.

Hypotheses 6 and 7 predicted, respectively, that the homogeneity of syndicate members would have an inverted U-shaped relationship with the likelihood that the focal startup would be successful, and that the interaction of prior ties and homogeneity would be negatively related to the likelihood of success. Homogeneity was measured as the extent of similarity between syndicate members in terms of characteristics including their prestige, age, total experience, the similarity of their prior industry experience, and the similarity of their prior stage experience. Hypothesis 6 was not supported regardless of the operationalization (models 2 to 9, 21 and 22). Hypothesis 7 was supported when homogeneity was operationalized as the similarity of prior industry experience (models 4, 6, 8 and 9; in model 9, $\beta = -0.253$; $p < .05$), but not when it was operationalized as the similarity of prior total experience (models 21 and 22). In models not reported here, where homogeneity was operationalized as the similarity of partner prestige, age and the similarity of prior stage experience, neither homogeneity nor its interaction with prior ties was significant.

Hypothesis 8, which predicted an inverted U-shaped relationship between syndicate size and the focal startup's likelihood of success, was also not supported. Finally, the results are not supportive of either hypothesis 9 or hypothesis 10, which argued that since the liability of newness decreases as a new organization matures and successfully progresses through various stages of development, startups at later stages would be more robust to the negative effects, or costs, of being funded by inappropriate or sub-optimal VC firms.

To summarize the results discussed so far, the hypotheses regarding the main effects of effects of prior ties, cohesion, prestige and experience were supported. In addition, the hypothesis regarding the interaction of homogeneity with prior ties was also supported, although the main effect of homogeneity was not significant. Hypotheses relating to syndicate size and startup stage were also not supported. Moreover, significant results were obtained using only some of the alternative operationalizations of cohesion, experience and homogeneity.

Control Variables

In addition to the above hypothesized effects, some results with respect to control variables are also noteworthy. The analyses showed that once the prestige of round 1 VCs is controlled for, the prestige of round j VCs does not affect the likelihood of the focal startup's success. Moreover, contrary to the general belief, the rate of prior success of the VC firms in the syndicate that provided funding to the focal startup did not significantly affect the likelihood of exit. Thus, these results suggest instead that once the VC firm's experience and prestige are controlled for, prior success does not necessarily predict future success. In post-hoc analyses, I tested for the mediation of the effect of prior success by prestige. The Sobel-Goodman test for mediation showed that prestige mediates approximately 23% of the effect of prior success and the ratio of the indirect effect of prior success to the direct effect is 0.30. This provides preliminary evidence of mediation.

The cumulative amount of funding received by the startup also has a positive and significant effect on the likelihood of a successful outcome. This finding is in line with prior theory and research, namely that an influx of resources early in their lives improves the life chances of new organizations. Further, the number of IPOs during the window year is positive and highly significant, suggesting that the odds of an exit by a startup are greater when market conditions for IPOs are favorable. Again, this finding is consistent with prior research which suggests that, all else equal, the likelihood of exit by a startup is greater when market conditions are more favorable (Higgins and Gulati, 2003). Table 5 also shows that the number of rounds of funding a startup receives has a positive and significant effect on the likelihood of success while the square of the number of rounds has a negative and significant effect, that is, the number of rounds of funding is related to the startup's likelihood of exit in an inverted U-shaped manner. This finding is also in line with prior research suggesting that after they provide initial funding to a startup, VCs don't necessarily use the new information they receive about those startups in their decisions regarding whether or not to provide further funding to the startup (Guler, 2002). Finally, intuitively, the number of rounds received during any given year is negatively related to the likelihood that the startup will exit.

CHAPTER 6: DISCUSSION AND FUTURE RESEARCH

The findings of the empirical analyses presented in chapter 5 are largely supportive of my arguments. To summarize, as expected, repeated ties with the same partners have an inverted U-shaped relationship with the likelihood that the resulting partnership will be successful; the level of cohesion in the network, partners' prior experience and the interaction between prior ties and the degree of homogeneity among partners all reduce the partnership's odds of success and; the odds of success increase at a decreasing rate as the status/prestige of partners increases. The theory developed in this dissertation and the empirical findings make a number of contributions to the strategy and organizational theory literatures. These contributions are discussed in this chapter and potential areas for future research highlighted by the study are identified.

REPEATED TIES AND NETWORK COHESION

Research on social networks in general and on inter-organizational alliances in particular has tended to focus on their myriad beneficial effects while largely ignoring their negative effects or costs. Such beneficial effects are thought to include access to information and resources, legitimacy, and so on. Similarly, prior ties between partners are thought to enhance the level of trust between them, enable better coordination and the exchange of complex and tacit information. The costs of social networks, on the other hand, have received relatively less research attention. Even when considered, the costs of social networks have been limited to the time and effort expended to establish and maintain social ties. Moreover, most of this research makes the tacit assumption that such costs are exceeded by their beneficial effects.

The primary finding and the first contribution of this study is that prior ties have an inverted U-shaped relationship with the likelihood of success of the focal partnership. In the present context, where investments are made on an ongoing basis, and more than half of those investments are made in syndicates, the net marginal benefits of prior ties are decreasing and eventually, at 13 prior ties, turn negative, that is, their marginal costs outweigh their marginal benefits. This finding is consistent with the perspective that while initially, prior ties with partners have beneficial effects, as the number of prior ties increases beyond a certain level, their costs may begin to offset those benefits, eventually outweighing them completely. The first of these costs is the selection of sub-optimal partners for the focal situation because of an over-estimation of the quality of familiar partners and an under-estimation of the differences in the prior and the focal situation because of which the partners may be unable to make the contributions required from them in the focal situation.

Secondly, familiar partners may also be monitored inadequately because of an over-estimation of their quality, combined with a reluctance to monitor them due to the belief that monitoring betrays a lack trust and may damage the relationship itself. Such inadequate levels of monitoring of partners can be detrimental in situations where the success of the partnership is dependent on the quantity and quality of effort expended by the one partner to whom the management of the partnership is delegated, this effort is non-contractible and the partner to whom the management is delegated has interests or priorities that conflict with the collective interests of the group. For example, in the present context, the time consuming task of monitoring and advising funded startups is delegated to the Lead VC. However, startups funded by the Lead VC individually require the VC's time and resources as much as the startup funded by the syndicate, creating a conflict between the VC's individual interests and the syndicate's collective interests. In the absence of effective monitoring mechanisms regarding the extent of time and effort the Lead VC devotes to the startup funded by the syndicate, the Lead VC may place his individual interests above the syndicate's interests, and not devote the necessary amount of effort to the startup funded by the syndicate, which may compromise the syndicate's performance. Monitoring of such partners can solve this moral hazard problem at least partially by providing an early warning to the other partners, enabling them to take corrective measures. Finally, the use of insufficiently adapted, sub-optimal routines that have persisted beyond the prior exchanges during which they were developed may be detrimental to the focal partnership's performance because they may prevent the partnership from utilizing the expertise and/or resources available from the partners.

As with research on repeated ties, research on network cohesion has also tended to be more focused on its benefits, while devoting relatively little attention to the costs. Network cohesion is thought to help control opportunistic behavior by network members because it facilitates the spread of reputational information through the network and enhances both coordination and cooperation. Consequently, much of this research has revolved around the role of network cohesion in controlling opportunistic behavior by actors and relatedly, the mechanisms that are thought to facilitate trust and cooperation. This research has theorized and provided empirical evidence that actors prefer to interact with their prior partners, and their partners' partners (e.g., Gulati, 1995). Network cohesion is therefore associated with greater network density, which makes reputational information about actors available to members seeking to establish relationships with them. Because the speed of information diffusion is greater in dense networks, density is also thought to facilitate the establishment and enforcement of norms through collective disciplining of normative violators. Together, these characteristics of cohesive networks are thought to control opportunism among members.

One aspect of network cohesion that has been ignored however, is that the direction of information transmission is not just one-way, but two-way, making networks completely transparent. As this study suggests, a side effect of the same properties of cohesive networks that facilitate these beneficial outcomes, is a reduction in monitoring of partners to sub-optimal levels such that it compromises their joint performance. Said differently, in the same way that the focal actor can access information about potential partners' past behavior, those other members can also access information about the focal actor's past behavior. This transparency places constraints on the behavior of not only those potential partners but also the focal actors themselves. In the context of this study therefore, syndicate members may be unlikely to monitor or challenge the Lead VC firm since such behavior violates the established industry norms. However, given the conflicting demands on the Lead VC's time from the focal startup on the one hand, and from its own portfolio of investments on the other, and absent other means to ensure adequate involvement by the Lead VC in the management of the focal startup, monitoring of the level of involvement by the Lead VC is critical. Thus, a constraint on monitoring of partners may be detrimental to the collective interests of the partners, that is, the syndicate as a whole. In sum, the second contribution of this study is to show that in addition to discouraging "bad" behavior by members, the social control facilitated by network cohesion may also suppress "good" behavior that would be beneficial for the collective interests of network members.

As mentioned in chapter 3, startups funded by syndicates consisting of cohesive members may inherently have a lower likelihood of being successful because the redundancy in the information their members receive through their networks may promote "satisficing" in their information search and exchange behavior. In addition, by isolating the entire network from the environment, high levels of cohesion may also limit the inflow of novel information into the network as a whole, due to which the quality of the startups about which information is available to network members may not be the best to begin with. Together, this may lead actors to fund startups of sub-optimal quality. On the other hand, high levels of cohesion could also lead to a reduction in the likelihood of the focal syndicate's success due to the reduction in monitoring of fellow partners. Disentangling these explanations by isolating the theoretical mechanisms that lead to each of these effects may be a fruitful area for future research.

It is worth noting here that the main effect of cohesion was negative and significant when it was operationalized as Simmelian ties as well as ego network density, but was insignificant when Burt's measure of dyadic constraint was used. Although not conclusive, this finding is consistent with Simmel's (1950) contention that constraint stems from being embedded in multiple cliques because actors need to satisfy the norms of each clique in which they are embedded. As Krackhardt (1999) argues, Burt's measure of constraint, which focuses only on the presence of common third parties, fails to capture the constraints faced by actors embedded in multiple cliques.

Together the findings of the study with respect to social networks suggest that prior research on social networks may have been too sanguine about the beneficial effects of prior ties and network cohesion. This may have led to the conclusions that familiar actors always make better partners than unfamiliar ones and that being embedded in dense, cohesive networks is always beneficial. This study suggests that recognizing the benefits of prior ties while ignoring their costs, or side effects, may lead to unexpected outcomes. The importance of better understanding these negative effects is further underscored by the fact that many outcomes associated with social networks have been shown to ultimately affect firms' survival rates and financial performance (D' Aveni, 1990; Baum and Oliver, 1991; Uzzi, 1996; Pfeffer, 1997; Stuart, Hoang and Hybels, 1999; Higgins and Gulati, 2003). Thus, this study is an important step in furthering social network research.

In addition, the findings of this study also suggest that while the availability of prior partners provides short term benefits by reducing uncertainty and search costs, and enabling actors to make quick decisions relating to partner selection, it may, at the same time, introduce considerable biases into those decisions in terms of the selection of partners for co-investment and the post-investment monitoring of those partners. Thus, the need to recognize both the long and short-term effects of using social networks for decision making is also highlighted by this study.

The theoretical arguments developed in this study are highly relevant to contexts other than VC syndication characterized by high levels of reciprocity, such as investment banking syndicates. In such contexts, the existence of prior ties between service or resource providers is generally viewed as a considerable advantage because by giving them access to their partners' networks, it multiplies their overall access to resources, making prior partners highly desirable partners. However, this study takes a first step in suggesting that such reliance on prior ties may impose significant, though previously unrecognized costs by leading actors to select sub-optimal partners, monitor familiar partners inadequately and utilize inadequately adapted, ossified routines, which may have detrimental effects on performance.

These findings also contribute to research on venture capital and new ventures by expanding social structural perspectives on venture capitalist decision making. One of the reasons VC firms participate in syndicates is to reduce the overall amount of risk they face. This study suggests on the contrary that the actual reduction in the risk VC firms face when they invest in syndicates may be considerably less than they believe it is. Further, an important aspect of this negative performance effect of repeated syndication with the same other firms is that in addition to the syndicates themselves, that is, the VC investors, this effect extends to the funded startups as well. In general, startups are both new and small, and thus, suffer from the liabilities of newness and smallness. The effects of these liabilities, combined with funding by sub-optimal VC firms using insufficiently adapted, ossified routines, may prove fatal for the focal startup. Thus, by relying disproportionately on their prior partners, VC firms may be doing themselves as well as the startups they fund, a considerable disservice.

Partner Prestige

In addition to the above contributions to the strategy and organization theory literatures, this study also contributes to the literatures on prestige and endorsements. Not unlike the social networks literature, the literatures on prestige and endorsements have also largely focused on their beneficial consequences and those of association with prestigious / high status actors (Podolny, 1994; Podolny, Stuart and Hannan, 1996). Among the benefits of high levels of prestige / status are legitimacy, an assumption of competence, and access to high quality resources (e.g., Higgins and Gulati, 2003; Gulati and Higgins, 2003). In addition, association with high status/prestigious partners is thought to enhance the legitimacy and prestige/status of actors with lower levels of prestige/status because of the abovementioned presumption of competence regarding prestigious actors due to which they are considered unlikely to enter into relationships with poor quality actors. As a result of these beneficial effects, prestigious actors are highly sought after as partners.

This study suggests however, that relationships with high status or prestigious actors may carry previously unrecognized costs which can be considerable. In addition to making them difficult to monitor because they are accustomed to deference, partner status/prestige also heightens concerns about protecting existing relationships with them, which in turn can make actors more reluctant to monitor them. In addition, actors may under-estimate the need to monitor their prestigious partners because of the presumption of competence, due to which they are given the benefit of the doubt to a greater extent. As mentioned above, the resulting inadequate levels of monitoring of partners can be detrimental when the partnership's success depends upon the quantity and quality of effort expended by the one partner to whom the management of the partnership is delegated, this effort is non-contractible and the partner to whom the management is delegated has interests or priorities that conflict with the collective interests of the group. This increase in costs may offset some of the beneficial effects of partner prestige, and consequently, the net benefits from partner prestige increase at a decreasing rate. Thus, contrary to prior beliefs, partner prestige may be a double-edged sword, that is, both its benefits and costs may increase as prestige increases.

An intriguing finding of the study is that while success has a positive and significant effect on the likelihood of the focal startup's success in the model including only the control variables, this effect becomes less significant once prestige is included as an explanatory variable. Although this evidence is not conclusive, it is certainly suggestive of actors' network driven prestige mediating the relationship between their prior and future success. Said differently, contrary to expectations that actors' prior success would predict their success in the future directly, prior success seems to directly affect the actors' prestige, which in turn affects their future success. Further inquiry into the mediation of the effect of prior success by prestige promises to be a fruitful exercise.

PRIOR EXPERIENCE

Experience in a domain is thought to have performance enhancing effects since it increases the extent of knowledge about that domain. While greater experience increases knowledge, the benefits of experience increase at a declining rate because an increasing portion of the knowledge gained from the additional experience is redundant with pre-existing knowledge. At the same time, psychology-based research on expertise has also argued that very high levels of experience can actually be detrimental to performance since it creates a rigidity in he individuals' thinking ability. As I argued in chapter 3, this would predict that experience would have an inverted U-shaped relationship with performance. However, I find that syndicate members' prior experience, total as well as in the industry of the focal startup, has a negative effect on success likelihood, that is, even at low levels, the costs of prior experience may offset its benefits completely. The reason for this stronger than expected effect may be startups are so different from each other in terms of their organizational and strategic requirements, that any learning from even modest levels of prior investment experience may reduce the flexibility in the VCs' thinking, and actually interfere with their ability to advice the focal startup appropriately.

HOMOGENEITY

The next key finding of the study was the strong negative interaction between homogeneity between syndicate members in terms of their prior experience and prior ties. This homogeneity has a strong enough intensification effect to completely negate the initial positive main effects of prior ties. Consequently, in the presence of even low levels of homogeneity of prior experience, as shown in Figure 3, the effect of prior ties on the likelihood of the partnership's success is always negative. This finding is consistent with my argument that homogeneity between syndicate members will intensify the negative effects of prior ties by facilitating communication, trust building and cohesion between them, which in turn may speed up premature consensus formation and groupthink.

While the study found that similarity across syndicate members in terms of the diversity of their industry experience interacted negatively with prior ties, there was no evidence of a similar interaction effect of their total prior experience. This may suggest that VCs perceive themselves as similar or different from other VCs in terms of the diversity of their prior experience rather than simply their total experience. This may be an interesting area further inquiry and future research could explore what determines the characteristics along which firms categorize themselves.

Although the interaction of homogeneity with prior ties was negative and significant, the main effect hypothesis relating to syndicate member homogeneity was not supported. This lack of support for the main effect hypothesis may be interpreted as evidence that, at least in this context, homogeneity by itself does not necessarily affect a group's performance. Rather, in order for its effects on the group's performance to become apparent, homogeneity requires an enabling mechanism or a trigger, which is provided by prior ties. Future research should explore whether similar effects are apparent in other contexts.

SYNDICATE SIZE

The present study did not find support for the hypothesized inverted U-shaped effect of the number of partners. One reason for this lack of finding could be the extremely limited variance on this variable, given that 96 percent of all syndicates that funded startups during the study period consisted of three or fewer members. Future research on multi-party alliances would profit from looking at the effects of group size on the performance of the alliances. Research exploring the effects of group size should be implemented in settings with a broader range in group size in order to be able to test the hypothesis.

STARTUP STAGE

The study also did not find support for the hypothesized effect of startup stage, which predicted that the liabilities of newness and smallness decline as startups move through successive stages of development. In addition, the hypothesized interaction of prior ties and startup stage, which argued that startups at later stages, which are more robust, would be better able to overcome any negative effects of prior ties, was also not supported. This lack of findings could be due to the previously mentioned problems with the available data relating to startup stage. Future research may profit from collecting more accurate and refined stage-related information regarding startups funded by VC syndicates.

OTHER IMPLICATIONS

The number of rounds the focal startup received during any given year is negatively related to the likelihood that the startup will exit. This finding seems logical since from the perspective of the startup, the objective of an exit is that same as that of a VC funding round, namely, an infusion of funds into the company for further growth and expansion. Therefore, a startup is unlikely to go public very soon after VCs have disbursed funds.[14]

[14] One exception to this may be a situation when VC funding is provided specifically as a sort of "bridge" financing, to meet the expenditure of an IPO.

The number of rounds of funding a startup receives is related to its likelihood of exit in an inverted U-shaped manner. This finding is in line with prior research which has argued that if VCs were to update the information they have regarding funded startups prior to making follow-on investments, the likelihood of those startups being successful would increase with the number of rounds of funding they receive (Guler, 2002). As discussed earlier, one of the reasons VCs disburse funds in rounds is that further disbursements can be made contingent on the achievement of certain pre-agreed milestones. Together with the regular monitoring the VCs conduct after funding a startup, the process of assessing whether or not the agreed milestones have been achieved provides them a considerable amount of additional information about the startup's prospects. This should result in the VCs terminating their investment in a startup when they receive information to suggest that the likelihood of its success has declined. The inverted U-shaped relationship between the number of rounds and the likelihood of exit suggests conversely that VCs don't necessarily update their beliefs about the startups they have funded. Instead, they continue to make further investments in the startups.

CONCLUSION

Taken together, the theoretical arguments developed in this study and the empirical results suggest that the very factors that lead firms to seek out and select certain types of firms as partners, may also reduce the chances that the partnership will achieve its goals. Prior ties, partners' status/prestige, network cohesion and partners' experience are generally thought to be beneficial to firms and thus are highly valued characteristics in potential partners. However, this study suggests that each of these characteristics comes at a considerable cost and that firms may unwittingly pay a price when they repeatedly partner with other firms that possess these characteristics.

FIGURE 1: CONCEPTUAL MODEL: EFFECTS OF REPEATED SYNDICATION TIES BETWEEN VC FIRMS

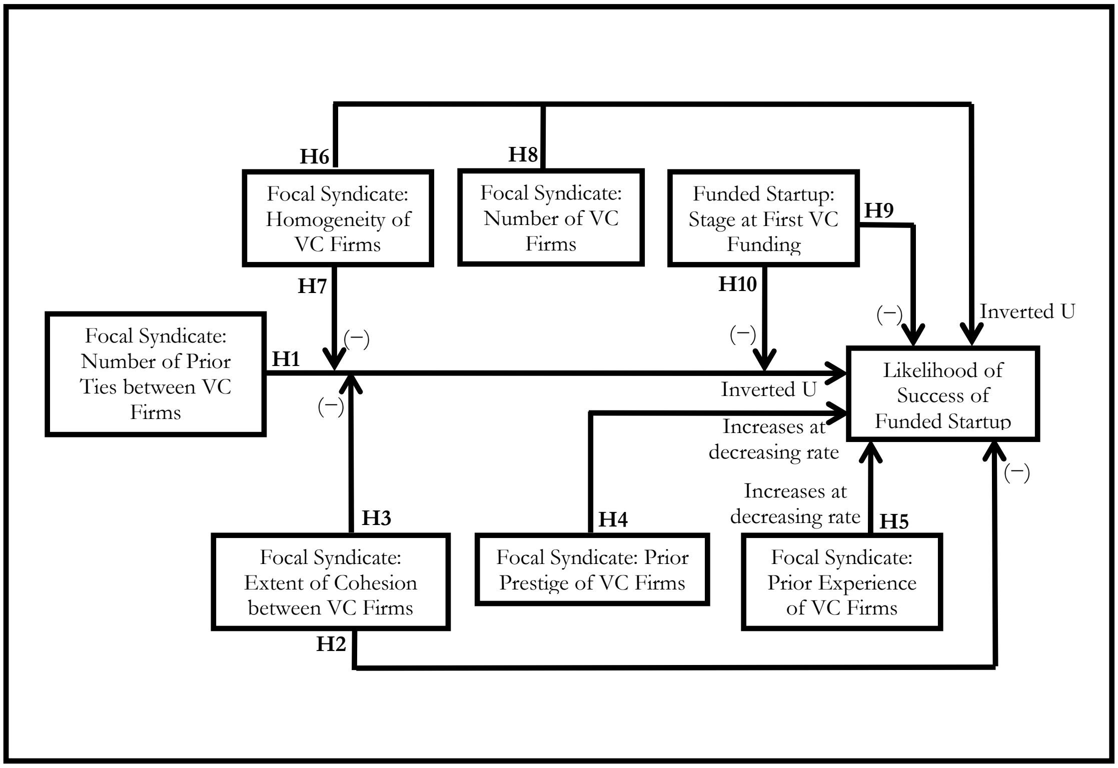
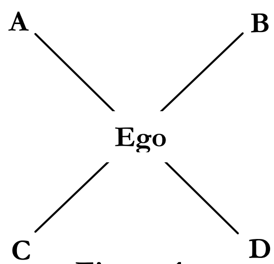
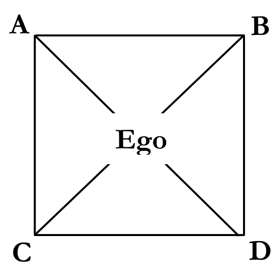
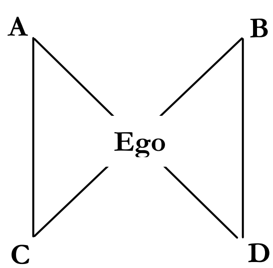
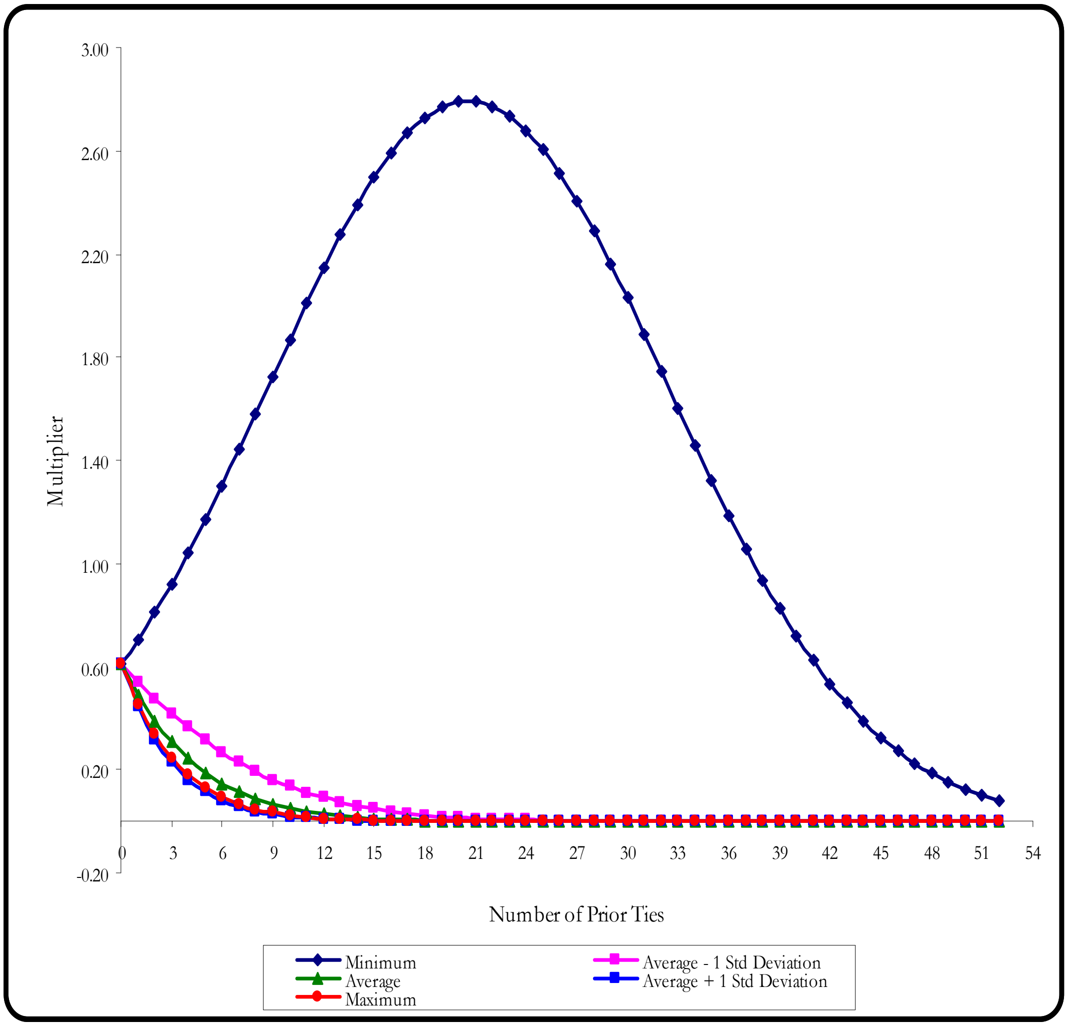


FIGURE 2: CONSTRAINTS ON EGO ACCORDING TO STRUCTURAL HOLES VS. SIMMELIAN TIE THEORIES[15]

	Dyadic constraint according to Burt's Structural Holes Theory	**Constraint according to Simmelian Tie Theory**
 **Figure 1a**	Least constraint	Least constraint
 **Figure 1b**	Least constraint	Somewhat constrained, but only by one clique
 **Figure 1c**	Somewhat constrained, but also empowered as bridge between two cliques	Most constrained, must satisfy two cliques

[15] Adapted from Krackhardt, 1999.

FIGURE 3: THE EFFECT OF PRIOR TIES AT DIFFERENT LEVELS OF HOMOGENEITY[16]



[16] The above figure is based on the entire range of the number of ties observed in the sample.

TABLE 1: SUMMARY OF HYPOTHESES AND OPERATIONALIZATION OF MEASURES

HYPOTHESIS	CONSTRUCT	OPERATIONALIZATION (WITH ALTERNATIVE MEASURES)	PREDICTED EFFECT
H1	Prior ties	Average number of ties between syndicate members	Inverted U-shaped[17]
H2	Cohesion	1) Dyadic constraint	Negative
		2) Dyadic Simmelian ties	
		3) Ego network density	
H3	Prior Ties X Cohesion	1) Prior ties X Dyadic constraint	Negative
		2) Prior ties X Dyadic Simmelian ties	
		3) Prior ties X Ego network density	
H4	Prestige	Prestige (Bonacich eigenvector centrality)	Increases at decreasing rate
H5	Experience	1) Total experience	Increases at decreasing rate
		2) Focal industry experience	
		3) Focal stage experience	
H6	Homogeneity	1) Coefficient of variation (inverted): age	Inverted U-shaped
		2) Coefficient of variation (inverted): prestige	
		3) Coefficient of variation (inverted): total experience	
		4) Coefficient of variation (inverted): entropy of industry experience	
		5) Coefficient of variation (inverted): entropy of stage experience	
H7	Prior ties X Homogeneity	1) Prior Ties X Coefficient of variation (inverted): age	Negative
		2) Prior Ties X Coefficient of variation (inverted): prestige	
		3) Prior Ties X Coefficient of variation (inverted): total experience	
		4) Prior Ties X Coefficient of variation (inverted): entropy of industry experience	
		5) Prior Ties X Coefficient of variation (inverted): entropy of stage experience	
H8	Syndicate size	Number of VCs in syndicate	Inverted U-shaped
H9	Stage	Stage dummy = 1 if startup stage at first funding was Seed/Early, 0 otherwise	Negative (i.e., startups at seed/early stage have lower success likelihood)
H10	Prior ties X Stage	Prior ties X Stage dummy	Negative

[17] Base term positive and square term negative.

TABLE 2: SUMMARY STATISTICS[a]

	VARIABLE	OBS.	MEAN	STANDARD DEVIATION	MINIMUM	MAXIMUM
1.	Exit	5143	0.06	0.23	0.00	1.00
2.	Prior ties	5143	2.09	4.80	0.00	52.00
3.	Prior ties square	5143	23.11	127.01	0.00	2471.98
4.	Dyadic Simmelian ties	5143	15.01	25.54	0.00	119.00
5.	Ego network density	5143	27.16	17.01	0.00	100.00
6.	Prestige of round 1 VCs[b]	5143	6.03	7.33	0.00	44.67
7.	Prior experience: Total[b]	5120	50.47	43.11	1.00	317.00
8.	Prior experience: Focal industry	5143	16.09	16.54	0.00	119.50
9.	Homogeneity: Prior total experience	5143	1.09	0.42	0.00	1.79
10.	Homogeneity: Prior total experience square	5143	0.18	0.18	0.00	1.21
11.	Homogeneity: Prior industry experience	5143	1.44	0.40	0.00	1.73
12.	Homogeneity: Prior industry experience square	5143	0.16	0.35	0.00	2.08
13.	Number of VCs in syndicate	5143	2.39	0.69	2.00	7.00
14.	Number of VCs in syndicate square	5143	0.47	1.28	0.16	21.20
15.	Startup stage at round 1: Seed/early/startup	5143	0.81	0.40	0.00	1.00
16.	Number of VCs in round j[c]	5064	3.28	2.51	1.00	18.00
17.	Prestige of round j VCs[b]	5143	5.33	5.95	0.00	44.67
18.	Prior ties of round j VCs	5143	1.75	3.50	0.00	52.00
19.	Amount of funding received: Cumulative[b]	5143	28.33	37.01	0.05	442.86
20.	Amount of funding received: Round 1[b]	5072	7.87	9.96	0.05	149.37
21.	Industry 1000	5143	0.33	0.47	0.00	1.00
22.	Industry 2100	5143	0.08	0.27	0.00	1.00
23.	Industry 2700	5143	0.34	0.47	0.00	1.00
24.	Industry 2800	5143	0.27	0.45	0.00	1.00
25.	Industry 3000	5143	0.09	0.29	0.00	1.00
26.	Industry 4000	5143	0.05	0.21	0.00	1.00
27.	Industry 5000	5143	0.11	0.31	0.00	1.00
28.	Industry 7000	5143	0.04	0.20	0.00	1.00
29.	Industry 8000	5143	0.01	0.12	0.00	1.00

	VARIABLE	OBS.	MEAN	STANDARD DEVIATION	MINIMUM	MAXIMUM
30.	Number of rounds received during window year	5143	0.76	0.72	0.00	5.00
31.	Number of rounds: Cumulative	5143	2.57	1.65	1.00	11.00
32.	Number of rounds: Cumulative square	5143	2.71	5.44	0.18	71.03
33.	Round 1 year: 1997	5143	0.15	0.35	0.00	1.00
34.	Round 1 year: 1998	5143	0.18	0.38	0.00	1.00
35.	Round 1 year: 1999	5143	0.26	0.44	0.00	1.00
36.	Round 1 year: 2000	5143	0.31	0.46	0.00	1.00
37.	Startup age at round 1[b]	5143	1.13	1.42	0.00	6.79
38.	Days Since Round 1[b]	5143	788.52	554.22	0.00	2856.00
39.	Prior success rate	5120	0.22	0.13	0.00	0.68
40.	Number of IPOs in window year	5143	241.99	179.90	63.00	602.00

[a] Summary statistics are based on 1,284 startups.
[b] Variable was logged for the purpose of analysis; summary statistics are for the untransformed variable.
[c] Round j refers to the latest funding round during the window year. If a startup received more than one funding round in a year, the relevant variables were averaged across the rounds to arrive at the value for the window year.

TABLE 3: BIVARIATE CORRELATIONS[a]

	VARIABLE	1	2	3	4	5	6	7
1.	Exit	1.00						
2.	Prior ties	0.00	1.00					
3.	Prior ties square	-0.01	0.83	1.00				
4.	Dyadic Simmelian ties	0.00	0.64	0.34	1.00			
5.	Ego network density	0.00	-0.20	-0.08	-0.28	1.00		
6.	Prestige of round 1 VCs[b]	0.04	0.29	0.12	0.45	-0.22	1.00	
7.	Prior experience: Total[b]	0.01	0.36	0.15	0.55	-0.46	0.86	1.00
8.	Prior experience: Focal industry	-0.01	0.35	0.17	0.53	-0.31	0.53	0.68
9.	Homogeneity: Prior total experience	0.00	0.15	0.09	0.13	-0.16	-0.20	-0.12
10.	Homogeneity: Prior total experience square	0.01	-0.09	-0.01	-0.16	-0.01	-0.09	-0.05
11.	Homogeneity: Prior industry experience	0.00	0.19	0.08	0.23	-0.08	0.26	0.28
12.	Homogeneity: Prior industry experience square	0.00	-0.14	-0.04	-0.19	0.02	-0.29	-0.27
13.	Number of VCs in syndicate	0.00	-0.03	-0.05	0.13	0.01	0.14	0.11
14.	Number of VCs in syndicate square	0.00	-0.04	-0.03	0.05	0.01	0.07	0.05
15.	Startup stage at round 1: Seed/early/startup	0.00	0.09	0.06	0.12	-0.11	0.13	0.15
16.	Number of VCs in round j[c]	0.03	0.09	0.02	0.17	-0.06	0.18	0.15
17.	Prestige of round j VCs[b]	0.02	0.23	0.09	0.37	-0.16	0.74	0.64
18.	Prior ties of round j VCs	-0.01	0.52	0.35	0.42	-0.15	0.24	0.29
19.	Amount of funding received: Cumulative[b]	0.07	0.13	0.05	0.26	-0.12	0.29	0.29
20.	Amount of funding received: Round 1[b]	0.02	0.03	0.01	0.16	-0.11	0.19	0.26
21.	Industry 1000	0.01	0.14	0.09	0.16	-0.07	0.11	0.15
22.	Industry 2100	-0.01	-0.03	0.02	-0.03	0.01	0.01	0.02
23.	Industry 2700	0.00	-0.06	-0.04	-0.07	0.02	-0.03	-0.03
24.	Industry 2800	0.01	-0.08	-0.04	-0.11	0.05	-0.10	-0.12
25.	Industry 3000	-0.01	0.03	0.05	0.02	-0.05	0.06	0.08
26.	Industry 4000	0.02	-0.04	-0.03	0.01	0.02	0.01	0.00
27.	Industry 5000	-0.04	0.01	-0.02	0.03	0.02	0.06	0.01
28.	Industry 7000	0.00	-0.04	-0.03	-0.05	-0.03	-0.05	-0.05
29.	Industry 8000	-0.01	0.02	-0.01	0.03	0.00	-0.06	-0.02
30.	Number of rounds received during window year	-0.14	0.05	0.02	0.06	-0.02	0.04	0.03
31.	Number of rounds: Cumulative	0.05	0.08	0.03	0.09	-0.03	0.08	0.04
32.	Number of rounds: Cumulative square	0.01	0.03	0.01	0.04	0.01	0.02	-0.02
33.	Round 1 year: 1997	0.06	0.00	0.01	-0.02	0.06	0.00	-0.11
34.	Round 1 year: 1998	0.03	0.03	0.00	0.03	-0.01	0.06	0.01
35.	Round 1 year: 1999	-0.01	0.03	-0.02	0.03	0.02	0.00	0.01
36.	Round 1 year: 2000	-0.03	-0.07	-0.02	-0.06	-0.06	-0.05	0.03
37.	Startup age at round 1[b]	0.02	-0.01	-0.02	0.03	-0.03	0.02	0.01
38.	Days Since Round 1[b]	0.08	0.04	0.02	0.05	-0.01	0.04	0.00
39.	Prior success rate	0.02	0.31	0.17	0.42	-0.22	0.52	0.58
40.	Number of IPOs in window year	-0.02	0.00	-0.01	-0.02	0.03	0.00	-0.05

	VARIABLE	8	9	10	11	12	13	14
8.	Prior experience: Focal industry	1.00						
9.	Homogeneity: Prior total experience	0.00	1.00					
10.	Homogeneity: Prior total experience square	-0.04	0.01	1.00				
11.	Homogeneity: Prior industry experience	0.23	0.07	-0.30	1.00			
12.	Homogeneity: Prior industry experience square	-0.18	0.10	0.33	-0.89	1.00		
13.	Number of VCs in syndicate	0.00	-0.23	-0.07	-0.01	-0.10	1.00	
14.	Number of VCs in syndicate square	-0.01	-0.14	-0.03	-0.01	-0.05	0.77	1.00
15.	Startup stage at round 1: Seed/early/startup	0.11	0.01	0.01	-0.02	0.01	0.03	0.01
16.	Number of VCs in round j[c]	0.09	-0.02	-0.04	0.08	-0.08	0.20	0.15
17.	Prestige of round j VCs[b]	0.43	-0.15	-0.07	0.22	-0.24	0.11	0.07
18.	Prior ties of round j VCs	0.26	0.06	-0.09	0.14	-0.12	0.02	-0.01
19.	Amount of funding received: Cumulative[b]	0.26	-0.03	-0.02	0.13	-0.11	0.14	0.07
20.	Amount of funding received: Round 1[b]	0.25	-0.05	-0.02	0.09	-0.06	0.18	0.13
21.	Industry 1000	0.35	0.01	-0.01	0.04	-0.02	0.02	-0.03
22.	Industry 2100	0.04	-0.04	0.02	0.06	-0.04	0.00	0.00
23.	Industry 2700	0.23	-0.03	-0.01	0.05	-0.05	-0.01	0.00
24.	Industry 2800	-0.11	0.04	0.07	-0.02	0.06	-0.03	0.02
25.	Industry 3000	-0.02	-0.06	0.03	0.03	-0.03	0.04	0.02
26.	Industry 4000	-0.08	-0.01	-0.01	-0.02	-0.01	0.02	-0.02
27.	Industry 5000	-0.05	0.02	-0.05	-0.07	0.00	0.04	0.01
28.	Industry 7000	-0.08	0.02	0.00	-0.01	0.01	-0.04	-0.03
29.	Industry 8000	-0.07	-0.02	0.00	-0.04	0.03	0.01	-0.01
30.	Number of rounds received during window year	0.02	0.02	-0.01	0.03	-0.03	0.01	-0.02
31.	Number of rounds: Cumulative	0.03	0.02	-0.03	0.04	-0.05	0.03	-0.01
32.	Number of rounds: Cumulative square	-0.02	0.02	-0.02	0.03	-0.03	0.03	0.00
33.	Round 1 year: 1997	-0.12	-0.02	-0.04	-0.04	-0.01	0.01	0.00
34.	Round 1 year: 1998	-0.04	0.06	-0.03	0.03	-0.02	-0.08	-0.06
35.	Round 1 year: 1999	0.05	0.02	-0.01	0.06	-0.04	-0.01	0.00
36.	Round 1 year: 2000	0.03	-0.03	0.08	-0.08	0.09	0.09	0.06
37.	Startup age at round 1[b]	0.03	-0.02	-0.05	-0.02	0.03	0.05	0.03
38.	Days Since Round 1[b]	0.00	-0.01	-0.01	-0.01	0.00	0.01	-0.01
39.	Prior success rate	0.44	0.05	-0.03	0.19	-0.14	0.01	0.00
40.	Number of IPOs in window year	-0.07	0.01	-0.02	0.00	-0.01	-0.02	-0.02

	VARIABLE	15	16	17	18	19	20	21	22
15.	Startup stage at round 1: Seed/early/startup	1.00							
16.	Number of VCs in round j[c]	0.07	1.00						
17.	Prestige of round j VCs[b]	0.12	0.21	1.00					
18.	Prior ties of round j VCs	0.09	0.02	0.28	1.00				
19.	Amount of funding received: Cumulative[b]	0.01	0.45	0.30	0.08	1.00			
20.	Amount of funding received: Round 1[b]	-0.12	-0.01	0.15	0.00	0.47	1.00		
21.	Industry 1000	0.07	0.08	0.09	0.07	0.17	0.13	1.00	
22.	Industry 2100	-0.05	0.00	0.00	-0.02	0.03	0.03	0.00	1.00
23.	Industry 2700	-0.02	-0.05	-0.01	-0.05	-0.01	0.04	-0.09	0.01
24.	Industry 2800	-0.03	-0.03	-0.08	-0.08	0.01	0.02	-0.22	-0.06
25.	Industry 3000	0.07	0.05	0.06	0.03	0.07	0.04	-0.01	0.00
26.	Industry 4000	0.00	0.04	-0.03	-0.02	-0.04	-0.17	-0.15	-0.06
27.	Industry 5000	0.06	0.04	0.03	0.04	-0.02	-0.10	-0.24	-0.08
28.	Industry 7000	-0.11	-0.05	-0.05	-0.04	-0.01	0.01	-0.12	-0.05
29.	Industry 8000	-0.01	-0.01	-0.05	0.01	-0.08	-0.10	-0.04	0.00
30.	Number of rounds received during window year	0.04	-0.03	0.05	0.04	0.02	-0.05	0.02	0.02
31.	Number of rounds: Cumulative	0.04	0.16	0.13	0.07	0.53	-0.15	0.02	0.02
32.	Number of rounds: Cumulative square	0.00	-0.06	0.03	0.06	0.12	-0.12	-0.01	0.00
33.	Round 1 year: 1997	-0.07	0.00	-0.03	-0.01	-0.07	-0.21	-0.07	-0.01
34.	Round 1 year: 1998	-0.05	0.11	0.04	0.02	0.05	-0.14	0.01	-0.03
35.	Round 1 year: 1999	0.00	0.10	0.05	0.02	0.12	0.02	0.03	-0.06
36.	Round 1 year: 2000	0.05	-0.13	-0.04	-0.04	-0.05	0.22	0.01	0.08
37.	Startup age at round 1[b]	-0.06	0.08	0.02	0.01	0.14	0.12	0.03	0.01
38.	Days Since Round 1[b]	0.01	0.18	0.09	0.03	0.45	-0.06	-0.01	0.00
39.	Prior success rate	0.05	0.09	0.37	0.23	0.23	0.20	0.05	-0.01
40.	Number of IPOs in window year	-0.06	-0.05	-0.04	-0.02	-0.30	-0.09	-0.01	-0.03

	VARIABLE	23	24	25	26	27	28	29	30	31
23.	Industry 2700	1.00								
24.	Industry 2800	-0.10	1.00							
25.	Industry 3000	-0.20	-0.19	1.00						
26.	Industry 4000	-0.15	-0.13	-0.07	1.00					
27.	Industry 5000	-0.20	-0.17	-0.09	0.09	1.00				
28.	Industry 7000	-0.12	0.14	-0.05	-0.05	-0.07	1.00			
29.	Industry 8000	-0.06	-0.07	0.05	-0.02	-0.01	-0.03	1.00		
30.	Number of rounds received during window year	0.01	0.01	-0.01	0.02	0.00	0.00	-0.01	1.00	
31.	Number of rounds: Cumulative	0.04	-0.02	-0.01	0.05	0.05	-0.02	0.00	0.15	1.00
32.	Number of rounds: Cumulative square	0.01	-0.03	-0.03	0.07	0.03	-0.02	-0.01	0.07	0.64
33.	Round 1 year: 1997	0.06	-0.15	0.01	0.06	0.14	0.00	0.03	0.03	0.16
34.	Round 1 year: 1998	-0.03	-0.08	-0.03	0.08	0.08	0.02	0.06	0.04	0.11
35.	Round 1 year: 1999	-0.01	0.27	-0.14	-0.08	-0.07	0.08	-0.04	0.00	0.01
36.	Round 1 year: 2000	-0.01	0.01	0.10	-0.05	-0.10	-0.06	-0.03	-0.05	-0.16
37.	Startup age at round 1[b]	0.09	-0.01	0.00	0.02	-0.05	-0.05	-0.01	0.04	0.08
38.	Days Since Round 1[b]	0.02	-0.05	0.02	0.02	0.07	-0.02	0.02	-0.26	0.62
39.	Prior success rate	-0.05	-0.02	0.03	0.00	0.01	-0.01	0.01	0.01	0.01
40.	Number of IPOs in window year	0.00	0.02	-0.06	0.01	0.03	0.05	0.01	0.33	-0.33

	VARIABLE	32	33	34	35	36	37	38	39	40
32.	Number of rounds: Cumulative square	1.00								
33.	Round 1 year: 1997	0.16	1.00							
34.	Round 1 year: 1998	0.07	-0.19	1.00						
35.	Round 1 year: 1999	-0.05	-0.25	-0.28	1.00					
36.	Round 1 year: 2000	-0.08	-0.28	-0.32	-0.41	1.00				
37.	Startup age at round 1[b]	0.02	-0.02	0.00	0.01	0.01	1.00			
38.	Days Since Round 1[b]	0.18	0.08	0.06	-0.05	-0.05	0.05	1.00		
39.	Prior success rate	-0.02	-0.04	0.04	0.02	-0.03	0.00	0.01	1.00	
40.	Number of IPOs in window year	-0.10	0.29	0.13	0.09	-0.24	-0.03	-0.53	-0.02	1.00

[a] Summary statistics are based on 1,284 startups.

[b] Variable was logged for the purpose of analysis; bivariate correlations are for the transformed variable.

[c] Round j refers to the latest funding round during the window year. If a startup received more than one funding round in a year, the relevant variables were averaged across the rounds to arrive at the value for the window year

TABLE 4: SUMMARY OF FINDINGS

HYPOTHESIS	CONSTRUCT	OPERATIONALIZATION (WITH ALTERNATIVE MEASURES)	PREDICTED EFFECT	SUPPORTED?
H1	Prior ties	Average number of ties between syndicate members	Inverted U-shaped[18]	Yes
H2	Cohesion	1) Dyadic constraint	Negative	No
		2) Dyadic Simmelian ties		Yes
		3) Ego network density		Yes
H3	Prior Ties X Cohesion	1) Prior ties X Dyadic constraint	Negative	No
		2) Prior ties X Dyadic Simmelian ties		No
		3) Prior ties X Ego network density		No
H4	Prestige	Prestige (Bonacich eigenvector centrality)	Increases at decreasing rate	Yes
H5	Experience	1) Total experience	Increases at decreasing rate	Yes
		2) Focal industry experience		Yes
		3) Focal stage experience		No
H6	Homogeneity	1) Coefficient of variation (inverted): age	Inverted U-shaped	No
		2) Coefficient of variation (inverted): prestige		No
		3) Coefficient of variation (inverted): total experience		No
		4) Coefficient of variation (inverted): entropy of industry experience		No
		5) Coefficient of variation (inverted): entropy of stage experience		No
H7	Prior ties X Homogeneity	1) Prior Ties X Coefficient of variation (inverted): age	Negative	No
		2) Prior Ties X Coefficient of variation (inverted): prestige		No
		3) Prior Ties X Coefficient of variation (inverted): total experience		No
		4) Prior Ties X Coefficient of variation (inverted): entropy of industry experience		Yes
		5) Prior Ties X Coefficient of variation (inverted): entropy of stage experience		No
H8	Syndicate size	Number of VCs in syndicate	Inverted U-shaped	No
H9	Stage	Stage dummy = 1 if startup stage at first funding was Seed/Early, 0 otherwise	Negative (i.e., startups at seed/early stage have lower success likelihood)	No
H10	Prior ties X Stage	Prior ties X Stage dummy	Negative	No

[18] Base term positive and square term negative.

TABLE 5: COX PROPORTIONAL HAZARD RATE MODELS: ESTIMATED LIKELIHOOD OF STARTUP EXIT – PRIMARY MODELS[19, 20]

VARIABLE	MODEL 1	MODEL 2	MODEL 3	MODEL 4	MODEL 5	MODEL 6	MODEL 7	MODEL 8	MODEL 9
Prior ties		0.090**	0.088**	0.122***	0.090**	0.118***	0.088**	0.122***	0.118***
		(0.037)	(0.038)	(0.040)	(0.037)	(0.042)	(0.038)	(0.040)	(0.042)
Prior ties square		-0.003**	-0.004**	-0.003**	-0.003**	-0.003*	-0.004**	-0.003**	-0.004*
		(0.001)	(0.002)	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)	(0.002)
Dyadic Simmelian ties		-0.007*	-0.008*	-0.007*	-0.007*	-0.008*	-0.008*	-0.007*	-0.008*
		(0.004)	(0.005)	(0.004)	(0.004)	(0.005)	(0.005)	(0.004)	(0.005)
Log of prestige of round 1 VCs		0.201***	0.200***	0.200***	0.200***	0.200***	0.200***	0.200***	0.199***
		(0.072)	(0.072)	(0.072)	(0.072)	(0.072)	(0.072)	(0.072)	(0.072)
Log of prior experience: Total		-0.374***	-0.372***	-0.371***	-0.370***	-0.366***	-0.368***	-0.367***	-0.363***
		(0.131)	(0.131)	(0.131)	(0.132)	(0.131)	(0.132)	(0.132)	(0.132)
Homogeneity: Prior industry experience		0.204	0.204	-0.06	0.202	-0.066	0.202	-0.069	-0.077
		(0.364)	(0.363)	(0.378)	(0.364)	(0.377)	(0.364)	(0.381)	(0.379)
Homogeneity: Prior industry experience square		0.356	0.353	0.636	0.358	0.635	0.356	0.640	0.640
		(0.410)	(0.410)	(0.433)	(0.410)	(0.432)	(0.409)	(0.433)	(0.432)
Number of VCs in syndicate		0.024	0.027	0.02	0.021	0.026	0.024	0.016	0.022
		(0.139)	(0.140)	(0.139)	(0.139)	(0.140)	(0.140)	(0.139)	(0.140)
Number of VCs in syndicate square		0	-0.001	0.003	0.001	0.002	0.001	0.004	0.004
		(0.067)	(0.067)	(0.066)	(0.067)	(0.066)	(0.067)	(0.066)	(0.066)

[19] Unstandardized coefficients are reported; robust standard errors in parentheses; *p<.10; **p<.05; ***p<.01; two-tailed tests.

[20] All variables (other than startup stage, which is a dummy variable) were centered prior to forming squared and interaction terms.

VARIABLE	MODEL 1	MODEL 2	MODEL 3	MODEL 4	MODEL 5	MODEL 6	MODEL 7	MODEL 8	MODEL 9
Startup stage at round 1: Seed/early/startup		0.251	0.253	0.254	0.274	0.259	0.277	0.282	0.288
		(0.169)	(0.170)	(0.169)	(0.176)	(0.170)	(0.178)	(0.179)	(0.180)
Prior ties X Dyadic Simmelian ties			0			0	0		0
			(0.001)			(0.001)	(0.001)		(0.001)
Prior ties X Homogeneity: Prior industry experience				-0.243**		-0.249**		-0.247**	-0.253**
				(0.115)		(0.113)		(0.118)	(0.115)
Prior ties X Startup stage at round 1: Seed/early/startup					0.026		0.026	0.03	0.031
					(0.052)		(0.052)	(0.055)	(0.054)
Number of VCs in round j[21]	-0.031	-0.032	-0.032	-0.034	-0.032	-0.034	-0.032	-0.034	-0.034
	(0.027)	(0.028)	(0.028)	(0.028)	(0.028)	(0.028)	(0.028)	(0.028)	(0.028)
Log of prestige of round j VCs	0.029	0	0	0.001	0	0.001	0	0.001	0
	(0.033)	(0.046)	(0.046)	(0.045)	(0.046)	(0.045)	(0.046)	(0.045)	(0.045)
Prior ties of round j VCs	-0.015	-0.018	-0.018	-0.026	-0.019	-0.025	-0.018	-0.026	-0.026
	(0.022)	(0.027)	(0.027)	(0.029)	(0.027)	(0.029)	(0.027)	(0.029)	(0.029)
Amount of funding received: Cumulative	0.201*	0.180*	0.180*	0.182*	0.179*	0.183*	0.180*	0.182*	0.183*
	(0.106)	(0.109)	(0.109)	(0.109)	(0.109)	(0.109)	(0.109)	(0.109)	(0.109)
Amount of funding received: Round 1	0.044	0.1	0.1	0.102	0.1	0.102	0.1	0.101	0.101
	(0.084)	(0.090)	(0.090)	(0.090)	(0.089)	(0.090)	(0.089)	(0.090)	(0.090)
Industry 1000	-0.08	-0.102	-0.103	-0.105	-0.105	-0.108	-0.106	-0.109	-0.113

[21] Round j refers to the latest funding round during the window year. If a startup received more than one funding round in a year, the relevant variables were averaged across the rounds to arrive at the value for the window year.

VARIABLE	MODEL 1	MODEL 2	MODEL 3	MODEL 4	MODEL 5	MODEL 6	MODEL 7	MODEL 8	MODEL 9
	(0.149)	(0.153)	(0.153)	(0.153)	(0.153)	(0.154)	(0.154)	(0.154)	(0.155)
Industry 2100	-0.162	-0.134	-0.134	-0.151	-0.128	-0.152	-0.128	-0.144	-0.145
	(0.235)	(0.239)	(0.240)	(0.239)	(0.240)	(0.239)	(0.240)	(0.240)	(0.240)
Industry 2700	-0.175	-0.181	-0.183	-0.18	-0.181	-0.185	-0.183	-0.181	-0.185
	(0.147)	(0.148)	(0.149)	(0.149)	(0.148)	(0.150)	(0.149)	(0.149)	(0.150)
Industry 2800	0.084	0.033	0.031	0.022	0.033	0.015	0.031	0.02	0.013
	(0.159)	(0.161)	(0.162)	(0.160)	(0.161)	(0.161)	(0.162)	(0.159)	(0.161)
Industry 3000	-0.396	-0.381	-0.386	-0.397	-0.38	-0.411	-0.385	-0.397	-0.411
	(0.245)	(0.253)	(0.257)	(0.253)	(0.254)	(0.259)	(0.257)	(0.253)	(0.259)
Industry 4000	0.216	0.245	0.245	0.264	0.242	0.265	0.243	0.26	0.261
	(0.315)	(0.323)	(0.323)	(0.324)	(0.323)	(0.324)	(0.323)	(0.324)	(0.324)
Industry 5000	-1.067***	-1.139***	-1.139***	-1.194***	-1.140***	-1.196***	-1.139***	-1.197***	-1.199***
	(0.292)	(0.301)	(0.301)	(0.304)	(0.301)	(0.305)	(0.301)	(0.305)	(0.306)
Industry 7000	-0.203	-0.169	-0.17	-0.286	-0.168	-0.292	-0.169	-0.278	-0.283
	(0.306)	(0.306)	(0.306)	(0.318)	(0.306)	(0.318)	(0.306)	(0.316)	(0.316)
Industry 8000	-0.411	-0.339	-0.339	-0.279	-0.298	-0.278	-0.297	-0.233	-0.23
	(0.604)	(0.614)	(0.614)	(0.613)	(0.632)	(0.613)	(0.632)	(0.631)	(0.630)
Number of rounds received during window year	-1.412***	-1.436***	-1.436***	-1.431***	-1.434***	-1.432***	-1.435***	-1.429***	-1.430***
	(0.164)	(0.165)	(0.165)	(0.165)	(0.165)	(0.165)	(0.165)	(0.165)	(0.165)
Number of rounds: Cumulative	0.176*	0.200**	0.200**	0.210**	0.199**	0.209**	0.199**	0.208**	0.207**
	(0.090)	(0.091)	(0.091)	(0.091)	(0.091)	(0.091)	(0.091)	(0.091)	(0.091)
Number of rounds: Cumulative square	-0.039**	-0.041**	-0.041**	-0.042**	-0.041**	-0.042**	-0.041**	-0.042**	-0.042**
	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)

VARIABLE	MODEL 1	MODEL 2	MODEL 3	MODEL 4	MODEL 5	MODEL 6	MODEL 7	MODEL 8	MODEL 9
Round 1 year: 1997	1.517***	1.388***	1.387***	1.381***	1.387***	1.379***	1.386***	1.379***	1.377***
	(0.400)	(0.407)	(0.407)	(0.407)	(0.407)	(0.407)	(0.407)	(0.407)	(0.407)
Round 1 year: 1998	1.103***	1.013***	1.012***	1.024***	1.015***	1.023***	1.014***	1.026***	1.025***
	(0.383)	(0.388)	(0.388)	(0.388)	(0.388)	(0.388)	(0.388)	(0.388)	(0.388)
Round 1 year: 1999	0.762**	0.721*	0.722*	0.727*	0.729*	0.730*	0.729*	0.736*	0.739*
	(0.379)	(0.381)	(0.381)	(0.380)	(0.381)	(0.380)	(0.381)	(0.381)	(0.381)
Round 1 year: 2000	0.802**	0.781**	0.782**	0.777**	0.781**	0.780**	0.782**	0.777**	0.780**
	(0.356)	(0.358)	(0.358)	(0.358)	(0.358)	(0.358)	(0.358)	(0.358)	(0.358)
Log of startup age at round 1	0.011	0.012	0.012	0.011	0.012	0.01	0.012	0.011	0.011
	(0.011)	(0.012)	(0.011)	(0.011)	(0.012)	(0.011)	(0.012)	(0.012)	(0.012)
Log of days since round 1	-0.026	-0.044	-0.043	-0.053	-0.042	-0.053	-0.042	-0.05	-0.05
	(0.107)	(0.107)	(0.107)	(0.106)	(0.107)	(0.106)	(0.107)	(0.107)	(0.107)
Prior success rate	0.329	0.495	0.494	0.519	0.497	0.518	0.496	0.524	0.523
	(0.503)	(0.553)	(0.553)	(0.553)	(0.552)	(0.552)	(0.552)	(0.553)	(0.552)
Number of IPOs in window year	0.001**	0.001**	0.001**	0.001**	0.001**	0.001**	0.001**	0.001**	0.001**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Observations	4975	4975	4975	4975	4975	4975	4975	4975	4975
Number of events	287	287	287	287	287	287	287	287	287
VIF maximum	6.31	7.45	9.19	9.95	7.46	10.95	9.21	9.98	10.96
VIF average	2.12	2.81	3.11	3.09	2.79	3.35	3.08	3.06	3.32
Wald chi^2	243.67	273.02	273	274.960	273.730	276.060	273.890	275.470	276.34
df	25	35	36	36	36	37	37	37	38
Log pseudolikelihood	-2282.142	-2271.796	-2271.773	-2269.425	-2271.684	-2269.303	-2271.656	-2269.284	-2269.151

VARIABLE	MODEL 1	MODEL 2	MODEL 3	MODEL 4	MODEL 5	MODEL 6	MODEL 7	MODEL 8	MODEL 9
Δ log likelihood χ^2		20.69**	0.05	4.74**	0.22	4.99*	0.28	5.02*	5.29
As compared to		Model 1	Model 2	Model 2	Model 2	Model 2	Model 2	Model 2	Model 2
χ^2 **df**		10	1	1	1	2	2	2	3

TABLE 6: COX PROPORTIONAL HAZARD RATE MODELS: ESTIMATED LIKELIHOOD OF STARTUP EXIT – ADDITIONAL TESTS FOR PRESTIGE[22, 23]

VARIABLE	MODEL 2	MODEL 10	MODEL 11	MODEL 12
Prior ties	0.090**	0.088**	0.088**	0.088**
	(0.037)	(0.037)	(0.037)	(0.037)
Prior ties square	-0.003**	-0.003**	-0.003**	-0.003**
	(0.001)	(0.001)	(0.001)	(0.001)
Dyadic Simmelian ties	-0.007*	-0.008*	-0.007*	-0.007*
	(0.004)	(0.004)	(0.005)	(0.005)
Log of prestige of round 1 VCs	0.201***			
	(0.072)			
Prestige of round 1 VCs			-0.001	-0.003
			(0.013)	(0.025)
Prestige of round 1 VCs square				0
				(0.001)
Log of prior experience: Total	-0.374***	-0.082	-0.078	-0.075
	(0.131)	(0.092)	(0.100)	(0.107)
Homogeneity: Prior industry experience	0.204	0.131	0.129	0.128
	(0.364)	(0.366)	(0.367)	(0.367)
Homogeneity: Prior industry experience square	0.356	0.242	0.243	0.243
	(0.410)	(0.415)	(0.415)	(0.415)
Number of VCs in syndicate	0.024	0.059	0.057	0.057
	(0.139)	(0.139)	(0.142)	(0.142)
Number of VCs in syndicate square	0	-0.008	-0.008	-0.008
	(0.067)	(0.068)	(0.068)	(0.068)
Startup stage at round 1: Seed/early/startup	0.251	0.267	0.267	0.268
	(0.169)	(0.169)	(0.169)	(0.172)
Number of VCs in round j[24]	-0.032	-0.037	-0.038	-0.038
	(0.028)	(0.028)	(0.028)	(0.028)

[22] Unstandardized coefficients are reported; robust standard errors in parentheses; *p<.10; **p<.05; ***p<.01; two-tailed tests.

[23] All variables (other than startup stage, which is a dummy variable) were centered prior to forming squared and interaction terms.

[24] Round j refers to the latest funding round during the window year. If a startup received more than one funding round in a year, the relevant variables were averaged across the rounds to arrive at the value for the window year.

VARIABLE	MODEL 2	MODEL 10	MODEL 11	MODEL 12
Log of prestige of round j VCs	0	0.053	0.054	0.054
	(0.046)	(0.044)	(0.045)	(0.046)
Prior ties of round j VCs	-0.018	-0.025	-0.025	-0.025
	(0.027)	(0.027)	(0.027)	(0.028)
Amount of funding received: Cumulative	0.180*	0.213**	0.214**	0.214**
	(0.109)	(0.107)	(0.107)	(0.108)
Amount of funding received: Round 1	0.1	0.078	0.077	0.077
	(0.090)	(0.086)	(0.086)	(0.086)
Industry 1000	-0.102	-0.096	-0.096	-0.096
	(0.153)	(0.153)	(0.153)	(0.153)
Industry 2100	-0.134	-0.126	-0.125	-0.125
	(0.239)	(0.238)	(0.238)	(0.238)
Industry 2700	-0.181	-0.182	-0.182	-0.181
	(0.148)	(0.147)	(0.147)	(0.147)
Industry 2800	0.033	0.069	0.07	0.07
	(0.161)	(0.160)	(0.160)	(0.160)
Industry 3000	-0.381	-0.416	-0.415	-0.414
	(0.253)	(0.254)	(0.255)	(0.254)
Industry 4000	0.245	0.276	0.276	0.278
	(0.323)	(0.316)	(0.317)	(0.317)
Industry 5000	-1.139***	-1.102***	-1.103***	-1.102***
	(0.301)	(0.299)	(0.299)	(0.298)
Industry 7000	-0.169	-0.174	-0.174	-0.175
	(0.306)	(0.308)	(0.308)	(0.307)
Industry 8000	-0.339	-0.422	-0.422	-0.423
	(0.614)	(0.612)	(0.612)	(0.613)
Number of rounds received during window year	-1.436***	-1.422***	-1.422***	-1.422***
	(0.165)	(0.165)	(0.164)	(0.164)
Number of rounds: Cumulative	0.200**	0.177**	0.177**	0.177**
	(0.091)	(0.090)	(0.090)	(0.090)
Number of rounds: Cumulative square	-0.041**	-0.039**	-0.039**	-0.039**
	(0.019)	(0.019)	(0.019)	(0.019)
Round 1 year: 1997	1.388***	1.517***	1.523***	1.525***
	(0.407)	(0.403)	(0.409)	(0.408)

VARIABLE	MODEL 2	MODEL 10	MODEL 11	MODEL 12
Round 1 year: 1998	1.013***	1.093***	1.098***	1.099***
	(0.388)	(0.385)	(0.387)	(0.386)
Round 1 year: 1999	0.721*	0.722*	0.725*	0.726*
	(0.381)	(0.379)	(0.379)	(0.378)
Round 1 year: 2000	0.781**	0.777**	0.779**	0.780**
	(0.358)	(0.357)	(0.357)	(0.356)
Log of startup age at round 1	0.012	0.012	0.013	0.012
	(0.012)	(0.012)	(0.012)	(0.012)
Log of days since round 1	-0.044	-0.032	-0.032	-0.031
	(0.107)	(0.107)	(0.107)	(0.107)
Prior success rate	0.495	0.626	0.63	0.635
	(0.553)	(0.553)	(0.552)	(0.556)
Number of IPOs in window year	0.001**	0.001**	0.001**	0.001**
	(0.001)	(0.001)	(0.001)	(0.001)
Observations	4975	4975	4975	4975
Number of events	287	287	287	287
VIF maximum	7.45	7.44	7.45	8.52
VIF average	2.81	2.65	2.69	2.91
Wald chi^2	273.02	259.530	260.07	260.020
df	35	34	35	36
Log pseudolikelihood	-2271.796	-2276.765	-2276.761	-2276.758
Δ log likelihood χ^2	9.94***		0.01	0.02
As compared to	Model 10		Model 10	Model 10
χ^2 df	1		1	2
Δ log likelihood χ^2				0.01
As compared to				Model 11
χ^2 df				1

TABLE 7: COX PROPORTIONAL HAZARD RATE MODELS: ESTIMATED LIKELIHOOD OF STARTUP EXIT – ADDITIONAL TESTS FOR EXPERIENCE [25, 26]

VARIABLE	MODEL 2	MODEL 13	MODEL 14	MODEL 15
Prior ties	0.090**	0.082**	0.079**	0.078**
	(0.037)	(0.037)	(0.036)	(0.036)
Prior ties square	-0.003**	-0.003**	-0.003**	-0.003**
	(0.001)	(0.001)	(0.001)	(0.001)
Dyadic Simmelian ties	-0.007*	-0.009**	-0.004*	-0.004*
	(0.004)	(0.004)	(0.005)	(0.005)
Log of prestige of round 1 VCs	0.201***	0.064	0.118**	0.116**
	(0.072)	(0.045)	(0.053)	(0.056)
Log of prior experience: Total	-0.374***			
	(0.131)			
Prior experience: Total			-0.007**	-0.007*
			(0.003)	(0.004)
Prior experience: Total square				0
				0.000
Homogeneity: Prior industry experience	0.204	0.148	0.18	0.179
	(0.364)	(0.367)	(0.367)	(0.368)
Homogeneity: Prior industry experience square	0.356	0.304	0.395	0.396
	(0.410)	(0.410)	(0.416)	(0.416)
Number of VCs in syndicate	0.024	0.045	-0.017	-0.018
	(0.139)	(0.139)	(0.143)	(0.143)
Number of VCs in syndicate square	0	-0.004	0.009	0.009
	(0.067)	(0.067)	(0.067)	(0.067)
Startup stage at round 1: Seed/early/startup	0.251	0.218	0.204	0.203
	(0.169)	(0.166)	(0.165)	(0.166)
Number of VCs in round j[27]	-0.032	-0.035	-0.035	-0.035
	(0.028)	(0.028)	(0.028)	(0.028)

[25] Unstandardized coefficients are reported; robust standard errors in parentheses; *p<.10; **p<.05; ***p<.01; two-tailed tests.

[26] All variables (other than startup stage, which is a dummy variable) were centered prior to forming squared and interaction terms.

[27] Round j refers to the latest funding round during the window year. If a startup received more than one funding round in a year, the relevant variables were averaged across the rounds to arrive at the value for the window year.

VARIABLE	MODEL 2	MODEL 13	MODEL 14	MODEL 15
Log of prestige of round j VCs	0	0.002	0.004	0.004
	(0.046)	(0.045)	(0.047)	(0.047)
Prior ties of round j VCs	-0.018	-0.022	-0.019	-0.019
	(0.027)	(0.027)	(0.027)	(0.027)
Amount of funding received: Cumulative	0.180*	0.193*	0.199*	0.199*
	(0.109)	(0.109)	(0.108)	(0.108)
Amount of funding received: Round 1	0.1	0.072	0.084	0.083
	(0.090)	(0.087)	(0.088)	(0.088)
Industry 1000	-0.102	-0.109	-0.098	-0.098
	(0.153)	(0.153)	(0.153)	(0.153)
Industry 2100	-0.134	-0.155	-0.157	-0.157
	(0.239)	(0.237)	(0.239)	(0.239)
Industry 2700	-0.181	-0.19	-0.169	-0.169
	(0.148)	(0.148)	(0.148)	(0.148)
Industry 2800	0.033	0.073	0.041	0.042
	(0.161)	(0.161)	(0.161)	(0.161)
Industry 3000	-0.381	-0.414	-0.364	-0.363
	(0.253)	(0.254)	(0.254)	(0.255)
Industry 4000	0.245	0.234	0.209	0.209
	(0.323)	(0.319)	(0.320)	(0.320)
Industry 5000	-1.139***	-1.122***	-1.158***	-1.159***
	(0.301)	(0.300)	(0.301)	(0.301)
Industry 7000	-0.169	-0.187	-0.192	-0.192
	(0.306)	(0.307)	(0.307)	(0.307)
Industry 8000	-0.339	-0.399	-0.432	-0.433
	(0.614)	(0.614)	(0.613)	(0.613)
Number of rounds received during window year	-1.436***	-1.413***	-1.427***	-1.427***
	(0.165)	(0.163)	(0.165)	(0.165)
Number of rounds: Cumulative	0.200**	0.182**	0.190**	0.190**
	(0.091)	(0.090)	(0.090)	(0.090)
Number of rounds: Cumulative square	-0.041**	-0.038**	-0.040**	-0.040**
	(0.019)	(0.019)	(0.019)	(0.019)
Round 1 year: 1997	1.388***	1.526***	1.405***	1.405***
	(0.407)	(0.404)	(0.406)	(0.406)

VARIABLE	MODEL 2	MODEL 13	MODEL 14	MODEL 15
Round 1 year: 1998	1.013***	1.099***	1.027***	1.026***
	(0.388)	(0.385)	(0.387)	(0.387)
Round 1 year: 1999	0.721*	0.748**	0.712*	0.712*
	(0.381)	(0.380)	(0.381)	(0.381)
Round 1 year: 2000	0.781**	0.778**	0.778**	0.777**
	(0.358)	(0.357)	(0.358)	(0.359)
Log of startup age at round 1	0.012	0.012	0.012	0.012
	(0.012)	(0.012)	(0.011)	(0.011)
Log of days since round 1	-0.044	-0.025	-0.041	-0.041
	(0.107)	(0.107)	(0.108)	(0.108)
Prior success rate	0.495	0.129	0.507	0.502
	(0.553)	(0.571)	(0.563)	(0.566)
Number of IPOs in window year	0.001**	0.001**	0.001**	0.001**
	(0.001)	(0.001)	(0.001)	(0.001)
Observations	4975	4975	4975	4975
Number of events	287	287	287	287
VIF maximum	7.45	7.41	7.41	7.45
VIF average	2.81	2.66	2.72	2.78
Wald chi^2	273.02	265.790	271.02	271.090
df	35	34	35	36
Log pseudolikelihood	-2271.796	-2276.084	-2273.082	-2273.078
Δ log likelihood χ^2	8.58***		6.00**	6.01*
As compared to	Model 13		Model 13	Model 13
χ^2 df	1		1	2
Δ log likelihood χ^2				0.01
As compared to				Model 14
χ^2 df				1

TABLE 8: COX PROPORTIONAL HAZARD RATE MODELS: ESTIMATED LIKELIHOOD OF STARTUP EXIT – ALTERNATE MEASURE OF COHESION[28, 29]

VARIABLE	MODEL 1	MODEL 16	MODEL 17
Prior ties		0.053*	0.094**
		(0.030)	(0.038)
Prior ties square		-0.002**	-0.002**
		(0.001)	(0.001)
Ego network density		-0.008*	-0.007
		(0.005)	(0.006)
Log of prestige of round 1 VCs		0.231***	0.231***
		(0.069)	(0.069)
Log of prior experience: Total		-0.534***	-0.527***
		(0.149)	(0.148)
Homogeneity: Prior industry experience		0.127	-0.149
		(0.366)	(0.380)
Homogeneity: Prior industry experience square		0.256	0.574
		(0.418)	(0.443)
Number of VCs in syndicate		-0.002	-0.01
		(0.140)	(0.141)
Number of VCs in syndicate square		0.005	0.01
		(0.067)	(0.066)
Startup stage at round 1: Seed/early/startup		0.219	0.25
		(0.168)	(0.178)
Prior ties X Ego network density			0
			(0.002)
Prior ties X Homogeneity: Prior industry experience			-0.261**
			(0.118)
Prior ties X Startup stage at round 1: Seed/early/startup			0.029
			(0.055)

28 Unstandardized coefficients are reported; robust standard errors in parentheses; *p<.10; **p<.05; ***p<.01; two-tailed tests.

29 All variables (other than startup stage, which is a dummy variable) were centered prior to forming squared and interaction terms.

VARIABLE	MODEL 1	MODEL 16	MODEL 17
Number of VCs in round j[30]	-0.031	-0.032	-0.035
	(0.027)	(0.028)	(0.028)
Log of prestige of round j VCs	0.029	0	0.001
	(0.033)	(0.044)	(0.044)
Prior ties of round j VCs	-0.015	-0.02	-0.029
	(0.022)	(0.027)	(0.029)
Amount of funding received: Cumulative	0.201*	0.172	0.174
	(0.106)	(0.109)	(0.109)
Amount of funding received: Round 1	0.044	0.093	0.095
	(0.084)	(0.089)	(0.090)
Industry 1000	-0.08	-0.091	-0.099
	(0.149)	(0.152)	(0.154)
Industry 2100	-0.162	-0.12	-0.133
	(0.235)	(0.240)	(0.241)
Industry 2700	-0.175	-0.161	-0.161
	(0.147)	(0.147)	(0.148)
Industry 2800	0.084	0.039	0.025
	(0.159)	(0.161)	(0.159)
Industry 3000	-0.396	-0.349	-0.374
	(0.245)	(0.252)	(0.255)
Industry 4000	0.216	0.264	0.28
	(0.315)	(0.323)	(0.325)
Industry 5000	-1.067***	-1.148***	-1.216***
	(0.292)	(0.300)	(0.305)
Industry 7000	-0.203	-0.187	-0.307
	(0.306)	(0.306)	(0.316)
Industry 8000	-0.411	-0.356	-0.248
	(0.604)	(0.613)	(0.637)
Number of rounds received during window year	-1.412***	-1.445***	-1.436***
	(0.164)	(0.166)	(0.165)
Number of rounds: Cumulative	0.176*	0.201**	0.208**

[30] Round j refers to the latest funding round during the window year. If a startup received more than one funding round in a year, the relevant variables were averaged across the rounds to arrive at the value for the window year.

VARIABLE	MODEL 1	MODEL 16	MODEL 17
	(0.090)	(0.091)	(0.091)
Number of rounds: Cumulative square	-0.039**	-0.043**	-0.043**
	(0.019)	(0.019)	(0.019)
Round 1 year: 1997	1.517***	1.385***	1.371***
	(0.400)	(0.408)	(0.409)
Round 1 year: 1998	1.103***	1.012***	1.028***
	(0.383)	(0.390)	(0.391)
Round 1 year: 1999	0.762**	0.749**	0.761**
	(0.379)	(0.382)	(0.382)
Round 1 year: 2000	0.802**	0.793**	0.787**
	(0.356)	(0.358)	(0.359)
Log of startup age at round 1	0.011	0.01	0.01
	(0.011)	(0.011)	(0.011)
Log of days since round 1	-0.026	-0.048	-0.056
	(0.107)	(0.107)	(0.107)
Prior success rate	0.329	0.466	0.511
	(0.503)	(0.574)	(0.574)
Number of IPOs in window year	0.001**	0.001**	0.001**
	(0.001)	(0.001)	(0.001)
Observations	4975	4975	4975
Number of events	287	287	287
VIF maximum	6.31	6.84	9.73
VIF average	2.12	2.76	3.16
Wald chi^2	243.67	270.35	274.72
Df	25	35	38
Log pseudolikelihood	-2282.142	-2272.135	-2269.237
Δ log likelihood χ^2		20.01**	5.80
As compared to		Model 1	Model 16
χ^2 df		10	3

TABLE 9: COX PROPORTIONAL HAZARD RATE MODELS: ESTIMATED LIKELIHOOD OF STARTUP EXIT – ALTERNATE MEASURE OF EXPERIENCE[31, 32]

VARIABLE	MODEL 13	MODEL 18	MODEL 19	MODEL 20
Prior ties	0.082**	0.082**	0.083**	0.083**
	(0.037)	(0.037)	(0.036)	(0.036)
Prior ties square	-0.003**	-0.003**	-0.003**	-0.003**
	(0.001)	(0.001)	(0.001)	(0.001)
Dyadic Simmelian ties	-0.009**	-0.009**	-0.007*	-0.007*
	(0.004)	(0.004)	(0.004)	(0.004)
Log of prestige of round 1 VCs	0.064	0.063	0.092*	0.089*
	(0.045)	(0.047)	(0.048)	(0.049)
Log of prior experience: Focal industry		0.002		
		(0.035)		
Prior experience: Focal industry			-0.013**	-0.012
			(0.006)	(0.009)
Prior experience: Focal industry square				0
				(0.000)
Homogeneity: Prior industry experience	0.148	0.148	0.209	0.207
	(0.367)	(0.368)	(0.370)	(0.371)
Homogeneity: Prior industry experience square	0.304	0.305	0.371	0.372
	(0.410)	(0.410)	(0.418)	(0.418)
Number of VCs in syndicate	0.045	0.045	0.011	0.01
	(0.139)	(0.139)	(0.141)	(0.141)
Number of VCs in syndicate square	-0.004	-0.004	0.004	0.005
	(0.067)	(0.067)	(0.069)	(0.069)
Startup stage at round 1: Seed/early/startup	0.218	0.218	0.205	0.203
	(0.166)	(0.166)	(0.165)	(0.166)
Number of VCs in round j[33]	-0.035	-0.035	-0.036	-0.036
	(0.028)	(0.028)	(0.028)	(0.028)

[31] Unstandardized coefficients are reported; robust standard errors in parentheses; *p<.10; **p<.05; ***p<.01; two-tailed tests.

[32] All variables (other than startup stage, which is a dummy variable) were centered prior to forming squared and interaction terms.

[33] Round j refers to the latest funding round during the window year. If a startup received more than one funding round in a year, the relevant variables were averaged across the rounds to arrive at the value for the window year.

VARIABLE	MODEL 13	MODEL 18	MODEL 19	MODEL 20
Log of prestige of round j VCs	0.002	0.002	0.007	0.007
	(0.045)	(0.045)	(0.046)	(0.046)
Prior ties of round j VCs	-0.022	-0.022	-0.019	-0.019
	(0.027)	(0.027)	(0.027)	(0.027)
Amount of funding received: Cumulative	0.193*	0.193*	0.196*	0.196*
	(0.109)	(0.109)	(0.108)	(0.109)
Amount of funding received: Round 1	0.072	0.072	0.077	0.076
	(0.087)	(0.087)	(0.087)	(0.087)
Industry 1000	-0.109	-0.111	0.039	0.034
	(0.153)	(0.161)	(0.169)	(0.171)
Industry 2100	-0.155	-0.155	-0.109	-0.109
	(0.237)	(0.237)	(0.238)	(0.238)
Industry 2700	-0.19	-0.193	-0.026	-0.031
	(0.148)	(0.155)	(0.166)	(0.168)
Industry 2800	0.073	0.073	0.095	0.096
	(0.161)	(0.161)	(0.160)	(0.160)
Industry 3000	-0.414	-0.415	-0.378	-0.376
	(0.254)	(0.256)	(0.255)	(0.255)
Industry 4000	0.234	0.235	0.263	0.266
	(0.319)	(0.319)	(0.319)	(0.321)
Industry 5000	-1.122***	-1.124***	-1.034***	-1.038***
	(0.300)	(0.306)	(0.304)	(0.304)
Industry 7000	-0.187	-0.187	-0.148	-0.146
	(0.307)	(0.307)	(0.308)	(0.308)
Industry 8000	-0.399	-0.4	-0.431	-0.43
	(0.614)	(0.616)	(0.615)	(0.615)
Number of rounds received during window year	-1.413***	-1.413***	-1.426***	-1.425***
	(0.163)	(0.163)	(0.164)	(0.164)
Number of rounds: Cumulative	0.182**	0.182**	0.183**	0.183**
	(0.090)	(0.090)	(0.090)	(0.090)
Number of rounds: Cumulative square	-0.038**	-0.039**	-0.039**	-0.039**
	(0.019)	(0.019)	(0.019)	(0.019)
Round 1 year: 1997	1.526***	1.528***	1.423***	1.423***
	(0.404)	(0.404)	(0.406)	(0.406)

VARIABLE	MODEL 13	MODEL 18	MODEL 19	MODEL 20
Round 1 year: 1998	1.099***	1.100***	1.020***	1.019***
	(0.385)	(0.385)	(0.387)	(0.387)
Round 1 year: 1999	0.748**	0.748**	0.715*	0.714*
	(0.380)	(0.380)	(0.380)	(0.381)
Round 1 year: 2000	0.778**	0.778**	0.760**	0.758**
	(0.357)	(0.357)	(0.357)	(0.358)
Log of startup age at round 1	0.012	0.012	0.012	0.012
	(0.012)	(0.012)	(0.011)	(0.011)
Log of days since round 1	-0.025	-0.025	-0.034	-0.034
	(0.107)	(0.108)	(0.108)	(0.109)
Prior success rate	0.129	0.126	0.331	0.324
	(0.571)	(0.574)	(0.567)	(0.570)
Number of IPOs in window year	0.001**	0.001**	0.001**	0.001**
	(0.001)	(0.001)	(0.001)	(0.001)
Observations	4975	4975	4975	4975
Number of events	287	287	287	287
VIF maximum	7.41	7.42	7.41	7.42
VIF average	2.66	2.66	2.7	2.77
Wald chi^2	265.790	267.42	276.17	276.87
df	34	35	35	36
Log pseudolikelihood	-2276.084	-2276.082	-2273.795	-2273.772
Δ log likelihood χ^2		0.00	4.58**	4.63*
As compared to		Model 13	Model 13	Model 13
χ^2 df		1	1	2
Δ log likelihood χ^2				0.05
As compared to				Model 20
χ^2 df				1

TABLE 10: COX PROPORTIONAL HAZARD RATE MODELS: ESTIMATED LIKELIHOOD OF STARTUP EXIT – ALTERNATE MEASURE OF HOMOGENEITY[34, 35]

VARIABLE	MODEL 1	MODEL 21	MODEL 22
Prior ties		0.088**	0.092**
		(0.037)	(0.039)
Prior ties square		-0.003**	-0.004*
		(0.001)	(0.002)
Dyadic Simmelian ties		-0.007*	-0.008*
		(0.004)	(0.005)
Log of prestige of round 1 VCs		0.208***	0.211***
		(0.073)	(0.073)
Log of prior experience: Total		-0.380***	-0.381***
		(0.132)	(0.132)
Homogeneity: Prior total experience		0.158	0.119
		(0.158)	(0.154)
Homogeneity: Prior total experience square		0.262	0.316
		(0.350)	(0.358)
Number of VCs in syndicate		0.029	0.031
		(0.137)	(0.138)
Number of VCs in syndicate square		0	0.001
		(0.066)	(0.066)
Startup stage at round 1: Seed/early/startup		0.26	0.285
		(0.168)	(0.178)
Prior ties X Dyadic Simmelian ties			0
			(0.001)
Prior ties X Homogeneity: Prior total experience			-0.043
			(0.029)
Prior ties X Startup stage at round 1: Seed/early/startup			0.027
			(0.052)

[34] Unstandardized coefficients are reported; robust standard errors in parentheses; *p<.10; **p<.05; ***p<.01; two-tailed tests.

[35] All variables (other than startup stage, which is a dummy variable) were centered prior to forming squared and interaction terms.

VARIABLE	MODEL 1	MODEL 21	MODEL 22
Number of VCs in round j[36]	-0.031	-0.033	-0.032
	(0.027)	(0.028)	(0.028)
Log of prestige of round j VCs	0.029	-0.002	-0.001
	(0.033)	(0.045)	(0.045)
Prior ties of round j VCs	-0.015	-0.018	-0.019
	(0.022)	(0.027)	(0.028)
Amount of funding received: Cumulative	0.201*	0.179*	0.180*
	(0.106)	(0.109)	(0.109)
Amount of funding received: Round 1	0.044	0.106	0.11
	(0.084)	(0.090)	(0.090)
Industry 1000	-0.08	-0.1	-0.113
	(0.149)	(0.152)	(0.153)
Industry 2100	-0.162	-0.124	-0.117
	(0.235)	(0.237)	(0.238)
Industry 2700	-0.175	-0.184	-0.193
	(0.147)	(0.148)	(0.150)
Industry 2800	0.084	0.038	0.031
	(0.159)	(0.162)	(0.162)
Industry 3000	-0.396	-0.384	-0.422
	(0.245)	(0.255)	(0.265)
Industry 4000	0.216	0.243	0.233
	(0.315)	(0.321)	(0.321)
Industry 5000	-1.067***	-1.148***	-1.155***
	(0.292)	(0.301)	(0.301)
Industry 7000	-0.203	-0.174	-0.184
	(0.306)	(0.306)	(0.306)
Industry 8000	-0.411	-0.293	-0.269
	(0.604)	(0.616)	(0.633)
Number of rounds received during window year	-1.412***	-1.441***	-1.436***
	(0.164)	(0.165)	(0.165)
Number of rounds: Cumulative	0.176*	0.202**	0.200**

[36] Round j refers to the latest funding round during the window year. If a startup received more than one funding round in a year, the relevant variables were averaged across the rounds to arrive at the value for the window year.

VARIABLE	MODEL 1	MODEL 21	MODEL 22
	(0.090)	(0.091)	(0.091)
Number of rounds: Cumulative square	-0.039**	-0.042**	-0.042**
	(0.019)	(0.019)	(0.019)
Round 1 year: 1997	1.517***	1.383***	1.383***
	(0.400)	(0.405)	(0.405)
Round 1 year: 1998	1.103***	1.002***	1.011***
	(0.383)	(0.388)	(0.388)
Round 1 year: 1999	0.762**	0.719*	0.735*
	(0.379)	(0.381)	(0.381)
Round 1 year: 2000	0.802**	0.786**	0.792**
	(0.356)	(0.357)	(0.357)
Log of startup age at round 1	0.011	0.013	0.012
	(0.011)	(0.012)	(0.012)
Log of days since round 1	-0.026	-0.043	-0.04
	(0.107)	(0.106)	(0.107)
Prior success rate	0.329	0.467	0.495
	(0.503)	(0.560)	(0.561)
Number of IPOs in window year	0.001**	0.001**	0.001**
	(0.001)	(0.001)	(0.001)
Observations	4975	4975	4975
Number of events	287	287	287
VIF maximum	6.31	7.45	9.55
VIF average	2.12	2.56	2.83
Wald chi^2	243.67	274.25	279.99
Df	25	35	38
Log pseudolikelihood	-2282.142	-2271.497	-2270.735
Δ log likelihood χ^2		21.29**	1.52
As compared to		Model 1	Model 22
χ^2 df		10	3

TABLE 11: HAZARD RATIOS OF SELECTED VARIABLES (FROM MODEL 9 IN TABLE 5)

VARIABLE	HAZARD RATIO
Prior ties	1.125
Prior ties square	0.996
Dyadic Simmelian ties	0.992
Log of prestige of round 1 VCs	1.220
Log of prior experience: Total	0.696
Prior ties X Homogeneity: Diversity of prior industry experience	0.776
Log of amount of funding received: Cumulative	1.200
Log of amount of funding received: Round 1	1.106
Industry 5000	0.301
Number of rounds received during window year	0.239
Number of rounds: Cumulative	1.230
Number of rounds: Cumulative square	0.959
Round 1 year: 1997	3.962
Round 1 year: 1998	2.788
Round 1 year: 1999	2.094
Round 1 year: 2000	2.182
Number of IPOs in window year	1.001

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