UNIVERSITY OF OKLAHOMA

GRADUATE COLLEGE

EFFECTS OF VENTURE CAPITAL SOCIAL ADVICE NETWORKS ON ESCALATION OF COMMITMENT.

A DISSERTATION

SUBMITTED TO THE GRADUATE FACULTY

in partial fulfillment of the requirements for the

Degree of

Doctor of Philosophy

By

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Norman, Oklahoma
2006

EFFECTS OF VENTURE CAPITAL SOCIAL ADVICE NETWORKS ON ESCALATION OF COMMITMENT

A DISSERTATION APPROVED FOR THE MICHAEL F. PRICE COLLEGE OF BUSINESS

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Acknowledgements

I'd like to thank my committee members for their patience and their help and my two committee chairs, Leon Price and Larry Michaelsen, for their support. I'd also like to thank Gina Amundson for all the last minute running around she did for me.

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Abstract

This study examined the advice networks of venture capital (VC) firms that funded new start-up entrepreneurial companies in the high technology sector. Three outcomes were associated with VC firms' funding of start-up companies. Two were classified as successful decisions making. These were funding a company until it went public with an IPO, was acquired, or merged with an established company and deciding to terminate funding a faltering company that would eventually fail after no more than two round of funding. The third outcome, which was classified as unsuccessful decision making, was funding a faltering company that eventually failed beyond two funding rounds. This unsuccessful investment represents the escalation of commitment case.

Characteristics of focal VC firms and the various advice network indices attached to their position in the network were used to predict escalation of commitment in new start-ups where the first round of funding was between 1990 and 1995. Data for the study came from Thompson Financial's VentureXpert database. The 294 VC firms in this study funded 498 new start-ups. When the focal VC firm worked with another VC firm prior to 1990, that VC firm was part of the focal firm's advice network. Two different advice networks were identified. The first consisted of every VC firm that funded at least one round of a particular start-up company. The second was the advice network consisting only of the VC firms which funded Rounds 1 or 2. These were the VC firms which made the initial decision to continue funding a company that eventually failed and, as a result, escalated commitment to a failing course of action.

Three major findings emerged from the study. First, the network of VC firms that invest in new high technology start-up companies has become far more interconnected

and dense over the last 15 or so years. It was not possible to identify regional hubs based on VC firm funding ties. Second, the dense interconnections between VC firms allowed information to flow freely throughout the network. Some of the network variables and characteristics of the VC firms in the advice network were significant predictors of escalation of commitment. Third, determining the boundaries of a network and defining that network's membership affected the underlying network structure and thus the results.

Introduction

This dissertation examines escalation of commitment by private equity venture capital (VC firms) within the context of their advice networks, specifically, within the context of their investing networks. On a theoretical level, this research will contribute to the literature on escalation of commitment by being the first large-scale study to examine the extent to which the context affects escalation of investment commitment decisions.

When previous decisions result in losses or performance below expectations, the decision-makers need to evaluate whether to continue with the course of action. Withdrawal behavior usually results when there is repeated, clear, and strong negative feedback. A problem arises, however, when the decision whether or not to withdraw from the project at a particular decision point in time is not clear-cut. Typically this is because the feedback is ambiguous, is negative mixed with positive feedback, or is not perceived as unequivocally or strongly negative by the decision-makers. For example, the decision-makers may interpret a downturn as a surmountable bump in the road that can be overcome with additional time, effort, or other resources. The decision-makers can decide to continue with their investments, hoping that they can save the situation, or they can cut their losses and move on to something else that has a greater chance of success (Bowen, 1987; McCain, 1986; Northcraft & Wolfe, 1984; Staw, 1976, 1981, 1997). When a decision-maker continues a commitment to a failing course of action, the behavior is called escalation of commitment (Staw, 1976, 1981, 1997).

It is not just individual decision-makers who escalate: groups and organizations do also (Moon, Conlon, Humphrey, Quigley, Devers & Nowakowski, 2003; Whyte, 1993). Escalation by venture capital syndicate groups has previously been documented

(Birmingham, Busenitz & Arthurs, 2003; De Clerc, 2002; Gompers & Lerner, 1999; Guler, 2003; Ryan, 1994, 1995; Steiner & Greenwood, 1995; Zacharakis & Meyer, 2000; Zacharakis & Shepherd, 2001).

While previous studies have documented escalation of commitment by individual venture capitalists and venture capital syndicates, little research explores the context of this escalation process. These investment decisions do not take place in a vacuum. The context in which individuals, groups and organizations are embedded influences the decision process (Moscovici & Doise, 1994; Chernyshenko, Miner, Baumann & Sniezek, 2003; Sniezek & Buckley, 1995).

One context receiving research attention recently has been the network of relationships in which the individual, group or organization is embedded (McDonald & Westphal, 2003; Elfring & Hulsink, 2003; Uzzi, 1996, 1999). Influence by network ties on focal individuals, groups, and organizations has been documented in other contexts. Both the location of the focal actor in the tie network and the information and advice flowing between ties has been shown to influence behavior (Hurlbert, Haines & Beggs, 2000; Elfring & Hulsink, 2003). No studies, however, have explored the influence of network ties on escalation of commitment. This study will be the first to examine the influence of venture capitalist advice networks on escalation of commitment.

Venture capitalists are an ideal population for studying advice networks and escalation of commitment. Venture capital (VC) firms generally invest in projects with other VC firms as a VC syndicate. These syndicates make repeated investments in a project over time. As a result, there is the potential for venture capitalists to escalate their commitment if the project is struggling. In order to be successful venture capitalists must be able to both recognize that they are escalating their commitment to a project and prevent themselves from escalating. Venture capitalists rely on their advice networks when they make initial investment decisions (Gompers & Lerner,1999), and it is likely that their advice network also influences other aspects of their decision-making. When, for example, a focal VC firm has a large number of ties to other successful VC firms, the focal VC firm may learn vicariously how not to escalate. Network research has documented the existence of venture capitalist networks and influences between these and other related network ties with regards to funding and assisting entrepreneurs (Sorenson & Stuart, 2001; Yli-Renko & Altio, 1998), IPO investment bankers, and IPO underwriters (Gompers & Lerner, 1999). No research, however, has examined the effects of these networks on escalation of commitment.

This dissertation will make theoretical contributions to VC literature in several areas. In this study, escalation of commitment is examined within an environmental context salient for VC firms, namely their investing networks with other VC firms. This study will be the first to look at the effects of the focal firm's social, or advice, network on escalation of commitment. The examination of advice networks' influence on decision-making and escalation of commitment will also contribute to the literature on social networks.

This research will also make a contribution to practitioners. Venture capital is one of the few funding sources for high-risk, high-technology start-up companies (Gompers & Lerner, 1999, 2001; Bygrave & Timmons, 1992; Guler, 2003; De Clerc, 2002). Venture capitalists invest billions of dollars in new ventures—over 60 billion dollars in 2001—but only about a third of the investments are ultimately successful (Gompers &

Lerner, 2001). The rest result in either a complete or partial loss of the investment. Helping venture capitalists find ways to make better decisions, including bailing from a failing start-up without escalating, will increase profits for VC firms and their investors by decreasing their losses.

Chapter two will review the existing literature on escalation of commitment as relevant to VC firm escalation and networks, review the relevant literature on social networks and groups, and propose how the later might affect the former. The hypotheses will be developed and presented. Chapter three, the research methods chapter, will discuss the operationalization of the variables, data, and data analyses to be used. The data comes from Thompson Financial's VentureXpert database of venture capital firm investments in new start-up companies. This dataset includes investment partners, dates of investments, amounts invested, and company outcomes. From this information an advice network will be created, based on who invested with whom. Social network analysis, which gives a variety of information about network ties between nodes of interest (in this case VC firms), will be used to create the data for the advice network variables. Regression will then be used to look for relationships between the advice network variables and escalation of commitment. Chapter four will present the research results, and chapter five will discuss the study's results, limitations, and the theoretical and practical applications of this research to venture capital decision-making.

Review of Literature

This study examines the influence of venture capitalists' advice networks on escalation of commitment to start-up companies. It proposes that a number of advice network variables do, in fact, influence the propensity to escalate commitment to a failing project. This chapter reviews the relevant literature on escalation of commitment and social networks. The model proposed and tested is based on the Staw (1997) model of escalation of commitment. This model includes escalation factors both internal and external to the project. While Staw did not explicitly include advice networks in his model, the network variables would be included under the "contextual determinants" portion of the model (see Figure 3.1).

Background Information on Escalation of Commitment

Escalation of commitment is a multi-staged process. Decision-makers often expend a significant "due diligence" effort before initially deciding to commit resources to a venture. Once the initial decision to invest is made, however, they tend to become overly committed to the venture, ignoring or putting a positive spin on new information that is ambiguous or negative. As a result, the decision-makers can get caught in a downward spiral that culminates in escalation of commitment to a failing course of action (Brockner, 1992; Staw, 1976). Individuals, groups, and organizations can all get trapped in such a losing course of action (Staw, 1997; Brockner, 1992).

Brocker (1992) and Staw (1976, 1981) describe the escalation of commitment process. The first step is deciding to commit resources to a venture where, although there is some uncertainty about the outcome, the decision-maker believes the outcome will be favorable. The second step is viewing new information that is either ambiguous or negative about the project either with a positive spin or as a temporary setback. The third step is continuing to invest, despite increasingly more negative information, in what ultimately becomes a failed course of action.

Venture capitalists investing in start-up companies provide a good context to study escalation of commitment. They repeatedly allocate resources over time to start-up companies believing the final outcome will be positive, even though there is no way to be absolutely certain. Venture capitalists frequently encounter temporary setbacks, even with ultimately successful ventures. There are significant risks involved when funding new start-ups. On average, at least 30% of the companies invested in fail and another 30% do not make the VC firm any money (Guler, 2003). Resource allocations involve repeated decisions to reinvest, called financing rounds; at any point one or all of the VC firms involved could decide to withdraw from the investment. Venture capitalists typically invest in groups called syndicates, which are limited-life legal entities made up of VC firms jointly funding a start-up entrepreneurial company. Since VC firms invest repeatedly in a large number of companies, there is, theoretically, the opportunity to learn from experience, which presumably would include learning to recognize failing investments early on (Guler 2003).

Ross and Staw (1993) have suggested that "perhaps those who work in occupations in which escalation is a routine problem may be socialized to avoid excess persistence" (p. 724). Unfortunately this statement has been demonstrated to be untrue, even with experienced venture capitalists (Shepherd, Zacharakis, & Baron, 2003).

A market perspective would suggest that market mechanisms would select out inefficient VC firms. Under this scenario, little escalation of commitment should occur amongst more experienced firms because VC firms that escalate and do not learn from experience should go out of business. But this is not always the case (Guler, 2003; De Clerc, 2002; Shepherd et al., 2003). Indeed, at least six studies have documented that VC syndicate groups do escalate (Birmingham et al., 2003; Guler, 2003; De Clerc, 2002; Zacharakis & Shepherd, 2001; Zacharakis & Meyer, 2000; Ryan, 1994,1995; Gompers & Lerner, 1999).

Other factors affect venture capitalists' decision-making process. Overconfidence by decision-makers contributes to escalation behavior. In a process that depends on the amount of information available, venture capitalists suffer from overconfidence in their decisions, which leads to poor decisions (Zacharakis & Shepherd, 2001). Venture capitalists may ignore incoming information when making additional financial round investments (Guler, 2003). Given that paying attention to new information helps individuals de-escalate (Ross & Staw, 1993), failure to do so contributes to escalation of commitment. The size of the syndication group, as well as adding or subtracting a venture capitalist from the group, also affects escalation (Birmingham et al., 2003).

Escalation of commitment has been documented in groups in laboratory studies (Moon et al., 2003; Whyte, 1993; Bazerman, Giuliano & Appleman, 1984). One major finding is that when group members have given individual consideration to their decision before the group makes a collective decision; both the individual members and the entire group are more prone to suffer from decision biases and to continue their commitment. In addition, the group's decision tends to fall between individual members' extreme opinions (Moon et al., 2003). Both De Clerc (2002) and Guler (2003) have documented that venture capitalists generally continue funding when feedback is ambiguous. Since they are used to having temporary setbacks during funding periods, they often view initial negative or ambiguous feedback as indications of problems that can be overcome rather than as signals that the new company should be terminated (Bygrave & Timmons, 1992; De Clerc, 2002; Guler, 2003; Gompers & Lerner, 1999).

Venture capitalists certainly would enter the decision to fund another round having thought about it in advance. With incremental decision-making, like the decision to grant another round of funding, where the outcome is to fund or not to fund, few compromise or integrative decision outcomes are possible. As a result, when there is not complete agreement within the syndicate, the fund/don't fund decision becomes a compromise one of funding less money more frequently (De Clerc, 2002; Guler, 2003). This may explain the finding of Birmingham et al (2003) that escalating venture capitalists tended to grant less money to a company each round with less time between rounds of funding. Thus, in a VC syndicate, the group may be more likely to fund than to terminate, leading to escalation. While larger VC syndicates are more prone to escalation, adding or subtracting a venture capitalist from the group investing over the life of the company actually decreases escalation. This is probably because a VC firm added to later rounds of funding would not choose to invest if their due diligence indicated existing problems were insurmountable and the added attention given to negative information when a VC firm leaves the group (Birmingham et al., 2003).

Moving from a market to a behavioral perspective gives another view. The behavioral perspective attempts to explain why escalation happens and what might be done in order to minimize this tendency. The behavioral decision-making literature presents evidence that decision-makers do deviate from rationality and that decision errors are systematic, not random (De Clerc, 2002; Zacharakis & Meyer, 2000).

Early behavioral escalation research was primarily experimental laboratory research. Several researchers have documented that students will pay more money than something is worth when they become overly committed to winning or to a goal that they are failing to obtain (Teger, 1980; Brokerner & Rubin, 1985). In addition, Arkes & Blumer (1985) demonstrated that as people invest more in a project they are more likely to continue their commitment until the project is completed.

Other laboratory experiments and field studies examined the behavior of decision-makers when the economic information was the same across conditions. Personal responsibility for the earlier investment decision, whether in the laboratory (Staw, 1976) or in the field (Staw, Koput, & Barsade, 1997), affected whether the decision-maker would escalate. In one of the earliest studies, Staw (1976) found that those who were responsible for an earlier investment decision that resulted in losses invested more in the next investment round than those who were not. In addition, those who made the original decision to invest were far more likely to reinvest than to terminate a failing project. In a field study using bank managers, Staw et al. (1997) documented that when there was a change in bank managers, new managers who were not personally responsible for granting the original loan were more likely to write off bad loans as compared to those responsible for granting the initial loan.

Escalation does not occur under all conditions, however. When there is repeated, strong negative feedback, decision-makers will terminate a project. Decision-makers are less likely to escalate when complete information, including the probabilities of future outcomes for various decision choices, is available (Bowen, 1987; Northcraft & Wolfe, 1984). Brockner & Rubin (1985) documented that giving decision-makers full information prior to making their initial decision had an effect on the decision made. This is consistent with how venture capitalists decide to invest in a start-up. Venture capital firms do due diligence before they decide to invest and often come to the conclusion not to invest. Brockner & Robin (1985) found conversely that full information given out after resources were committed had no affect on future reinvestment decisions. Venture capitalists also obtain more information after making their initial investment, such as the start-up missing targets or other unanticipated problems. As a result, there is potential for venture capitalists to be influenced by the same processes that Brockner & Robin (1985) documented.

Three explanations for escalation of commitment behavior have received support. The first is that the decision-maker continues to invest to avoid cognitive dissonance (Brownstein, 2003; Rosenfeld, Kennedy & Giacalone, 1986; Staw, 1976; Festinger, 1957). Experimentally, both groups and individuals feel pressure to justify previous decisions (Bazerman et al., 1984). Whyte (1993) found that groups escalated their commitment even more than individuals did. On the other hand, Leatherwood and Conlon (1988) found that the ability of groups to diffuse responsibility helped them escalate less than individuals. In this experiment, however, individuals had no opinions on what the decision should be prior to being presented with the decision that needed to be made—a context not relevant to the VC decision situation. If some group members wanted to abandon a project and others wanted to continue, the group members must reconcile their opinions, something that is not always easy (Wittenbaum & Park, 2001; Jehn, Northcraft & Neale, 1999; Stasser, 1992). In the VC setting, a VC firm does have the option to drop out. One consequence of dropping out is that the VC firm's holdings, and therefore the potential return on its investment, will be diluted by later-round investors. In addition, venture capitalists tend to pressure each other to continue funding, since to completely cut off funding guarantees that the project will fail and the money invested will be lost (Gompers & Lerner, 1999; De Clerc, 2002). In reconciling opinions, some individuals may not share information known only to them that contradicts their personal decision preference (Jehn, Northcraft & Neale, 1999; Wittenbaum & Park, 2001). In addition, because groups tend to pay more attention to information all group members have in common, conflicting information known only by a few individuals may be ignored (Stasser, 1992).

The second explanation for escalation behavior is that the decision-maker continues to invest because of cognitive limitations (Rosenfeld, Kennedy & Giacalone, 1986; Edwards, 1982; Nisbett & Ross, 1980). Shepherd, Zacharakis & Baron (2003) have documented how venture capitalists' cognitive limits lead them to use heuristics and cognitive shortcuts when they make investment decisions. Network contacts are used as cognitive shortcuts in information searches; when searching for information, the searcher tends to gather more information from trusted individuals than from using all reputable sources available (Reagans & McEvily, 2003; Reagans & Zuckerman, 2001).

The third explanation for escalation of commitment behavior is based on how heuristics and biases affect the decision-making process (Whyte, 1993; Bazweman, et. al., 1984; Tversky & Kahneman, 1974). Tversky & Kahneman (1974) have documented how decision-makers respond to framing, which is known as prospect theory. When something is "loss framed," or framed and perceived as a loss, decision-makers are willing to take larger risks to try to recoup that loss than when the identical situation is given a positive, “gain-framed” spin. An individual’s existing opinion biases the information search process such that information that supports the position is that which is most likely to be used. In addition, ambiguous information is interpreted as supporting the position held (Pinkley, Griffith, & Northcraft, 1995). Also, perceived responsibility for the decisions leads to self-justification which leads to higher levels of escalation (O’Connor, 1997).

Brockner (1992), testing these and competing categories of explanations for escalation behavior, found that these theories together, rather than individually, provided the best explanatory power. His main finding was that self-justification theory was important but could not stand alone. On the individual level of analysis, both expectancy theory and prospect theory provided explanatory power. On the interpersonal and group levels, group polarization, self-presentation theory, and modeling processes all contributed. At the organizational level, organizational inertia was important. He also found that these various theories had differing explanatory power depending on the decision-maker’s existing commitment to the project. He concluded that escalation and its antecedents needed to be examined longitudinally.

Most behavioral research on escalation of commitment has been laboratory experiments or case studies. The findings, although robust, have been criticized for over-reliance on experimental laboratory research that has limited external validity (Staw, 1997). Another problem is that people, groups, and organizations do not make decisions in a vacuum, but instead are influenced by social, environmental/contextual, political, and, in the case of individuals and groups, organizational forces. This was clearly documented in a case study concerning the spectacular and expensive Shoreham Nuclear Power failure (Ross & Staw, 1993).

General Model of Escalation of Commitment

Escalation of commitment research has been criticized for its lack of theoretical direction or limits. This is partly due to the many forces that come together to create conditions ripe for escalation behavior and, for a long time, no theoretical framework for considering all the variables studied (Brockner, 1992; Staw, 1997).

Ross & Staw (1987, 1989, 1993) proposed a classification scheme for existing escalation of commitment variables. Their proposed conceptual model integrated past research and escalation explanations. Using the Shoreham Nuclear Power Plant failure, they tested and then refined a multi-level temporal model for the escalation of commitment process. (Ross & Staw, 1993; Staw, 1997) Their final model (see Figure 2.1), a portion of which will be used in this research, includes five categories of variables: project, psychological, social, organizational, and environmental/contextual determinant variables (Ross & Staw, 1993; Staw, 1997).

The first category is project determinants related to the financial outcomes of the investment and broader economic concerns. Escalation of commitment is more likely if the setback is temporary, further investment might turn the situation around, the size of the payoff or goal is large, the level of expenditure needed to increase the project is high and the rewards are very important, few alternatives are available, withdrawing would bankrupt the firm, or the salvage value of the ended project would be low.. All of these project determinants and conditions are consistent with the kinds of projects venture capitalists fund.

The second category of variables includes psychological determinants, which are the psychological factors making it harder for people to pull the plug at the first signs of trouble. Ross & Staw (1987, 1989,1993) considered four factors to be most important.

The first psychological factor is optimism and the illusion of control. Although decision-makers are likely to consider their economic projections as accurate or unbiased, in fact economic data are neither objective nor are decision-makers unbiased in evaluating economic data. Decision-makers often are optimistic, overestimating the likelihood of positive events and underestimating the likelihood of negative events. They suffer from the illusion of control, believing that they will have better outcomes than others due to their skills. Therefore, similar to "winner's curse", decision-makers believe that with their experience and skill they can influence the odds in their favor and bring risks under their control. This biasing of information affects the initial decision to invest (Staw, 1997).

The second psychological factor, information bias, also influences decisions made beyond the initial funding level or funding round. As documented in self-justification theory, decision-making is a psychologically binding act causing attitude and belief changes. Decision-makers reduce cognitive dissonance by changing their attitudes and beliefs to those consistent with the decision made (Festinger, 1957; Staw, 1997). ,Needing to rationalize or justify their earlier decisions, decision-makers personally responsible for the initial decision to invest committed more resources than those not initially responsible for the decision to a losing course of action (Staw, 1976; Brocker, 1992). In addition, this responsibility for a losing course of action also affects the search for information and the evaluation of this information. Decision-makers were more likely to look for information that supported their initial decision and to interpret any new information in a light most positive to or consistent with their previous decision (Staw, 1997; Staw, Koput, & Barsade, 1997; Bazerman, Giuliano & Appleman, 1984).

The third psychological factor is sunk costs. Although these costs should be ignored, many decision-makers in fact take these costs into account in making investment decisions (Staw, 1997). When projects are nearly done, even in the face of very negative information, sunk costs are generally routinely not ignored and more money is allocated to finish the project (Garland, 1990; Arkes & Blumer, 1985).

The framing effect is the last psychological factor. Kahneman & Tversky (1979) documented how cognitive framing affects people's risk perception and subsequent behavior. When a situation is presented in a positive frame, people are risk adverse. The opposite is true when a situation is presented in negatively framed way. In the escalation context, negative feedback about a project creates a loss frame. If committing more resources to a project may turn it around, people are more likely to do so to avoid the certain loss of terminating the project (Staw, 1997).

Social determinants, the third category identified by Staw & Ross (Ross & Staw, 1993; Staw, 1997), are often overlooked in escalation of commitment research. The context in which decisions are made—including organizational context, ongoing personal relationships, and the constituents of the decision process—affect decision outcome. Similar to individual justification and decision binding, these may take place in a context external to the decision-maker (Staw, 1997). Terminating a failing project can be personally costly in an organization because it can be interpreted as an admission of personal failure. When decision-makers make decisions with potentially personally negative outcomes, they are motivated to try to turn the situation around (Fox & Staw, 1979). In an organization there are social rewards for persistence. Saving a failing project can mean that positive attributes are attributed to the leader. Leaders who were perceived as consistent were rated more positively than those who were not. Those who were consistent and turned a failing situation around received the highest evaluations (Staw & Ross, 1980). This tendency to rewarding for persistence can be a significant motivating factor for a decision-maker to stick with an initial decision, rather than pulling the plug on a failing project.

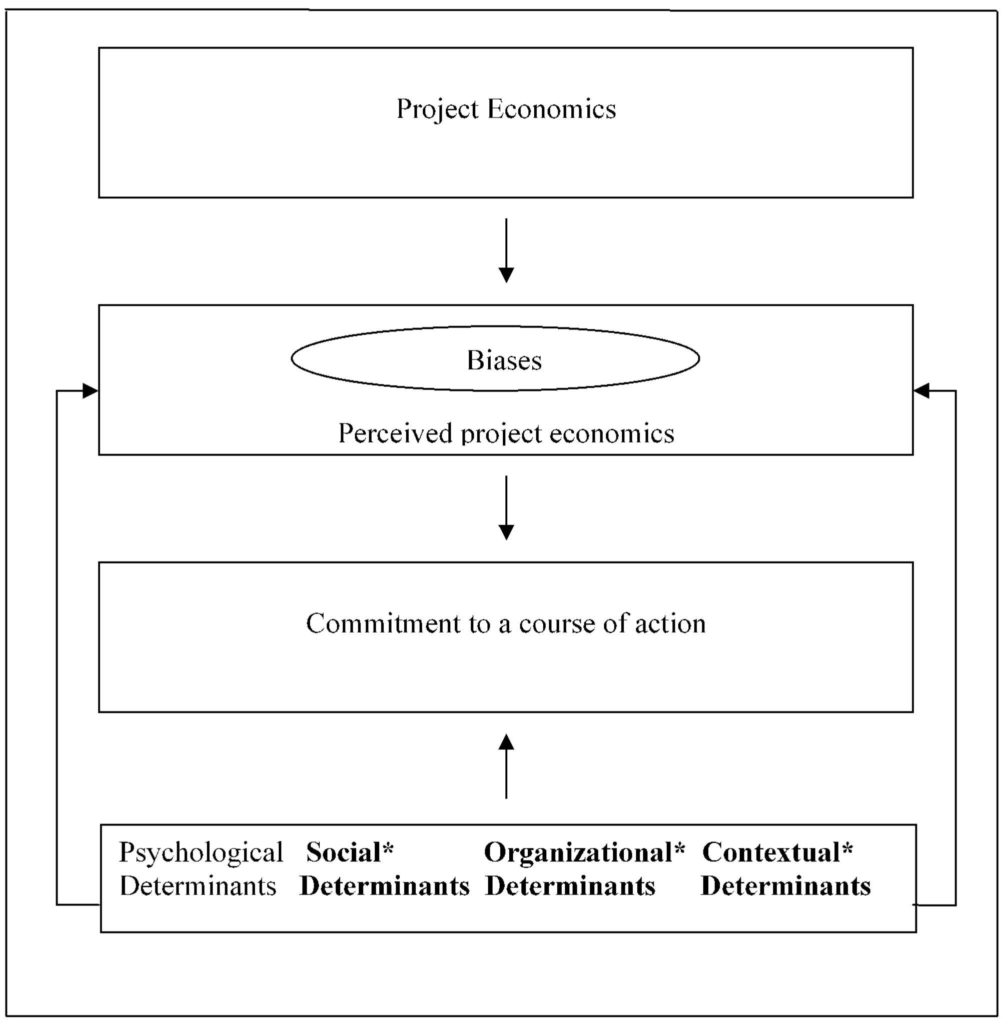
The last two categories in Staw & Ross's model (Ross & Staw, 1993; Staw, 1997) are organizational and contextual, or environmental, determinants. Organizational determinants are a product of social interactions; as such, they are a more macro-level set of variables. Institutional inertia, political problems and resistance, and product identification all affect the ability of decision-makers to withdraw from a situation even if their private preference is to do so (Staw, 1997). Contextual determinants are organizations or political processes and pressures external to the focal organization which can affect its ability to act. These environmental factors also can affect escalation of commitment (Staw, 1997).

The temporal model developed by Staw (1997) reflects the facts that some forces may not be activated until certain conditions are present and that conditions may change over time. When things deteriorate slowly, behavioral sources of commitment become important. When things go wrong quickly, it is easier for organizations and individuals to exit because fewer forces act on them to continue their commitment. Ross & Staw's model, which was partly supported, and later modified, by the Shoreham Nuclear Power

Plant failure case study, is as follows: Project economics are filtered though individual biases and result in perceived project economies which form the basis for individuals, groups, or organizations to commit to a course of action. The decision-makers' commitment is influenced by psychological, social, organizational, and contextual determinants. These determinants, in turn, influence biases, which serve to further influence commitment to the course of action. [See Figure 2.1]. Within the context of this model, this research will be examining some of the social determinants, in this case the networks of the venture capitalists, of escalation of commitment by venture capital firms (Figure 2.2 and Figure 2.3).

Figure 2.1

Staw (1997) model



* = Determinants of interest in this study (venture capitalist advice network)

Research Model

This study will examine the influence of the characteristics of the venture capitalist advice network, which function as a social, contextual and organizational determinant, on escalation of commitment. This provides a finer-grained overlay to the Staw model (1997) which further delineates influences on escalation of commitment. The following temporal model is proposed (see Figure 2.2 for the complete model and Figure 2.3 for the model component being tested):

Figure 2.2

Temporal Model of Social Network Effects on Escalation of Commitment by VC Firms

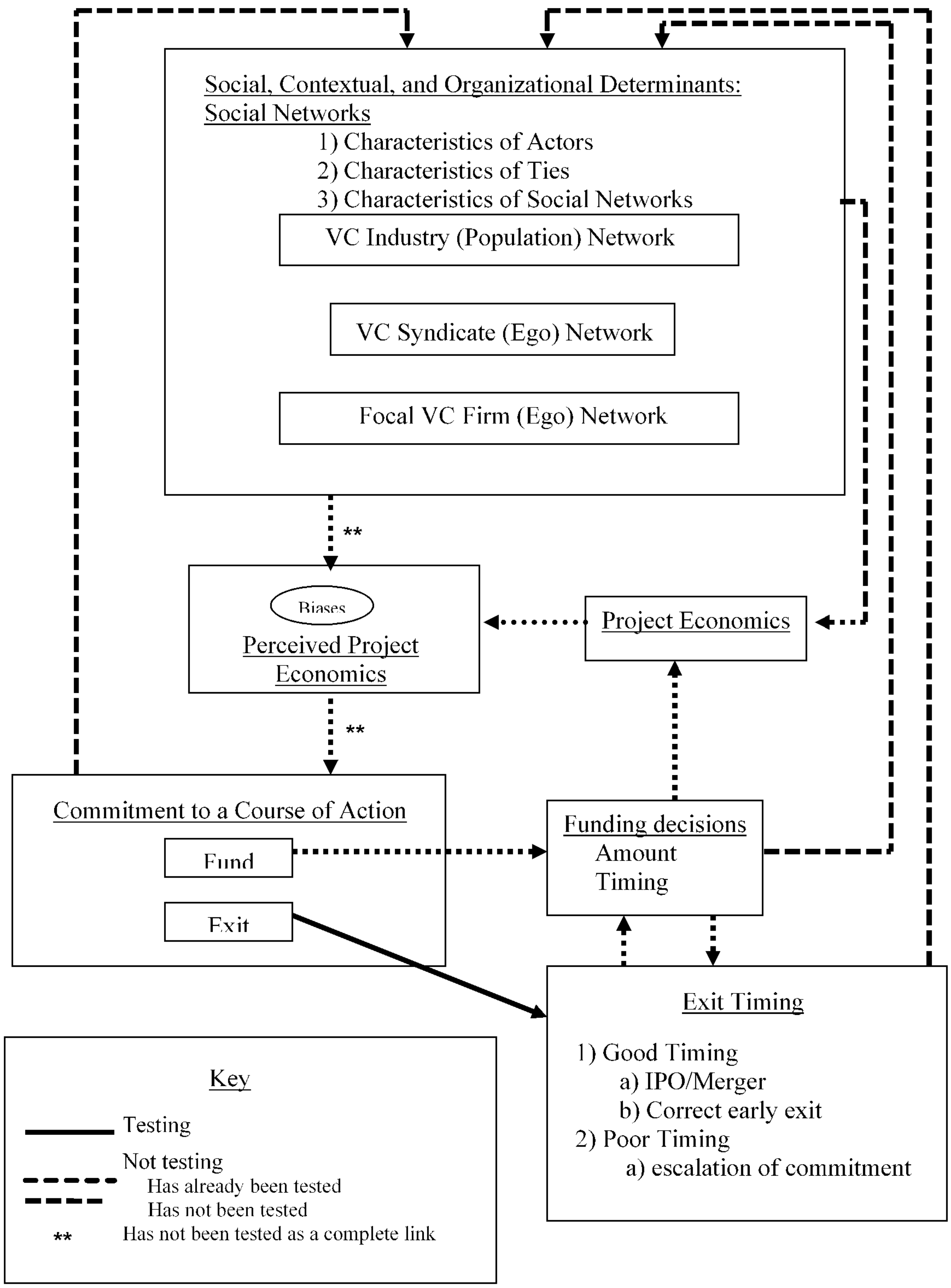
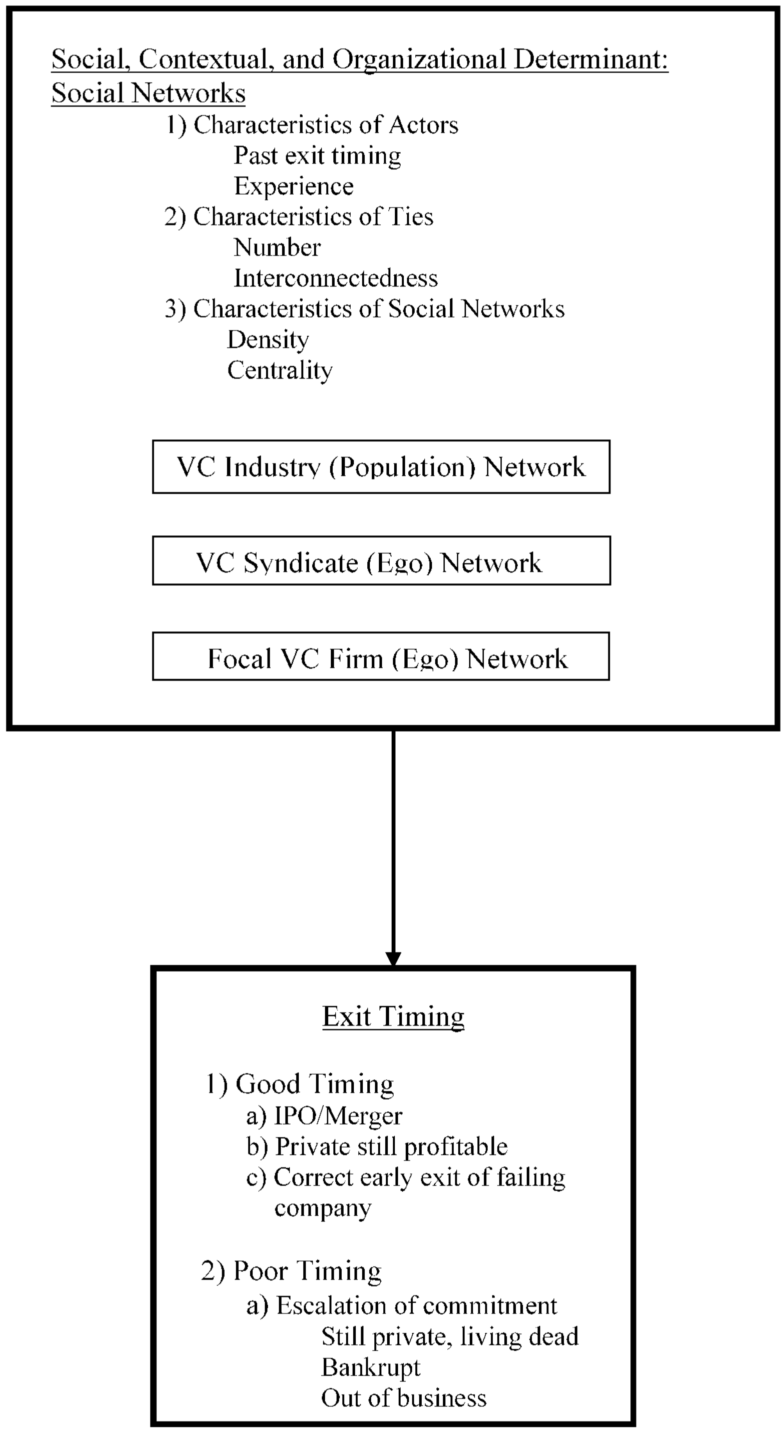


Figure 2.3

Model of Social Network Effects on Escalation of Commitment by VC firms
(Model testing, expansion of relevant part of Figure 3.2)



The figures illustrate an iterative model of the effects of social, contextual and organizational determinant components—the social networks of VC firms, syndicates, and the larger industry in which they are embedded—on escalation of commitment. The VC firm is embedded in several different networks which are nested within each other, all of which influence each other and project outcomes. Resources, information, and advice all flow through interfirm or syndicate ties. The egocentric networks, i.e., the direct ties the VC firm or the syndicate's firms have, of individual VC firms or syndicates differentially affect the VC firms' or syndicates' access to advice, information, and resources.

An individual VC firm partnering with another VC firm gains access to the partner's network relationships and information flows, like water through a pipe, through these network ties. All ties are not, however, created equal. A tie to a well-connected, experienced VC firm specializing in the same industry and stage of investment[1] would probably mean that the focal VC firm would have access to better advice, information, suggestions, resources, and potential partners than a tie to a VC firm that is inexperienced, funds companies in a different industry, or is more interested in funding late-stage rather than new companies. The skill sets of venture capitalists who are inexperienced, specialize in a different industry, or specialize in late stage funding are probably different than the skill set of venture capitalists in the former group. As a result, venture capitalists in the later group probably have less to offer in terms of directly useful advice.

The position of a VC firm in the larger industry-wide network affects its options as well. Poorly connected peripheral actors, for example, have less power and access to

[1] This would be the early stage in the case of this research.

resources than those who are densely, centrally located. As syndicates form and dissolve over time, as new venture capitalists enter or leave the industry, as individuals move from one VC firm to another or open their own firms, as individuals and syndicates are successful or unsuccessful and thus become desirable or undesirable partners, the configuration of all these nested networks changes.

Social networks' variables and configurations, as social, contextual and organizational determinants, affect commitment to a course of action. These networks, individually or together, influence biases and perceived project economics. Interpretations of events, "facts", and other information are often socially constructed. Over time, cohesive groups—in this case, syndicates—often come to hold similar opinions and beliefs. As a result, those with whom an actor is tied can affect biases and perceptions. When the actor is acting on their perceptions then they affect the particular decision made.

This research does not assess biases or perceived project economics on the basis of secondary data only. The link between networks and the course of action is examined with the intermediate step of perceptions and biases removed, as represented in the model in Figure 2.2 by the dark broken arrow that goes from the contextual dimension box to the course of action box through the perceived project economics box.

Once a fund or exit course of action has been decided upon, venture capitalists then need to decide how much to fund and when to fund, or, if the decision is to exit, how to exit. One timely or correct exit decision is an IPO/merger exit. A second is to terminate failing companies early on. An untimely or incorrect exit decision is to terminate late in the game after investing in many rounds of funding, which is the escalation of commitment scenario.

If the decision is to exit, regardless of exit timing, the reputation of the VC firm and its ability to raise money for further projects may be affected. The stakes are high, particularly in the case of a new VC firm funding its first project. If the venture is successful, the new firm will find it easier to raise money in the future. If the venture is not successful, the firm may experience negative consequences, including extreme difficulty in raising additional funds and the potential reluctance of others to syndicate on future projects. The new firm may potentially end up as an isolate, with no links to any other firm, or even drop out of the network entirely. On the other hand, when a highly experienced VC firm has a failed investment, it has other successes to soften the blow of failing; in addition, it benefits from the industry expectation that some failures are to be expected.

The history of a VC firm's success or failure affects its partnership opportunities and ultimately its position in the overall network. With repeated failures, a VC firm will probably find that it becomes progressively more peripheral in the overall industry-wide network, that the size of its egocentric networks decreases, and that any new ties are with VC firms even more poorly placed in the larger industry-wide network. As a result, the focal firm has progressively less access to "good" advice from network partners. The reverse would be true for firms with more successes and increasingly better reputations. Ultimately, the environment in which a VC firm is embedded will be changed by this cycle. Therefore, it should be possible to predict escalation based on the VC firm's demographics, including variables such as firm age and experience, track record, and industry and funding stage specialization, as well as individual VC firm network characteristics. The result is a dynamic model where the advice network of the VC firm influences the quality of advice a VC firm receives and, ultimately, whether a VC firm or syndicate escalates its commitment to a failing course of action.

Venture Capitalists' Demographics and Escalation of Commitment

In studying venture capitalists, Guler (2003) found that their reinvestment decisions were affected by individual biases, the structure of the investment and re-investment process, co-investor pressure, and the limited life of the fund. The result was that reinvestment decisions were not consistent with what would be expected under normative decision-making processes. While there was little difference between the ability of venture capitalists to manage and make rational reinvestment decisions for successful companies, the same was not true for their ability to terminate failing companies (Guler, 2003). VC firms that had more experience and fewer surplus financial resources were better at terminating failing investments than other experienced or inexperienced VC firms (Guler, 2003).

By itself, the experience level of a venture capitalist is not enough. Shepherd, Zacharakis, & Baron (2003) found that additional experience improved inexperienced venture capitalists' decision-making processes up to a point. Beyond a certain level of experience, however, the researchers documented decreased reliability and performance. They concluded that the more experience a venture capitalist has may not translate into better decisions. Shepherd et al. (2003) documented that venture capitalists' decision accuracy increased over time, with decision accuracy peaking at 12–15 years of experience. After this time period, good decision-making decreased somewhat. The explanation for these findings, the researchers suggested, was that inexperienced venture capitalists faced information overload, had a poor understanding of the all the complex factors involved in start-up success, and did not understand how these factors related to success, but experience helped them acquire an increasingly better understanding of these factors. Unfortunately, after 12–15 years of experience, venture capitalists tended to rely more on heuristic-influenced information processing based on past successes rather than on factors specifically relating to the new venture. Using heuristic-based or other automatic processing based models of decision-making such as mental short cuts or rules of thumb helped them become more efficient in quickly screening proposals or identifying problems. However, it also meant that they were often less systematic and less able to articulate explicitly how they evaluated proposals or identified potential problems early on in the life of their investment. As a result, these experienced venture capitalists may be less able to give specific advice to others about how they make decisions and problem-solve.

Based on Shepherd et al.'s (2003) findings, it may be that VC firms with direct ties to very experienced VC firms may actually get less concrete decision-making and problem-solving advice than if their ties were to VC firms with somewhat less experience, due to the tendency of these more experienced venture capitalists to be able to give less specific advice. On the other hand, ties with other young VC firms would result in less likelihood of good advice due to the young firms' lack of experience. Advice from venture capitalists with 12–15 years experience may be the most valuable.

De Clerc (2002) found that it was a venture capitalist's knowledge of a specific industry and previous investment history that affected future outcomes. These results were attributed to the added value a venture capitalist brings to an entrepreneurial company with regards to VC oversight, involvement with entrepreneur's strategic decisions, connections, and credibility. Experience in the industry increases what a venture capitalist brings to the table in terms of assistance to an entrepreneurial company (De Clerc 2002; De Clerc, et.al., 2001; Gupta & Sapienza, 1992). Clearly knowledge overlap is important. With strategic alliance and knowledge generation research, researchers have documented that the greater the knowledge overlap, or absorptive capacity, between the parties, the greater the depth of the learning and new knowledge creation (Cohen & Levinthal, 1990). One logical extension would be that when VC firms are specialists investing in, or in a network with others who are specialists in, the same or closely related industry, the VC syndicate is better able to recognize subtle problems and nip them in the bud, as compared to networks and syndicates where the venture capitalists have more diverse backgrounds. Another logical extension is that a VC firm's level of social capital, along with the benefits that are acquired from repeated investments, are what the experienced venture capitalists use to both manage successful investments and recognize failing investments. As a result, what may be important is not experience per se, but rather the specifics of a VC firm's experience. An experienced venture capitalist with a deep knowledge of the investment's industry or fewer investments that resulted in escalation of commitment may give more valuable advice than an experienced venture capitalist in another industry or with a poorer record of controlling escalation.

Taken together these literatures suggest the following hypotheses:

Hypothesis 1a: VC firms connected to primarily inexperienced or very experienced VC firms will escalate more than those with a higher percentage of connections to VC firms with 12–15 years of experience.

Hypothesis 1b: Syndicates with more VC firms with more industry relevant experience will escalate less than those with less past experience in that industry.

Hypothesis 1c: Syndicates with at least one VC firm with 12–15 years experience with fewer escalation outcomes and more experience in the industry of investment will escalate less.

Background Information on Social Networks

The success of a new company is not just dependent upon the quality of the entrepreneur's idea. As documented by social network research, entrepreneurs who are funded by well connected venture capitalists have preferential access to resources, people, and institutions that contribute both to the success of the venture and to a higher IPO valuation (Cable & Shane, 1997; Gompers & Lerner, 1999). However, social network research in the venture capital/entrepreneurial arena has had a limited focus to date. A mapping of connections between venture capitalists shows that venture capitalists are clustered in a limited number of areas in the United States, with the largest concentrations in the Silicon Valley area of California and along the Route 128, or greater Boston, area of Massachusetts (Bygrave, 1987; Bygraves & Timmons, 1992). In addition, wherever there are clusters of venture capitalists, there tend to be clusters of entrepreneurs and start-ups (Bygrave, 1987; Bygrave & Timmons, 1992; De Clerc, 2002; Gompers & Lerner, 1999).

Staw's (1997) model of escalation of commitment includes psychological, social, organizational, and contextual determinants. Although not discussed in the escalation of commitment literature, the social networks in the VC firm should influence these determinants at a variety of levels of analysis. VC firms are embedded in a larger venture capitalist network. The existence of these advice and investment networks has been documented by several researchers (Castilla, 2003; Sorenson & Stuart, 2001; Bygrave, 1987; Bygrave & Timmons, 1992). Venture capitalists ask trusted others in their network for their opinion of new ventures. If they decide to invest, they generally syndicate the investment with other trusted VC firms from their network whom they have relied on for advice or co-invested with in the past (Sorenson and Stuart, 2001). These social networks form a salient part of a VC firm's social environment and influence its investment decisions. As such, they should influence the propensity of venture capitalists to escalate commitment as well.

A social network is a set of actors, known as nodes, which can be individuals, groups, organizations or societies, and the relationships between these actors, known as ties (Wasserman & Faust, 1994; Burt, 1992). Social network theory posits that actors are embedded in networks and these relationships, or ties, best predict actor behavior. In addition, people behave similarly because they are in structurally equivalent positions, meaning located in similar locations in their respective networks. Structurally equivalent actors are subjected to similar pressures and constraints and have similar opportunities. Understanding the social system in which actors are embedded depends not only on direct ties between the individual actors but also on everyone else's ties, or lack of ties, with every other actor. Together, the structure of nodes and ties defines the characteristics of the network. As a result, there is interdependence among the units of the network, and the flow of information between two actors depends not only on their own relationship but also on how they are embedded in a cluster of relationships (Katz et al., 2004; Wasserman & Faust, 1994; Burt, 1992). In this research, the ties of interest are those between the focal VC firm, the VC firms in the syndicates in which the VC firm invests and the additional direct ties of the syndicate members.

There are two perspectives when modeling network ties. The first is to create an egocentric network, which is a collection of ties from the point of view of the focal actor. When modeling this kind of network, the ties and actors of interest are the ones connecting directly to the focal actor. The second perspective is to model the entire network and then look at network variables in the context of the outcomes of interest (Wasserman & Faust, 1994).

This research examines three levels of networks. The first level is the ties and actors directly connected to a focal VC firm. The second level examines the ties and actors directly connected to a focal VC syndicate. The last is the focal firm's position in the overall VC network and is modeled by all the actors and their ties, or lack of ties, in a defined environmental space (Wasserman & Faust, 1994). In the context of this research, the defined environmental space is all private equity VC firms, whether included in the syndicates or investing alone without a syndicate, that invest in early-stage start-up entrepreneurial companies in the high technology industry sector during the defined time period. The characteristics of the environmental space network, the focal VC firm ego network, and the collective VC firms within a syndicate's ego network will be used to predict escalation of commitment.

A broad range of ties exists between actors, including communication, formal, affective, work flow, proximity, and cognitive ties. Generally, actors are linked by more than one kind of tie and so networks are considered to be multiplex (Katz, Lazer, Arrow & Contractor, 2004). Ties can be strong, such as family and friends, or weak, such as acquaintances (Granovetter, 1973, 1982). Weak ties are especially important when the actor needs unique or diverse information. Strong ties often involve a high level of trust between the actors. Ties can be one-way connections, known as directional ties, or non-directional ties. The interactions between actors can vary in frequency, medium of connection, and may be positive or negative (Katz et al., 2004).

The relationships within a network have been quantified and include a number of measures. Actor degree centrality indicates the extent to which actors directly send or receive ties to each other. Closeness centrality is the extent to which actors are connected directly or indirectly—for example a friend of a friend—with other actors. Betweenness centrality measures the extent to which actors are connected to others who are not connected with each other. Information flow centrality measures not only how central an actor is but also how easily information can flow between two nodes in the network. All of these centrality measures will be used because it is this advice flow that is being used to predict escalation of commitment.

A clique is defined as a group of actors who are connected exclusively or almost exclusively with each other and not with others in the network. A structural hole is formed when one group is isolated from another group except for one node that has ties to both groups. The actor occupying the node which is the structural hole controls the flow of information between the two groups and gains power and information (Katz et al., 2004; Burt, 2001, 1997, 1992). The unit of analysis is *not* the individual actor, but rather the ties between the actors (Katz et al., 2004; Wasserman & Faust, 1994). As a result, the “n” of a network study is the number of ties rather than the number of nodes.

Social Networks, Venture Capitalists, and Escalation of Commitment

Several relevant theoretical approaches may be used to explain network influences on outcomes of interest. One approach presumes that people come together for self-interested reasons and form ties with those who may be able to help them. The tendency for actors to be constrained by the relationships in which they are embedded both limits self-interested activity and increases the actors’ access to additional resources they could not access on their own (Katz et al., 2004; Monge & Contractor, 2003; Coleman, 1988). The investment that actors make in social ties creates social resources known as social capital. Actors use social capital to gain access to opportunities or other resources from which they can profit (Lin, 2001; Nahapiet & Ghoshal, 1998; Coleman, 1988). For example, social capital has been documented as a factor affecting strategic alliance success (Gulati, 1998; Gulati & Singh, 1998). In this study, the resource that venture capitalists gain access to is advice, which varies in quality depending on a number of network and venture capitalist characteristics.

The social network approach to social capital also looks at the optimal communication network configuration for the task at hand. Early research on communication networks within groups consisted of laboratory experiments where patterns of communication between group members were manipulated to see the effects on group performance and functioning. One major early finding was that a person serving as a communication hub center, meaning a centralized network, was an important moderating variable. Centralization was best for simple tasks. On the other hand, a decentralized structure was best when a task was complex, information was ambiguous, or there was uneven distribution of information among group members; the decentralized structure made it more likely that needed information was available to the actor needing it (Leavit, 1951; Shaw, 1954, 1964, 1971). If the network of a focal VC firm is decentralized and not dense with ties, the firm would suffer from lack of information. If, on the other hand, the network is too cliquish, the firm would suffer a lack of information variety. In both cases, escalation would be more likely than with VC firms embedded in network relationships between these two extremes.

Outside the laboratory in real life work group settings, researchers replicated earlier findings and also found that decentralized groups outperformed centralized ones (Cummings & Cross, 2003; Sparrowe, Linden, Wayne & Kraimer, 2001). Groups with more ties outperform those with fewer ties (Baldwin, Bedell, & Johnson, 1997; Reagans & Zuckerman, 2001). Groups which have ties to other actors external to the group gain access to useful information (Mizurchi, 1996; Anacona & Caldwell, 1992). For example, board of director interlocks demonstrate that information from other boards on which an actor serves can be, and often is, brought to the focal board (Davis, 1991; Haunschild, 1993).

Hansen (1999) documented that the tie, or relationship, strength and information complexity interact and affect group performance. When complex information is needed, a number of redundant strong ties transmitting that information are necessary in order for a group to actually use that information. Lazer and Katz (2004) documented another benefit of many group members sharing overlapping external ties—group members were less likely to free ride. In addition, this structural embeddedness influenced group members' actions and effort (Granovetter, 1985; Uzzi, 1996).

On the other hand, Burt (1992) documented the benefit of having non-redundant external ties, which give greater access to resources and information. VC firms located in portions of the network that are more densely interconnected are more likely to have redundant strong ties. In addition, when examining the variety of ties that all the VC firms in the syndicate have, some ties should be unique to an individual VC firm in the syndicate, which would afford the focal VC firm, and therefore the syndicate, access to a larger variety of information and advice, thereby escalation less likely. On the other hand, a VC firm which only had a few contacts through less dense or clique-like networks would have access to less varied information. As a result, it might be more likely to miss finding critical information that might help it recognize a failing venture sooner and thus be more likely to escalate.

The cognitive approach to explaining network influences on outcomes of interest includes elements from both transactive memory and cognition theories. Network ties facilitate information and knowledge flows between actors, something measured by the various centrality measures. Communication between the actors helps them identify and use knowledge within the group. This reduces the need for any one actor to have all the skills or expertise needed if these attributes are available elsewhere within the network. In addition, two actors with a tie with each other would be more likely to consistently evaluate a third actor in the same way due to cognitive consistency (Hollingshead, Fulk, & Monge, 2002; Moreland, 1999; Wegner, 1995, 1987). Venture capitalists do invite other VC firms to co-invest with them in order to add a needed knowledge base or other resource (De Clerc, 2002).

Lockett & Wright (1999) documented that partner selection in syndication is influenced most by the following, in descending order of importance: reputation of the VC firm, trustworthiness of individual venture capitalists and their ability to deliver, past positive dealings with the venture capitalists or VC firm, and investment style, or refinancing and exit preferences. The reputation of an individual venture capitalist or VC firm affects access to other venture capitalists' investment/advice networks and their other networks such as IPO investment bankers and suppliers, (Ferrary, 2003). The connection of VC firms to these other networks can influence the outcome of a funded company. Venture capitalists add economic value to the companies they fund, in part due to resources, advantages, and reputation effects conferred on the start-up company because of the venture capitalists' network contacts (D'Amico, 2002).

Reputation can also help to reduce uncertainty because it is used to decide if information is credible. Knowing that information is credible increases its value. Information from a source which is considered credible is more likely to be believed credible and therefore useful (Ferrary, 2003). VC firms, which often have long-standing relationships with, and therefore knowledge of, other VC firms, are able to make these kinds of judgments about their investment partners and, therefore, about the credibility of their information and advice (Wright & Lockett, 2002; Ferrary, 2003). In addition, VC firms have different reputations and expertise in different market segments. Partners may be chosen explicitly for their expertise and experience in a certain industry segment or with a particular technology (Lockett & Wright, 1999).

The search for partners, as for example in strategic alliances, is frequently limited to network members as the searcher uses trusted network members as a heuristic shortcut. Generally, information about more distant network potential alliance partners is obtained through closer network partner connections (Reagans & McEvily, 2003; Duysters & Lemmens, 2003; Yli-Renko& Alito, 1998; Gulati & Singh, 1998; Gulati,1999). This is consistent with how venture capitalists find promising new ventures to fund. Those business plans forwarded to them by friends are much more likely to be funded than those received over the transom (Bygrave, 1987; Bygrave & Timmons, 1992; Gompers & Lerner, 1992). Also, venture capitalists do invite other VC firms to co-invest with them in order to add a needed knowledge base or other resource (De Clerc, 2002). Venture capitalists who have high information flow centrality, that is, those who are well connected and can easily reach other venture capitalists through fewer layers of "friends of friends", should have more opportunities to invest and better access to trustworthy specialized or needed advice and information, and therefore should escalate less.

The influence of network variables on escalation of commitment, as suggested by the literature, will be tested with the following hypotheses:

Hypothesis 2a: VC firms with less dense networks or with clique-like networks will be more likely to escalate.

Hypothesis 2b: VC firms located in a more densely interconnected portion of the network, where they themselves are more densely connected to other VC firms, will be less likely to escalate.

Hypothesis 2c: VC firms that are not tightly and exclusively connected with only a small number of other VC firms (i.e., are not in a clique) will escalate less.

Group Processes in Venture Syndicates, Social Network Functioning, and Escalation of Commitment

One perspective for explaining network influences on outcomes that is relevant to group processes is based on the similarity/attraction construct. Similarity between individuals reduces conflict or potential conflict between them (Byrne, 1971; Sherif, 1958). Similarity increases the likelihood of ties, as ties between actors are more likely to be created when the actors perceive themselves to be similar. Similarity makes communication easier, makes behavior more predictable, and increases trust and reciprocity (Brass, 1995). How similarity is determined is an area that has generated considerable research. Self-categorization theory argues that individuals self categorize themselves and in the process define their social identity. They then associate with those whom they perceive as similar to themselves (Turner & Oaks, 1986, 1989; Brass, 1995). If the close ties between venture capitalists are based on similarity, then venture capitalists might experience a decrease in the kinds of information and divergent viewpoints to which they have access. As a result, they might have more trouble acquiring divergent opinions as the investment progresses, increasing the possibility of escalation.

One problem when VC firms syndicate is the need for joint decision-making concerning the funded start-up company (Wright & Lockett, 2002). While many of the venture capital players may have worked with each other in the past, generally not all have. The VC firms that come together to fund a particular venture function as a group providing oversight when making decisions about continuing funding. Syndicated funds generally have a life of about ten years, with the option to extend the fund one to three additional years (Bygrave & Timmons, 1992; Gompers & Lerner, 1999). This means that the life of a VC syndicate group is also about ten to thirteen years.

During the funding of a start-up company, individual VC firms enter or leave the syndicate after funding one or more rounds. Generally VC firms which make the initial decision to fund a venture stay involved in funding the start-up until the hoped-for final successful conclusion, such as an IPO or merger. This is because the VC firms which are in the syndicate for the entire time, not late syndicate entrants, usually make the most money from a successful offering. However, some VC firms specialize in a certain stage of funding, such as early-stage, later- stage, or just prior to the IPO. Just as VC firms can leave the syndicate group, they also can enter it at later stages (Bygrave & Timmons, 1992; Guler, 2003). When a new group member enters an existing group, other group members have been documented to suppress conflict, something that can be detrimental to decision-making (Gruenfeld & Hollingshead, 1993; Gruenfeld et.al., 1993). Group pressures and other group factors also can affect decision-making. Gular (2003) documented how VC syndicates are subjected to pressures from each other and how their functioning is affected by interpersonal relationships.

Wright & Lockett (2002) documented that VC syndicates make decisions using consensus and collective discussion. The lead member may or may not be the most influential member in the decision-making process. Threats to withdraw, reciprocal actions, and threats of non-investment in future rounds were as or more important than legal sanctions in making sure syndicate members complied with the syndication agreements. When an investment is performing badly and there are differences of opinion about what to do, contractual rights become most important. As a result, some of these actions may impede good decision-making, increasing the importance of a syndicate having good conflict resolution skills.

The literature on groups and teams addresses these issues. It takes time for groups to learn to work together productively and to effectively resolve conflict (Jehn & Mannix, 2001). The ideal group size for complex tasks—which certainly describes the task of funding and guiding a new venture to success—involves tradeoffs between the greater resources available due to more members and the decreased member involvement due to larger group size (McGrath & Kravitz, 1982; Kowitz & Knutson, 1980; Scheidel & Crowell, 1979). On one hand, a larger group, which generally has more resources available, is better prepared to deal with more complex problems. As an example, venture capitalists sometimes invite a specific VC firm to participate in a syndicate because of the unique resources it can bring to the project (De Clerc, 2002). On the other hand, when a group is larger, fewer group members actively participate and members can be less committed (Bales, 1950). Diffusion of responsibility in larger groups occurs because individuals have lower levels of felt personal responsibility for the final outcome (Karau & Williams, 1993; Latané, Williams, & Harkins, 1979). De Clerc (2002) documented that when venture capitalists are less committed, the syndicate is more likely to escalate.

Larger groups have more problems with group processes as well. The literature suggests that for complicated tasks an ideal group size is between five to seven members

(Birmingham & McCord, 2002; McGrath & Kravitz, 1982; Kowitz & Knutson, 1980; Scheidel & Crowell, 1979). This may or may not be the ideal size for the total number of venture capitalists involved in funding a new venture or for the size of the group of VC firms funding any one round. VC syndicate member size generally does not remain constant over the life of the company being funded, which complicates group process-related issues. Although VC firms may partner with a relatively small set of other VC firms, some do syndicate with a wide variety of partners (Chiplin, Robbie & Wright, 1997). As a result, some VC syndicates have more experience working together than others. Although larger VC syndicate groups have been documented to escalate (Birmingham, et al., 2003), based on the groups literature, it could be expected that VC firms which syndicate with other VC firms they have worked with before will be less likely to escalate, largely because they will be able to sidestep the problems that are typical to new groups and move quickly have productive, rather than unproductive, conflict. As a result the following is expected:

Hypothesis 3a: When VC firms work with other VC firms they have worked with in the past they will, up to a point, escalate less than if they have never worked together. When they exclusively work only with each other, they will escalate more.

Anecdotal evidence indicates that the larger the size of a syndicate, the larger the number of inexperienced venture capitalists, and less committed investors all contribute to increased difficulty with syndicate decision-making and problem-solving coordination in new venture companies (D'Amico, 2002). There is also direct and indirect research evidence of this. Chiplin, Robbie & Wright (1997) document that syndication slows down and complicates decision-making, especially when the syndicate group is large and the investment underperforms. Wright & Lockett (2002) document that when VC syndicates are large, not only are there more coordination problems but that there are decision-making problems as well. Birmingham, et al., (2003) have documented that larger syndicates tend to escalate more frequently than smaller syndicates.

These findings suggest that larger VC syndicates have increased group process and decision-making problems and therefore a higher likelihood of escalation when a company is in trouble. On the other hand, the longitudinal group decision-making/ group process literature points out that experience working together as a group, use of consensus, and open discussion can actually improve decision-making and allow groups to take better advantage of the skills and knowledge of their members, resulting in improved performance (Arrow & McGrath, 1993; Birmingham & Michaelsen, 1999; Watson, Kumar & Michaelsen, 1993; Watson, Michaelsen & Sharp, 1991).

Group process is affected by a number of factors, the first of which is group diversity. Although group diversity may be needed to provide the range of resources necessary for project success, initial diversity has a potential negative impact on group processes (Watson, Kumar & Michaelsen, 1993; Chatman, 2001; Williams & O'Reilly, 1998) because diverse groups are less likely to be cohesive than more homogenous ones (Shaw, 1981). There are several reasons for this. More diverse groups typically have more initial difficulties, and it takes time for diverse groups to learn how to work together, trust each other, manage conflict, and utilize member resources effectively (Watson et al., 1993; Jehn, 1995, 1997; Jehn & Mannix, 2001). In addition, as trust in group members increases, the willingness of members to deal with conflict, rather than leave it unresolved or suppress it, increases. Increasing trust also leads to increasing group cohesion which improves group performance, in part because unproductive conflict is reduced (Jarvenpaa, Knoll & Leidner, 1998; Johnson, Johnson & Scott, 1978; Jehn & Mannix, 2001).

Although diverse groups have more initial difficulties, if they can resolve them they generally are more effective than more homogeneous groups in the long run (Watson et al., 1993; Jehn, 1995, 1997; Jehn & Mannix, 2001). The group think literature points out the danger of too much group cohesion (Janis, 1982; Janis & Mann, 1977). In highly homogenous groups, especially where conflict is suppressed due to conformity pressures, group think could be a danger and further decrease the group's ability to recognize or consider conflicting information. On the other hand, the literature documents many benefits of group cohesion on decision-making. As diverse groups resolve and process conflict their group cohesiveness tends to increase (Evans & Dion, 1991; Gruenfeld & Hollingshead, 1993; McGrath, 1984; Watson et al., 1993; Shaw 1981.). Watson et al. (1993) documented that a certain level of group cohesion is necessary in order for a group to be able to constructively use conflict and diversity to find better solutions to problems. The result is enhanced group effectiveness and performance (Evans & Dion, 1991; Gruenfeld & Hollingshead, 1993; McGrath, 1984; Watson et al., 1993; Shaw 1981.)

Experience working together as a group affects decision quality (Arrow & McGrath, 1993). One skill that is honed over time is constructive conflict resolution, a key skill for groups to master in order to utilize the resources available to them from both outside and inside the group. A productive group has little relationship conflict which is interpersonal conflict between group members. After group members have worked together for a while, they have little process conflict, or conflict over how to make decisions. Productive groups do, on the other hand, have moderate amounts of cognitive conflict, or conflict in the form of in depth discussions over ideas, decision options, and solutions. Under these conditions group performance is the highest, because when groups disagree over content and at the same time have little conflict in other areas, a broader range of ideas and information is more freely offered, discussions are not prematurely cut off, information is examined more carefully, better decisions processes are used, and ultimately better decisions are made resulting in higher group performance (Jehn, 1995, 1997; Jehn & Mannix, 2001; Birmingham & Michaelsen, 1999; Gruenfeld et al., 1993).

Jehn (1995, 1997) found that new groups and teams often perceived all conflict as interpersonal conflict which negatively impacts group performance and group cohesion. As time went on, successful groups and teams reduced interpersonal and process conflict and increased cognitive conflict which increased their problem-solving and group performance (Jehn, 1995, 1997; Jehn & Mannix, 2001). When groups learn to constructively manage cognitive conflict, their performance is increased because ideas are more thoroughly examined and new information is more likely to be brought to the table, both of which increase task performance (Jehn, 1995, 1997; Jehn & Mannix, 2001; Watson et al., 1993). When groups gain new members, however, other group members tend to suppress any kind of conflict, and this suppression can lead to poorer decisions (Gruenfeld & Hollingshead, 1993; Gruenfeld et.al., 1993). This is notable because VC syndicates generally have member change over time.

Self-selected groups tend to be more homogenous (Bies & Shapiro, 1988), which reduces their problem-solving potential. Venture capitalists generally invite other venture capitalists who are network members to syndicate with them. There is a tendency of close network members to be more homogenous than more distant or unconnected network members (D'Amico, 2002). This could decrease the syndicate's potential to have the diverse opinions and access to unique information that helps groups de-escalate (Brockner, 1992; Staw, 1997). In addition, when venture capitalists are deciding about additional funding rounds for the start-up company, they commonly do not have all the information they need, which makes them prone to conduct a biased information search. They are then more likely to pay more attention to information that supports their pre-decision preferences or chosen alternative, which is generally to fund in hopes of getting their investment back. In this situation, they are less likely to look for, pay attention to, bring to the table, or even consider conflicting or negative information (Galinsky & Moskowitz, 2000; Schulz-Hardt et al., 2000). In addition, groups tend to pay more attention to information they hold in common rather than to unique information known only to a few members (Stasser, 1992).

Groups tend not to seek disconfirming information when making decisions, a tendency which leads to poorer decisions (Kray & Galinsky, 2003). Groups need to actively seek, find and use disconfirming information to improve decision-making and to prevent escalation (Brittain, Sitkin, & Neale, 1986; Staw, 1997). De Clerc (2002) documented that venture capitalists do not complete a full due diligence when deciding on additional rounds of funding. Instead, they seek out and consider a more limited set of new information. In addition, many did not seek out disconfirming information when they did review the prospects of the investment. If a VC syndicate group is too homogenous, it may not have access to disconfirming or diverse information without a deliberate search. As a result, poorer decisions may be made when a company is in trouble, resulting in escalation. When this is combined with a situation where the VC syndicate has membership that is too fluid or members who are not well known to the rest of the group—for example, members who are more distantly linked in the network or physically not co-located so that there is less causal interaction—the group dynamics may not be conducive to allowing disconfirming information to be heard or considered, even if the venture capitalists actively searched out disconfirming or conflicting information.

Venture capitalists who have not worked together before may need to spend time building trust before they are effective in making joint decisions. This may be especially true if experienced venture capitalists invite less experienced ones to join a syndicate. In addition, disconfirming information that a less experienced VC firm brings to the attention of more experienced ones may be discounted if the firms have never worked together, due to less trust in the judgment of the less experienced venture capitalists. As a result, one might expect that when a less experienced VC firm joins a syndicate later in the financing rounds, the syndicate receives less new information from the new member than it would if the VC firm was more experienced. It may be, however, that experienced venture capitalists put too much trust in each other and do not question each others' judgments as much. The interaction of group size and previous experience working together suggest the following hypothesis:

Hypothesis 3b: Larger groups, when made up of more venture capitalists who have worked together in the past, will escalate less than larger groups made up of fewer venture capitalists who have worked together in the past.

Summary of hypotheses

Hypothesis 1a: VC firms connected to primarily inexperienced or very experienced VC firms will escalate more than those with a higher percentage of connections to VC firms with 12–15 years of experience.

Hypothesis 1b: Syndicates with more VC firms with more industry relevant experience will escalate less than those with less past experience in that industry.

Hypothesis 1c: Syndicates with at least one VC firm with 12–15 years experience with fewer escalation outcomes and more experience in the industry of investment will escalate less.

Hypothesis 2a: VC firms with less dense networks or with clique-like networks will be more likely to escalate.

Hypothesis 2b: VC firms located in a more densely interconnected portion of the network, where they themselves are more densely connected to other VC firms, will be less likely to escalate.

Hypothesis 2c: VC firms that are not tightly and exclusively connected with only a small number of other VC firms (i.e., are not in a clique) will escalate less.

Hypothesis 3a: When VC firms work with other VC firms they have worked with in the past they will, up to a point, escalate less than if they have never worked together. When they exclusively work only with each other, they will escalate more.

Hypothesis 3b: Larger groups, when made up of more venture capitalists who have worked together in the past, will escalate less than larger groups made up of fewer venture capitalists who have worked together in the past.

Methods

Previous research has documented that venture capital firms can escalate their commitment to failing new start-ups. This study examines the venture capital advice network's influence on escalation of commitment. Network analysis and regression are used to analyze the data.

Network Analysis

Basic network analysis is done using the network analysis program UCINET. The data collected is about the ties, or relationships, between nodes or actors. This program models networks graphically by showing actor ties between VC firms who have funded new start-ups together, tie strength, and information about both the individual VC firm actor and the network as a whole. For each node, UCINET computes network variables and can attach attribute information as well. UCINET's output can be exported to other statistical programs, with statistical network variable data and attribute data attached to each actor in the exported data. Pajek was used for drawing the graphic visualization of the network. It is better than UCINET in terms of graphics.

This study looks at the entire network rather than using samples. Although a given network may be chosen by a random sample of all networks in a larger population, when doing network analysis it is important to have information about every node in the chosen network sampled rather than having a random sample of network members. It is the nature of the entire network and each actor's position within it that is of interest. As a result, randomly sampling actors in the network would mean modeling an incomplete network, which could easily destroy the network's fundamental characteristics. As a result, having relatively little missing data is important. It is also important to be clear about the boundaries of the network under study (Wasserman and Faust, 1994).

Once all the connections between actors are entered into UCINET, a model of the entire network is obtained and it is possible to examine parts of the networks. UCINET statistically divides networks into components based on tie connections and density. In this study, the entire network is used. UCINET also makes it possible to look at "local neighborhoods" by considering only the ties between focal actor A and A's "neighbors", which are other actors, *Bi*, directly connected to focal actor A. The "friends of friends" level can be considered by observing actors *Ci* connected to *Bi* connected to A (Wasserman and Faust, 1994). Some hypotheses contrast network components. When considering advice networks, sometimes only the "neighbors" *Bi* are considered; sometimes the "friends of friends" *Ci* are used. It is the network actor tie variable values and sometimes the demographic values of the actor that are used as the independent variables.

Since the relationship between the actors, rather than the actors themselves, is the focus of study, *n* is generally the number of ties between actors. As a result, data collection consists of obtaining a list of all the ties that exist between all actors in the network. Data collection also includes demographic or other attribute variables for a given actor. For any given network, there are a maximum number of ties possible where every actor is connected to every other actor. There is also a minimum number of ties where no actor is connected to any other actor. In the latter case all actors would be isolates. All network variables are computed within the context of the number of actors in the specific network under study. As a result, it is not possible to directly compare the network variable values for one actor in one network to that of an actor in a different network. The values are specific and relative to the network under examination (Wasserman and Faust, 1994).

In this study, the focal VC firms consist of the entire population of VC firms who funded high technology companies between 1990 and 1995. In addition, information about the VC firms each focal VC firm partnered with in the past are of interest. The time period chosen provides enough time to learn the outcome of the companies funded and reflects the general ten-year lifespan of VC syndicates from first funding to final disposition. The industries chosen—computers, semi-conductors, and communications—are all in high-velocity environments where rapid change, along with rapid speed to market of new products, is the norm. This increases the likelihood that all companies in the study will have reached their final disposition by December 2005.

The study is a bi-modal network because it includes information about both the VC firms and the companies they funded, although the ties of interest are only those between the VC firms. As such, the network model represents only VC firm-to-VC firm ties. The companies funded are of interest because they determine the existence of those ties. A tie between two actors is coded as either present or absent based on whether or not they have funded a specific company together. Company-funded information is attached to each VC firm so that *Bi* and *Ci* ties can be determined. The final disposition of the companies first funded in the 1990–1995 time period is used as the dependent variable. Network analysis is used only to graphically model the network and to obtain values for network variables. The network variables attached to the relationships between VC firms, obtained by network analysis, are used to predict, using regression, target company outcomes. UCINET's other analytic possibilities and capabilities are not of interest for this study.

Data

Data for this study came from VentureXpert from Thompson Financial/Venture Economics. VentureXpert, a web-based commercial database, is one of the few comprehensive databases of new venture and venture capital information. It lists the following information about venture capital firms:

1) VC firm's name and primary address (secondary office addresses are not included),
2) A proprietary geographic location code of the primary address,
3) Date of founding,
4) Names and dates of funds raised,
5) Entrepreneurial companies invested in, including in which round, and
6) Any name changes for the VC firms.

This database lists the following information for entrepreneurial companies:

1) The date the company was first incorporated,
2) The company's industry [2],
3) The company's name and address,
4) Any name changes for the company,
5) A proprietary geographic location code, and
6) The ultimate disposition of the company—IPO date, merger date and merger partner, bankruptcy date, etc.

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[2] This a proprietary system that is more fine grained than SIC code, although the industry could be tracked back to SIC code if necessary.

Information about rounds of funding for each company includes the following:

1) The company's stage at each round of funding—early stage, late stage, expansion, etc.,
2) Date and total amount of funding received in each round, and
3) Names of the VC firms that contributed to each round.

Although VentureXpert is the best available source of date, it has weaknesses which affect its usefulness for this study. These weaknesses include the following:

1) There is some underreporting of unsuccessful companies relative to IPOs and mergers. About half the companies in this database went public or were acquired, even though the VC industry average is about one third (Birmingham, et al., 2003; Gompers & Lerner, 1999).
2) Private equity VC firms, the ones of interest in this study, are not required to report some of the information that would contribute to a less biased database.
3) Some information in reporting rounds of funding is missing for a few companies.
4) VentureXpert frequently reports a company's outcome as "active investment" when, in fact, the company is defunct. Fortunately, by using LexisNexis it is possible to find IPO, merger, and bankruptcy information for some of the companies with missing information, as well as "active investment" disposition information. In addition, the use of online business phone directories can help confirm the disposition of missing companies. Consistent with Birmingham, et al. (2003), a company is classified as out of

business if there is no trace of it for two years beyond the last round of funding from any of these sources.

Escalation of commitment is analyzed only with reference to private equity VC firms funding early stage new start-ups. The research is limited to start-up companies in the computer, communications, and superconductor industries because they are high-velocity, high-technology industries. Information is collected concerning all deals the focal VC firms made for the fifteen years prior to 1990 because this is needed to establish the advice network. Documenting prior embeddedness of the VC firms before examining the years of interest allows greater accuracy in demonstrating network influence on escalation. It also makes it possible to determine if a VC firm specializes in only certain industries, funds only new start-ups, or acts as a generalist.

The companies of interest are all high technology companies that were classified as early stage (new start-up) companies between 1990 and 1995, along with the VC firms that funded them. The funding and status of these companies is tracked through December 2005. The VC firm's fund that is used to fund a start-up company usually has a ten-year life with up to three years extension possible. Typically, the first four to seven years is spent developing the company with the intent of taking it public; most, if not all, of the money is spent during that time. The final years of the fund's life are spent recouping the investment and distributing the proceeds. Venture capitalists often retain a stake in the company for two years beyond an IPO due to legal restrictions, the issues involved in unloading large blocks of stock at once, and the sometimes dramatic growth of the stock's value (Gompers & Lerner, 1999). It is assumed that all funds used to fund any new company during this time period would be spent by December 2005.

Dependent and Independent Variables

Dependent variables

Company outcome: Consistent with entrepreneur and venture capital research, outcomes are classified as IPO, acquired/merger, still private, and out of business (Ruhnka, Feldman & Dean, 1992). While some companies that are still private may be profitable, the majority are not. In determining the status of a still-private company, if evidence shows that the company is still in business with corporate offices, employees, and a product generating income, then the company is coded as private and successful even though it has not yet had an IPO/merger. Where no evidence indicates that a company still exists and the company has gone at least two years without a round of funding, it is coded as out of business. Where no evidence can be found concerning a company's disposition, if it has been less than two years since the last round of funding, the company is coded as unknown. A company is categorized as private and unsuccessful if a record shows it exists and is not profitable; otherwise, it is categorized as out of business.

Timeliness of exit: Because it is impossible to determine in advance when escalation will occur, a judgment needs to be made after the fact. Consistent with Birmingham et al. (2003), there are fundamentally two types of good decisions concerning the funding of new ventures. The first is the decision to keep funding a company that results in an IPO, is acquired, merges, or is otherwise profitable. The second is recognizing, early in the funding process, that one is backing a failing company and deciding to cut off funding after one or two rounds of funding to minimize losses. In both cases, the venture capitalist's decision is coded as good decision-making. Poor decision-making is coded for companies that had more than two rounds of funding and are either out of business or are “living dead”—meaning companies still private in December 2005 but not profitable.

Independent variables

There are two different kinds of independent variables. The first are demographic variables such as date of founding for the VC firms, VC syndicates, and entrepreneurial companies. The second are network variables. The former, listed in the database referenced earlier, required additional research to fill in missing information. The latter required examining each new start-up of interest, as well as historical information going back 15 years prior to 1990, in order to list which VC firms funded which companies, and then entering each tie and tie type. Using UCINET, this matrix of ties was then used to create advice networks for the VC firms.

Demographic variables:

1) Date the VC firm was founded,
2) The number of companies the VC firm funded prior to 1990 (a measure of experience),
3) Industries in which the VC firm has funded - by number and by percent of total number of companies funded,
4) Percentages and absolute numbers of successes, good timing early failures, and escalations of past ventures the VC firm funded as a measure of venture capitalist skill.

Network independent variables

The variables for each network require first coding the ties between the VC firms in a matrix. UCINET is then used to create the network and network variable values for each VC firm. These network variables and their values are then exported and are used with regression analyses.

The network ties:

Network ties, those funding ties between VC firms that have funded in syndicates together, are entered in a matrix as non-directional ties. It is not possible to determine with the available data which is the lead VC firm. Using the resultant matrix, UCINET creates a picture of the network and calculates the network variables of interest for each node. The *n* for subsequent analysis then becomes the number of ties between VC firms rather than the number of VC firms.

The network variables created from the resulting network, using UCINET, are as follows:

1. Density is the number of connections in the entire graph over the number of possible connections. It is a property of the network (Wasserman and Faust, 1994).
2. K-plex measures the "local" density around each node. Because of the focus on the ties around the node, k-plex is used to measure cliques which do not have mutually exclusive memberships. It looks at the density of ties between the clique members compared to outside the clique ties (Wasserman and Faust, 1994). In this case the VC firms are ranked by k-plex score. This is abbreviated as *VCkplexRank1* in the analyses.

3. Information flow centrality is the best measure of centrality in a network with regards to how easily information can get to a specific node. This measure takes into account all paths, both direct and indirect, between the nodes. Paths are also weighted inversely with respect to their length. A short connection between two actors counts more than a long one, because information is more likely to be received by the node of interest if the path is short (Jaaskelainen, 2001; Wasserman and Faust, 1994).
4. Actor degree centrality is the extent to which actors directly send or receive ties to each other. An actor with a high degree of actor centrality would be able to easily send or receive advice directly from someone.
5. Closeness centrality, an inverse measure, is the extent to which actors are connected directly or indirectly (for example a friend of a friend) with other actors. Actors with a low degree of closeness centrality can get advice both from others they are directly connected to and indirectly from "friends of a friend". Networks themselves can be made up of few ties between actors or many ties between actors. To the extent that an actor has few ties in a dense network that actor would be "out of the loop".
6. Betweenness centrality is the extent to which actors are connected to others that are not connected with each other. This increases the amount of unique information to which the actor has access. High Betweenness centrality gives an actor power because the actor can control the flow of information.
7. Several variables measure the experience of the VC firms funding a particular company as well as the experience of the VC firms directly connected to these

focal actors. *VCAge1* is the collective age of the VC firms directly connected to the focal start-up company. *VCAge2* is the collective age of the VC firms which are not in *VCAge1* but which are directly connected to the VC firms in *VCAge1*

8. The 'worked together in the past' variable includes those VC firms that have worked together in the past, prior to the current investment. It is abbreviated as *VC1VC2WorkedInPast*.

Analysis of Hypotheses

First, general descriptive statistics are obtained about the network using UCINET. This includes how many components, how many VC firms in each component, and the network mean, median, and mode of the network variables listed above. The network is graphically modeled using Pajek.

UCINET is then used to determine each individual VC firm's network values for the variables listed above. This output is exported to SAS for further analysis using regression. For each hypothesis that has a curvilinear prediction, the data is checked for curvilinearity using the routine in SAS.

The demographic variable information remains attached to each VC firm and is included. Instead of a familiar regression data spreadsheet where *n* would be the number of VC firms or companies funded, *n* is the number of ties. This number of ties varies with the regression equation as some VC firms may be left out of some regressions due to missing demographic or other VC-specific information The ties are anchored to the individual VC firms and company outcomes so that it is possible to analyze them asking questions concerning VC tie influence on company outcome.

The hypotheses are analyzed using regression, specifically, SAS, PROC GLM. This was an exploratory analysis and it is recognized that with a categorical (3 levels) dependent variable logistical regression (specifically SAS PROC CATMOD) would have been a better choice. Problems were encountered when using PROC CATMOD which is discussed in Chapter Four.

The first set of hypotheses concern the experience of the VC firm and that of their advice network.

Hypothesis 1a: VC firms connected to primarily inexperienced or very experienced VC firms will escalate more than those with a higher percentage of connections to VC firms with 12–15 years of experience.

The demographic variables age of VC firm (*VCAge1* and *VCAge2*) and number of companies each VC firm funded in the past (*VCNumCompaniesHist1*) are used. Because this is a network question, the numbers "1" and "2" are attached to VCAge variables. The number 1 designates that syndicate members are funding the company. The number 2 designates that the VC firms have ties to the syndicate VC firms. Both are different measures of experience. All three are entered into the regression equation separately. The interactions of *VCAge1* and *VCAge2* with the number of companies funded in the past are also included because a young VC firm that has funded a large number of companies may have a different experience level than an older VC firm that has funded fewer companies. The interaction of *VCAge1* with *VCAge2* also is included because, for example, a less experienced focal VC firm's ties to more experienced VC firms may matter more than a more experienced focal VC firm's ties to less experienced VC firms. Again, *n* is ties. There is some missing age information for VC firms.

Hypothesis 1b: Syndicates with more VC firms with more industry relevant experience will escalate less than those with less past experience in that industry.

Looking at only syndicate members, experience has been coded as the number (*VCSameHis1*) and percent of the total number (*VCSameHisPct1*) of firms funded in the past in the same industry; the number (*VCRelatedHis1*) and percent (*VCRelatedHisPct1*) of firms funded in a related industry; and the number (*VCUnrelatedHis1*) and percent (*VCUnrelatedHisPct1*) of firms funded in an unrelated industry. Each variable is entered separately in the regression equation.

Hypothesis 1c: Syndicates with at least one VC firm with 12–15 years experience with fewer escalation outcomes and more experience in the industry of investment will escalate less.

This is a three-way interaction regression hypothesis at the syndicate level. Included in the regression are *VCNumComapniesHis1*, *VCAge1*, and *VCSameHis1*, all variables from hypothesis 1a and 1b. A count of the number of times the venture capitalist has escalated in the past (*VCEscalateHis1*) is also included. All two-way and three-way interactions are included.

The second set of hypotheses use the network variables. Due to potential colinearity problems with the measures of centrality, only those with correlations less than $p<0.8$ will be used in the same regression equation.

Hypothesis 2a: VC firms with less dense networks or with clique-like networks will be more likely to escalate.

The density network variable k-plex (*VCKplexRank1*) measures how easily information can flow to a particular node and is used to predict company outcome with regression. *N* in this regression is related to number of ties. It is a relaxed measure of a clique.

Hypothesis 2b: VC firms located in a more densely interconnected portion of the network, where they themselves are more densely connected to other VC firms, will be less likely to escalate.

This hypothesis looks at network density and centrality interactions. Because each centrality network variable measures a slightly different aspect of centrality, all the measures are included. Variables include the number 1 or 2, consistent with usage in the other hypotheses. Actor degree centrality, Betweenness centrality, closeness centrality, and information flow centrality are included. The density measure that also includes connections is k-plex (*VCKplexRank1*). All variables are entered individually. All two-way interactions are entered into the regression equation. As these variables measure different aspects of the same thing they tend to be highly correlated. As a result no variable pair with a correlation above 0.8 will be used in the same regression equation to prevent colinearity problems.

Hypothesis 2c: VC firms that are not tightly and exclusively connected with only a small number of other VC firms (i.e., are not in a clique) will escalate less.

This is a simple regression equation using the network k-plex variable (*VCK-plexRank1*) to predict escalation.

This last set of hypotheses concern the VC syndicate and their experience working together as a group in the past.

Hypothesis 3a: When VC firms work with other VC firms they have worked with in the past they will, up to a point, escalate less than if they have never worked together. When they exclusively work only with each other, they will escalate more.

The network ties of worked together in the past (*VC1VC2WorkedinPast*) is used to predict escalation using regression. The result is expected to be curvilinear.

Hypothesis 3b: Larger groups, when made up of more venture capitalists who have worked together in the past, will escalate less than larger groups made up of fewer venture capitalists who have worked together in the past.

This interaction regression equation uses *VC1VC2WorkedInPast*, also used in hypothesis 3a, and the VC syndicate's size (*CoNoVC's*). Each variable is entered into the regression equation separately and as an interaction term.

Summary

Using data obtained from VentureXpert, a dataset has been created from VC funding ties. Using UCINET, this dataset is turned into a network and various network variables are obtained for the VC firms. The variables are then exported, along with the demographic venture capitalist information, to SAS. Regression is then used to test the influence of the advice network variables and demographics on venture capitalist escalation of commitment. *N* is the number of ties, which may vary between different hypotheses if information for a particular VC firm is missing.

Chapter 4 will present the results of the analysis. Chapter 5 will include a summary and discussion of the results as well as suggestions for future research.

Results

The fundamental set of questions this research is trying to answer pertains to whether the advice networks of venture capital (VC) firms, along with the attributes of the VC firms that make up their advice networks, influence VC syndicate escalation of commitment to failing entrepreneurial companies. Venture capitalists are most likely to ask for advice from other members of their network. One major source of potential advice network members is another VC firm with which the focal VC firm has funded new start-up companies in the past. Not all advice network members, however, give equally good advice. It is hypothesized that the experience level, age, and past success/failure record of network members affects the value of their advice. As a result, the configuration of the advice networks of VC firms should affect their propensity to escalate their commitment to failing start-up companies.

The target population studied was the population of VC firms funding new (seed or early stage) high-technology start-up companies which received their first round of funding between 1990 and 1995. The advice network was derived from VC funding partnerships that existed prior to 1990. Data came from the Thompson Financial VentureXpert database. The network variables were created from doing a network analysis using the network computer program UCINET. When creating the network, a tie was said to exist between two firms if they funded together prior to 1990. These past ties were then used to determine VC firm network variable values. The network variables and the demographic variables were then used to examine current investment outcomes.

The VC network ended up being very dense, and as a result, many of the network variables had little variance. As a result of this problem, the data were analyzed twice.

The first set of analyses included the entire advice network (Net1), which included the entire pool of VC firms that might be utilized for advice by the focal VC firm. The second analyses (Net2) included only those VC firms connected to other VC firms which funded in the first two rounds of funding. Net2 was defined in these terms because it is the venture capitalists in these first two rounds (and not other venture capitalists in further rounds of funding) that make the decision to fund the third round. Escalation of commitment was operationalized as failed start-up companies that received more than two rounds of funding. Therefore, it made sense to look at the advice network (Net2) of those making the fateful decision to fund Round 3. It was also hoped that this network would be less dense and thus have more variance in the network variables. Each time results are presented, results from the complete network (Net1) are presented first, followed by results from the early rounds network (Net2). Regression (PROC GLM in SAS) was used to analyze the data.

Although the independent variables are continuous, the dependent variable is categorical (3 levels). While logistical regression (PROC CATMOD in SAS) would have been a more appropriate analysis technique due to the categorical nature of the outcome variable, several technical problems were encountered using CATMOD. According to the SAS manual website (2006):

> "Continuous Variables
> Computational difficulties may occur if you have a continuous variable with a large number of unique values and you use this variable in a DIRECT statement, since an observation often represents a separate population of size one. At this extreme of sparseness, the weighted least-squares method is inappropriate since there are too many zero frequencies. Therefore, you should use the maximum likelihood method. PROC CATMOD is not designed optimally for continuous variables and therefore may be less efficient and may be unable to allocate sufficient memory to handle this problem."

Using the CATMOD least squared method resulted in an error statement, and as a result, SAS defaulted to the maximum likelihood method. In addition, out of memory errors occurred repeatedly which meant the analyses could not be performed. This chapter reports the preliminary, exploratory outcomes of these hypotheses using regression (SAS PROC GLM) as the analysis tool.

Descriptive statistics

There were 498 firms in high-technology, high-velocity industries (computers, superconductors, and communication, as coded by VentureXpert) that received their first round of funding from private venture capital firms between January 1, 1990 and December 31, 1995. In the complete network (Net1), there were 297 different VC firms in this population; however, 3 were excluded due to errors in the original VentureXpert database. As a result, 294 different VC firms were used in this study. There were 31,087 different dyadic ties between the different VC firms from the inception of the VentureXpert database (data goes back to 1975) through 1989, the advice network time period. Table 4.1 gives the descriptive statistics for the companies.

For the time period of 1990–1995, VC firms invested in an average of 6.61 new start-ups with a standard deviation of 7.599. The range was 1–62 companies; the mode was 4 companies. There were 297 VC firms that funded start-up companies during 1990–1995, all of which are included in the Net1 advice network. In Net2, the early rounds network, 191 different VC firms funded in Rounds 1 and/or 2. As a result, the Net2 advice network includes the ties for only these 191 VC firms.

Of the 498 new start-ups funded, 62.49% were successful (IPO, merger, or acquisition) and 20.9% ventures, none of which were ultimately successful, were funded for only one or two rounds because of VC firms' recognition that they would not result in a successful outcome. Escalation of commitment occurred in 16.7% of the cases where the VC firms funded a new start-up beyond two rounds of funding but the venture ultimately failed. Past research has documented that approximately 33% of VC firms' investments result in an IPO, merger or acquisition (Gompers & Lerner, 2001). The VentureXpert database has about twice the percentage of successful outcomes as would be expected from previous research into VC firm success rates. As a result, it is clear that successful outcomes are over-represented in this database and unsuccessful outcomes (whether the good decision to stop funding a loser early or the escalation of commitment case) are under-represented. There is no public reporting requirement for VC firms, there is considerable secrecy surrounding investments, and to bolster their reputations some may not report to the media or to VentureXpert some start-up failures. Potential investors and fund seeking entrepreneurs use this database to research VC firms.

Network descriptive statistics include information about the advice network ties between nodes (VC firms), the extent to which these ties are non-random (i.e., the extent to which the network is scale-free), and advice network density. The number of non-duplicate ties between VC firms in the advice network is shown in Table 4.2. There were 31,087 unique ties between the different VC firms for Net1 and 13,486 ties for Net2.

A log plot (Table 4.3) of the frequency of the degree distribution is done to see if the network is scale-free, meaning that the ties between nodes in the network are not randomly distributed. When the probability of a tie between two nodes is not random and uniform, the relationships between actors (VC firms) are likely to be a result of social processes which drive the relationship, or tie, formation (Barabasi & Albert, 1999). If the network is scale-free, then the log plot is generally a straight line. In both Net1 and Net2, the log plot results in a straight line except for the left tail which drops off. As a result, the advice network is likely to be a non-random set of ties driven by social forces that influence VC firms to create relationships with each other. A log plot of this shape (with the tail drop off) is common in completely connected, very dense networks, as this one is, and, as such, presents analytic problems due to the current limitations of network analytic tools (Newman, Watts and Strogatz, 2002). In table 4.3 the first two graphs for Net1 and Net2 show the log transformation of frequency (infreq) plotted against the degree (indegree). The second two graphs drop the left tail outliers and put in a regression line through the scatter plot.

Both Net1 and Net2 are very dense networks (Table 4.4), which is not common. In fact, the creator of the UCINET network analysis program used in this research, Steven Borgatti (2006), stated, “I have seen a number of networks of the kind you describe, and none that size have had such high density”. While there is not a statistical significance test for network density, a rough idea of density can be obtained using the method described below (Borgatti, 2006; Preiss & Eng, 1997). Using the Preiss & Eng (1997) method to determine network density, for Net1 the average degree, or number of ties, is 11.04. The number of vertices, or number of VC firms in the main component, (v), is 277. Because this is an undirected graph, the maximum number of edges (ties) is 277(276)/2 = 38,226. This network, with 31,087 vertices, is nearly a completely connected network. The formula for figuring out density is $f*v^2$ = density. The factor f is 11.04/277 = 0.039856. Density then is $0.039856*(277)^2$ = 3058.11. Any network with a density of greater than 3 or 4 is considered dense. This network is very dense. For Net2, the maximum possible number of non-duplicate ties is 16,471 ties in the main component. There are 13,485 actual ties. Factor f = 4.29/181=0.023702. Density for Net2 = 776.49. Although less dense than Net1, Net2 is still a very dense network

Table 4.1

Descriptive statistics for new start-up companies

Statistics

		conofvcs
N	Valid	498
	Missing	0
Mean		6.61
Median		4.00
Mode		1
Std. Deviation		7.599
Minimum		1
Maximum		62

Conofvcs is the number of venture capitalists investing in a company.

CoEscalate

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	1	311	62.4	62.4	62.4
	2	104	20.9	20.9	83.3
	3	83	16.7	16.7	100.0
	Total	498	100.0	100.0	

CoEscalate is the outcome of the company variable:

1= good decision, good outcome (IPO, merger, acquisition, private – still successful)

2= good decision, poor outcome (no more than 1 or 2 rounds of funding)

3= poor decision, poor outcome (escalate commitment by continuing to fund past two rounds of funding and company ultimately failed)

Table 4.2

Number of non-duplicate ties between VC firms in the advice network

Statistics

Net1

		conofvcs
N	Valid	31087
	Missing	0

Net2

		conofvcs
N	Valid	13485
	Missing	0

N is the number of non-duplicate ties between VC firms in the advice network
Net1 is the entire advice network
Net2 is the advice network of Round 1 and Round 2 VC firms

Table 4.3

Log transformation of degree network distributions, scale free character

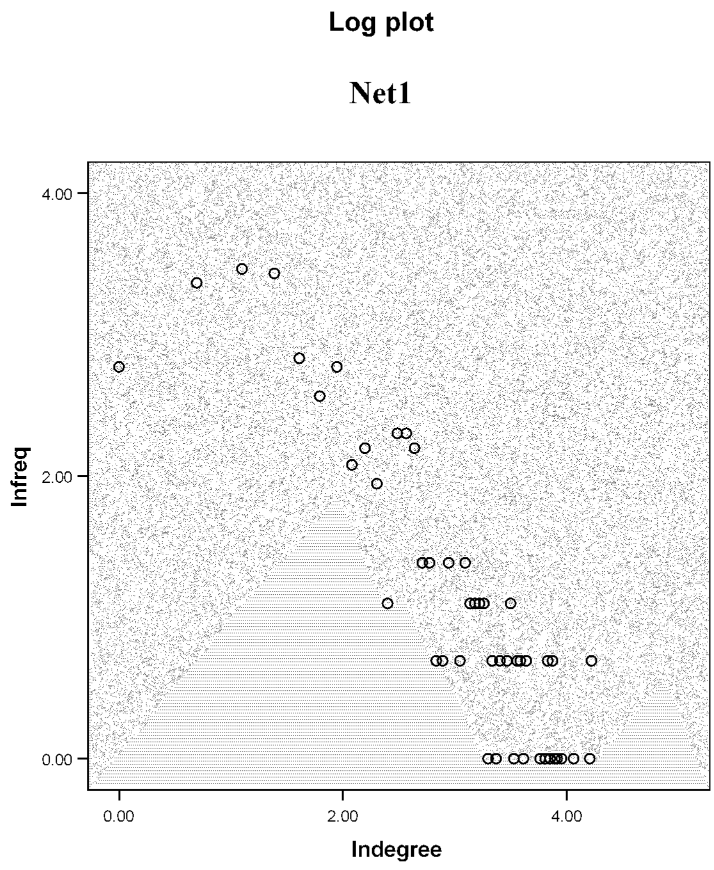
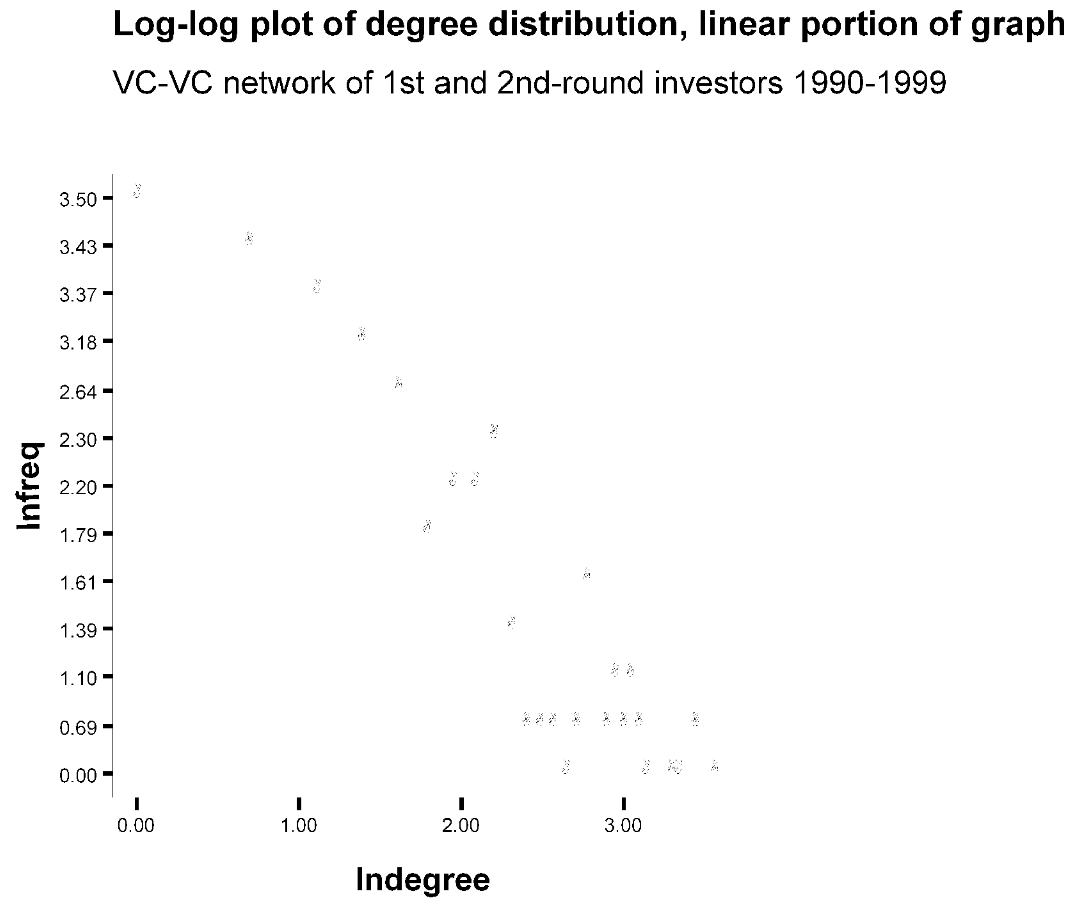


Table 4.3, continued

Net2



Shows "scale-free" character of VC-VC network

Table 4.3, continued

Net1

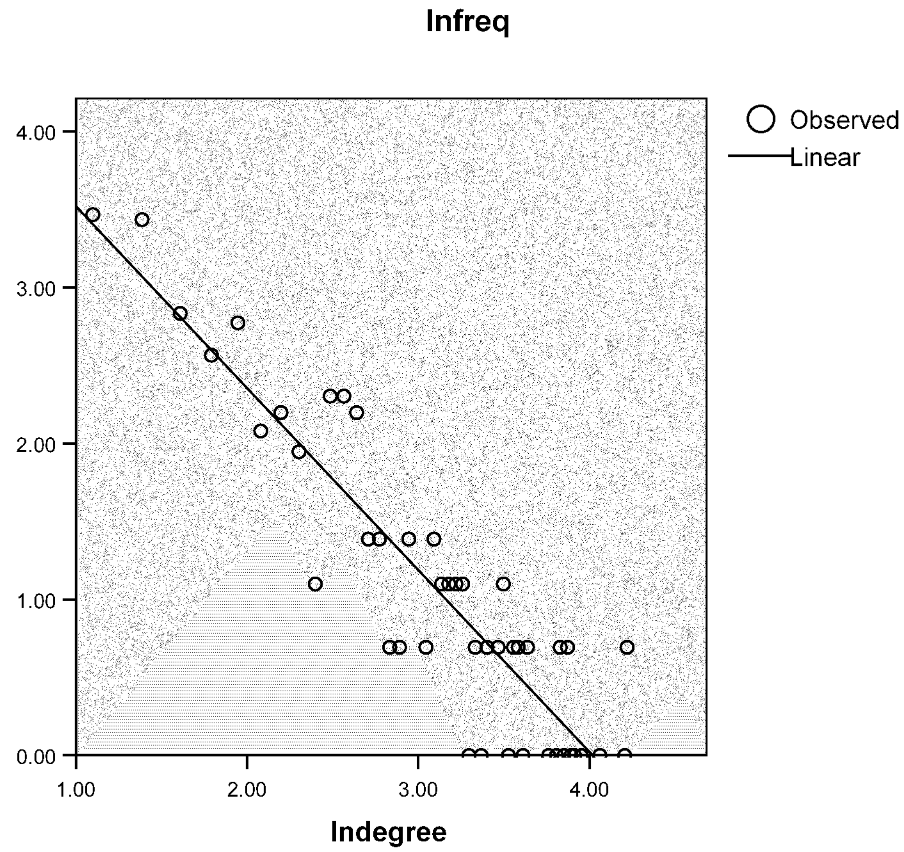
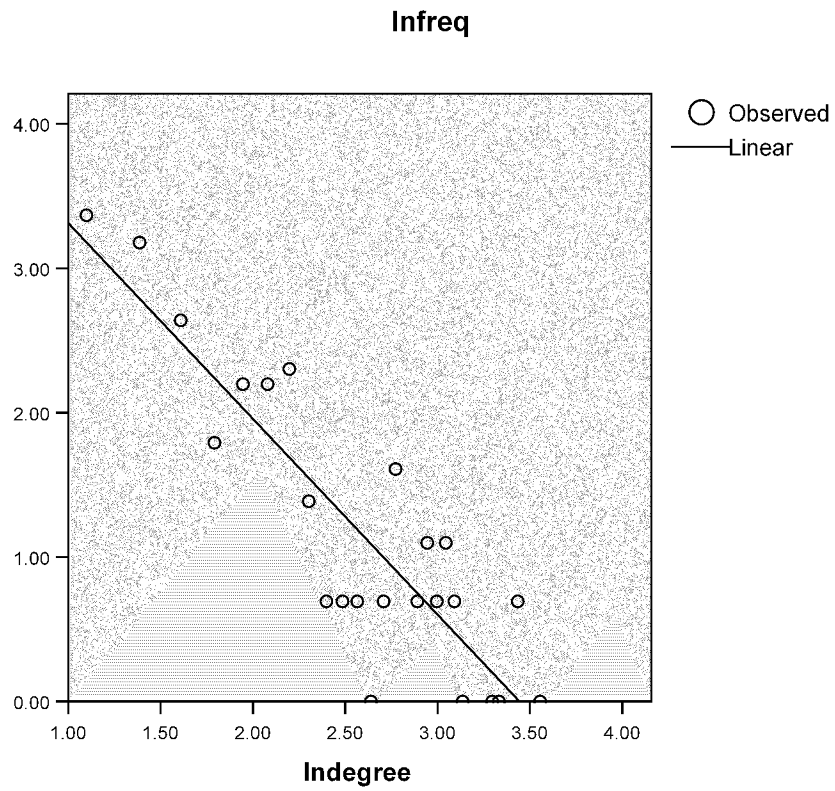


Table 4.3, continued

Net2



infreq – frequency
indegree – degree

Table 4.4

<u>Network density</u>

	Density
Net1	3058.11
Net2	776.49

The last set of descriptive statistics relates to the network indices (Table 4.5). In this case, the network variables are actor degree centrality, betweenness centrality, information centrality, closeness centrality, and k-plex rank.

Actor degree centrality is the extent to which actors have direct ties to each other. An actor with a high degree of actor centrality is directly connected to more actors and would be able to easily send advice to or receive advice directly from another actor. On average, Net1 VC firms send or receive information from 11.04 other VC firms. The median is 6 and the standard deviation is 12.921. Net2 VC firms send or receive ties from 4.29 other VC firms on average, with a median of 2 and a standard deviation of 6.127. These scores are different because the advice networks have been defined differently. Not all of the VC firms to which the focal VC firm is connected in Net1 are included in Net2. As a result it makes sense that the number of ties drops in Net2.

Betweenness centrality is the extent to which the focal VC firm has ties to two or more VC firms that do not have ties to each other. The focal VC firm is located "between" the other VC firms, meaning that the only way the other VC firms can communicate with each other is when the focal VC firm passes along information. This measure examines only the shortest path between two VC firms that passes through the VC firm of interest. Betweenness centrality scores range from 0 to 1. An actor with a high betweenness centrality score has more access to unique information. In addition, an actor with high betweenness centrality is powerful because the actor can control the flow of information through a network. In contrast, an actor with a low betweenness score is not occupying a structural hole in the network and does not need to rely on a high betweenness score actor to receive or send information.

Since information can take many paths, in most cases one actor cannot block a low betweenness-score actor's access to information by failing to pass it on. The two exceptions occur when the focal actors have a betweenness score of zero—i.e., they are not "between" anyone. The first is when the focal actor is an isolate or a member of an isolated dyad. The second is when the focal actor is a terminus, similar to being located at the end of a branch on a tree. The focal actor is connected to only one other actor, who then controls all the information flow to the focal actor.

With Net1 the mean betweenness centrality is 0.006, the median is 0.0003, and the standard deviation is 0.0128. These scores indicate that relatively few VC firms occupy structural holes or control information flow through the network. This is consistent with a highly interconnected network such as this one. For Net2 the mean is 0.0098, the median is 0.0008, and the standard deviation is 0.1768. Again, no VC firms are controlling the flow of information through the network. The actors have many ways to get the same information. The results are very similar for both networks.

Information flow centrality is the best measure of centrality in a network with regards to how easily information can get to a specific node. Information does not always take the shortest route between two nodes. Information flow centrality includes not only the betweenness measure of the shortest route but also all longer routes between two VC firms that pass through the focal VC firm. The risk of information not making it from point A to point B increases as the number of nodes that need to pass the information along increases. As a result, these paths are also weighted inversely with respect to their length, meaning that a short connection between two actors counts more than a long one. Actors with a high information centrality score are located on many paths between other nodes and are also on a higher number of “shorter” paths. They have multiple opportunities to receive and pass on information because they are located on “busy highway intersections” (Bonacich, 1987; Jaaskelainen, 2001; Wasserman and Faust, 1994). The results for both networks are similar. For Net1 the mean is 0.5507, the median is 0.5784, and the standard deviation is 0.27649; this means that the typical path length is midway between the minimum and maximum lengths, making it reasonably easy for information to flow through the network. For Net2 the mean is 0.5434, the median is 0.5659, and the standard deviation is 0.28052. Information flows relatively easily through Net2 as well.

Closeness centrality, an inverse measure of centrality, incorporates actor degree and the clustering of other actors around the actor’s direct ties. It also incorporates the notion of how far the actor is from each node. A focal actor with few ties in a dense network has low degree centrality. To the extent that the “friends” of this actor themselves have low degree centrality, the focal actor is “out of the loop”. In this position, the focal actor would receive less, and less varied, information, because the focal actor would be “further” from others and would have a longer path to reach distant actors. The further the focal actor is from other actors and the lower the actor degree, the higher the closeness centrality score. Indeed, due to the centrality score being an inverse measure, it is perhaps easier to think of it as a “farness” centrality score, because the higher the score the further the focal actor is from being central. VC firms with low closeness centrality are “closer” to other VC firms. Actors with a low degree of closeness centrality can get more advice directly from "friends" and indirectly from "friends of a friend" than can actors with a higher closeness centrality score. Scores range from 0 to 1. For Net1 the mean is 0.3618, the median is 0.3614, and the standard deviation is 0.07762. This means that the network is more interconnected than not in terms of getting advice from friends of friends. Again, this is consistent with a densely interconnected network. For Net2 the mean is 0.2754, the median is 0.2903, and the standard deviation is 0.08783. The average closeness of the VC firms in Net 2 is "closer" than in Net1, although both networks have low scores.

K-plex is a measure of the "local" density of ties around the focal VC firm, meaning the cluster of ties in the general vicinity of each node. Instead of looking at friends and friends of friends as closeness centrality does, this measure focuses on the extent to which the actors in the local density area are interconnected with each other and not with others. Because of the focus on the ties around the node, this measure also is used to measure cliques when cliques do not have mutually exclusive memberships. It looks at the density of ties between the clique members as compared to those outside the clique (Wasserman and Faust, 1994).

Due to the density of the network, the VC firm local density scores were normalized and then ranked by k-plex tie values. This was done both to artificially create more variance when testing the hypotheses and to try to identify clusters, since no clusters were identified in the main component when the two networks were examined for cliques and subcomponents. This attempt was not particularly successful, probably because of the extensive interconnection between VC firms across the entire network. The very low average betweenness scores imply that very few venture capitalists fill structural hole positions between groups, and the inability to identify subcomponents means that few opportunities for structural holes exist to begin with. Thus, the attempt to find clusters based on k-plex scores was a long shot that did not pay off.

A k-plex score of 1 indicates a lower density of interconnected clique-like ties, with 112 being the highest density of ties. For Net1 the mean is 57.63, the medium is 54, and the standard deviation is 31.090. This is consistent with a densely interconnected network where the advice network is relatively large and interconnected compared to the size of the network. For Net2 the mean is 32.38, the medium is 32.00, and the standard deviation is 17.715. These ranks are lower because there are fewer VC firms in this network; however, the results are structurally consistent with Net1.

The correlation matrix documents that many of the network measures of centrality are correlated, to the point of creating colinearity problems when calculating regressions. This is not surprising since these centrality measures are measuring different aspects of central location in a network and some measures incorporate aspects of other centrality measures. For both networks, all correlations between centrality measures are statistically significant at the .05 level. In Net1, degree and betweenness, degree and closeness, information centrality and closeness, information centrality and k-plex rank, and closeness and k-plex rank all have correlations greater than 0.8. For Net2, the only centrality measures that do *not* have correlations greater than 0.8 are betweenness and information centrality, betweenness and closeness, and betweenness and k-plex rank. All the other combinations create colinearity problems in regressions (see Table 4.6).

Table 4.5

Network descriptive statistics

Net1 Statistics

		vcdegree	VCbetweenness	VCInfocentrality	VCCloseness	VCkplexRank
N	Valid	294	277	277	277	271
	Missing[1]	0	17	17	17	23
Mean		11.04	.0060	.5507	.3618	57.63
Median		6.00	.0003	.5784	.3614	54.00
Mode		3	.00	.00	.01	40
Std. Deviation		12.921	.01280	.27649	.07762	31.090

Net2 Statistics

		vcdegree	VCbetweenness	VCInfocentrality	VCCloseness	VCkplexRank
N	Valid	191	181	181	181	181
	Missing[1]	103	113	113	113	113
Mean		4.29	.0098	.5434	.2754	32.38
Median		2.00	.0008	.5659	.2903	32.00
Mode		0	.00	.00	.01	41
Std. Deviation		6.127	.01768	.28052	.08783	17.715

VCdegree is Actor degree centrality
VCbetweenness is Betweenness centrality
VCInfocentrality is Information flow centrality
VCCloseness is Closeness centrality
VCKplexRank is K-plex

Note 1 – Missing data is not actually missing; rather, it means that a VC firm is not connected in the way the indices measure. For example, if the VC firm is an isolate, or a terminus (like the end of a branch on a tree), it will not be, for example, between two other VC nodes and therefore will have no betweenness score. In Net2 missing data also includes the VC firms from Net1 not included in the Net2 network.

Table 4.6

Network variables correlations

Net1 Correlations

		VCdegree1	VCbetweenness1	VCInfocentrality1	VCCloseness1	VCkplexRank1
VCdegree1	Pearson Correlation	1	.882	.794	.948	.793
VC1	Pearson Correlation	.882	1	.566	.781	.531
VCInfocentrality1	Pearson Correlation	.794	.566	1	.898	.904
VCCloseness1	Pearson Correlation	.948	.781	.898	1	.869
VCkplexRank1	Pearson Correlation	.793	.531	.904	.869	1

All correlation is significant at the 0.01 level (2-tailed).
N=31,084 ties

Net2 Correlations

		VCdegree1	VCbetweenness1	VCInfocentrality1	VCCloseness1	VCkplexRank1
VCdegree1	Pearson Correlation	1	.831	.807	.872	.740
VC1	Pearson Correlation	.831	1	.506	.686	.379
VCInfocentrality1	Pearson Correlation	.807	.506	1	.900	.907
VCCloseness1	Pearson Correlation	.872	.686	.900	1	.842
VCkplexRank1	Pearson Correlation	.740	.379	.907	.842	1

All correlation is significant at the 0.01 level (2-tailed).
N=13,495 ties

Networks can often be broken down into components, meaning there are hubs of activity that are not connected to other hubs, so the component size distribution is reported. In Net1, 271 VC firms (92.2%) are connected to each other in one component. Because there are there 3 dyadic groups connected only to each other, and 17 isolates not connected to anyone, the other components have only 1 or 2 VC firms in each one. This translates into one very large macro component having almost all of the VC firms as members. The remaining components are tiny, with only 1 or 2 members. Because these smaller components have so few members, they cannot be compared to the larger component. There is insufficient statistical power to do these comparisons. This affects some of the hypotheses because the a priori assumption was that multiple components could be compared. Another consequence of having essentially one densely interconnected component is the resulting lack of variance within many of the network variables, which makes it harder to find significance when using these variables to predict the outcome variable. Net2 also has one main component; however, it is somewhat less dense. There are four dyads, one group of 4, and no isolates. Again, it is not be possible to compare the smaller components against the larger one due to the lack of statistical power. Table 4.7 shows the component makeup.

Table 4.7

Component makeup of the network

Number of components and number of venture capitalists in each component

Net1 vccompno

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	1	271	92.2	92.2	92.2
	2	2	.7	.7	92.9
	3	2	.7	.7	93.5
	4	2	.7	.7	94.2
	5	1	.3	.3	94.6
	6	1	.3	.3	94.9
	7	1	.3	.3	95.2
	8	1	.3	.3	95.6
	9	1	.3	.3	95.9
	10	1	.3	.3	96.3
	11	1	.3	.3	96.6
	12	1	.3	.3	96.9
	13	1	.3	.3	97.3
	14	1	.3	.3	97.6
	15	1	.3	.3	98.0
	16	1	3	.3	98.3
	17	1	.3	.3	98.6
	18	1	.3	.3	99.0
	19	1	.3	.3	99.3
	20	1	.3	.3	99.7
	21	1	.3	.3	100.0
	Total	294	100.0	100.0	

Net2 vccompno

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	1	175	93.6	93.6	93.6
	2	2	1.1	1.1	94.7
	3	2	1.1	1.1	95.7
	4	2	1.1	1.1	96.8
	5	2	1.1	1.1	97.8
	6	4	2.1	2.1	100.0
	Total	187	100.0	100.0	

VCcompno is the number of components in VC network
Frequency is the number of VC firms in each component

The graphical representation of the network itself show visually what the frequency distribution, component numbers, and log transformation represent. Both Net1 and Net2 show one large network component. Only a very small number of VC firms are not included in the main component. (See Figure 4.1.)

Degree reduction (deleting network ties whose removal does not fundamentally alter the underlying structure of the network) of Net1 ties was performed multiple times to try to make the Net1 structure more visible. The Kamadi-Kawaii algorithm transformation removed some ties and repositioned the nodes to make the underlying structure more visible. This reveals that there is one large component with approximately 15 embedded, overlapping hubs, although statistically these hubs could not be identified as separate clusters within the component. Even with degree reduction, these hubs still are very interconnected with the other hubs. This embeddedness means that it is very easy for information to reach others in the network, that all the network measures have very little variance, and that venture capitalists' position in the network is less likely to matter when it comes to the flow of information though the network. Net2 is less dense on the network edges, making it easier to see the structure without doing a transformation. Again there appear to be some overlapping hubs but these cannot be identified statistically.

Figure 4.1

Graphic representation of the network

Net1

(a) Entire network (Dots are individual venture capitalists; lines are the links between them)

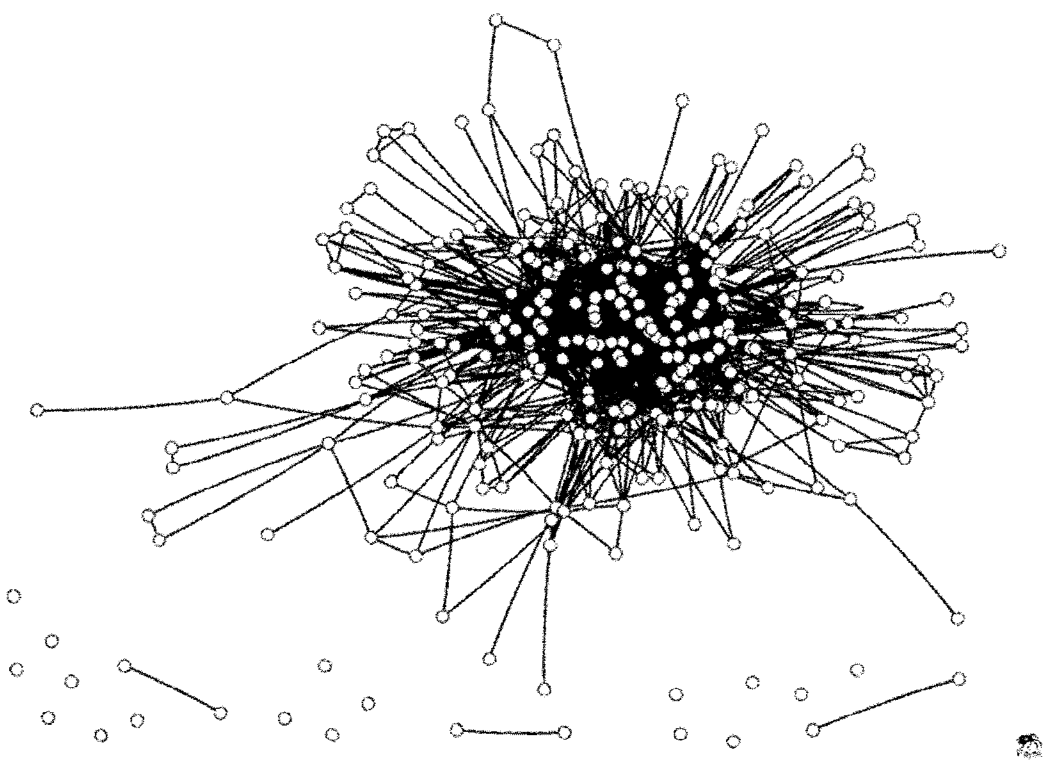
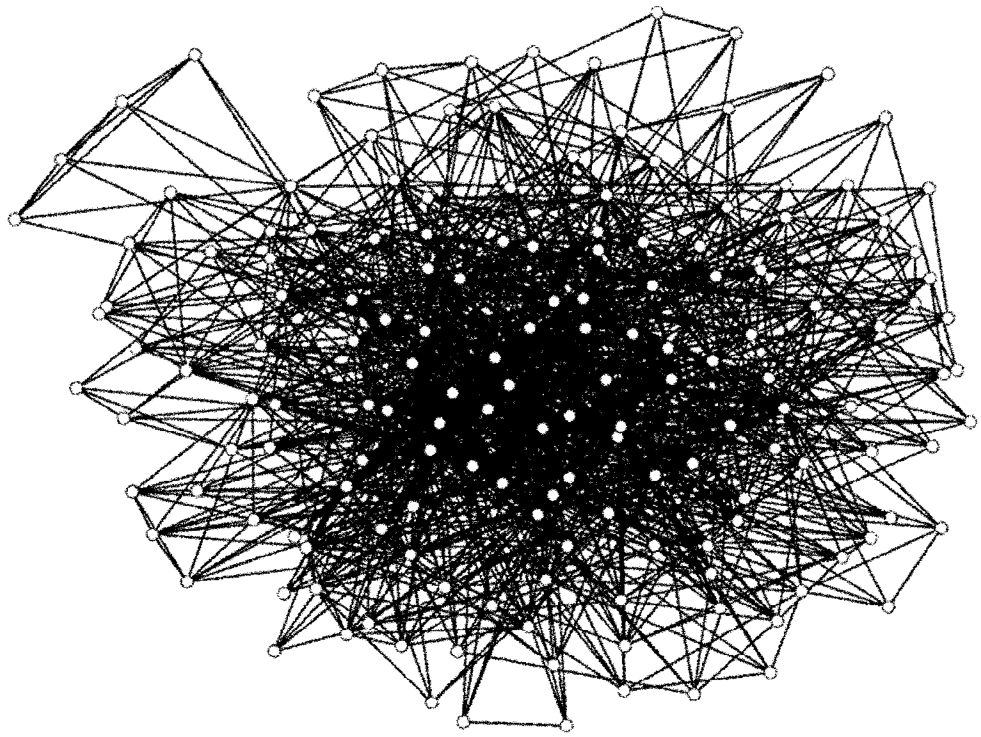


Figure 4.1, continued

(b) Same network, isolates and dyads removed, after 3 rounds of degree reduction and repositioning nodes using the Kamadi-Kawaii algorithm



(c) Further degree reduction (8 more rounds)

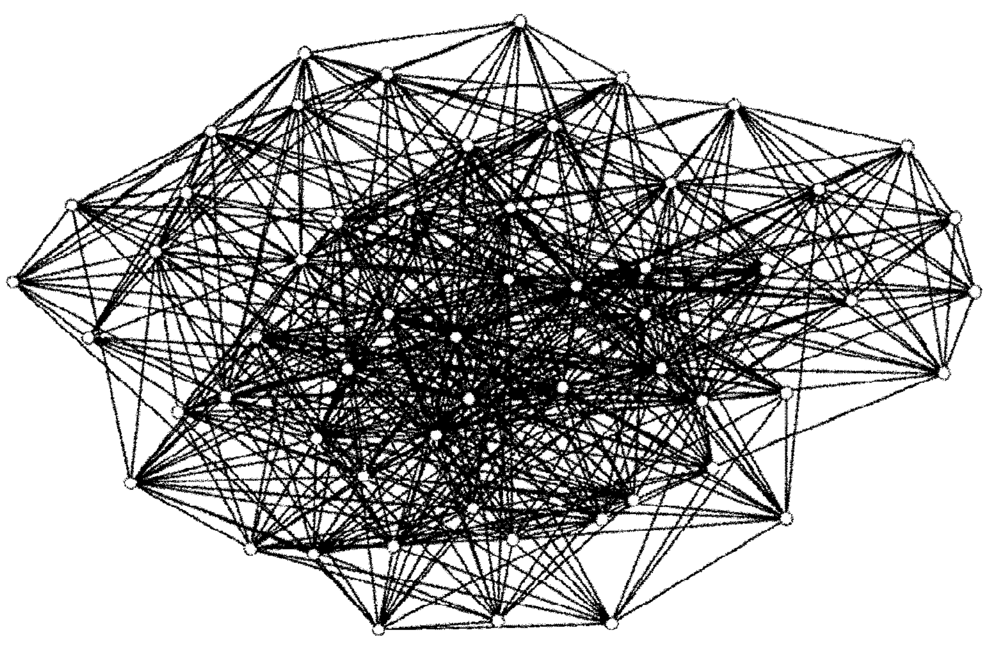


Figure 4.1, continued

(d) Same level of reduction as in (c) with nodes repositioned to make more visible the extensive interconnections

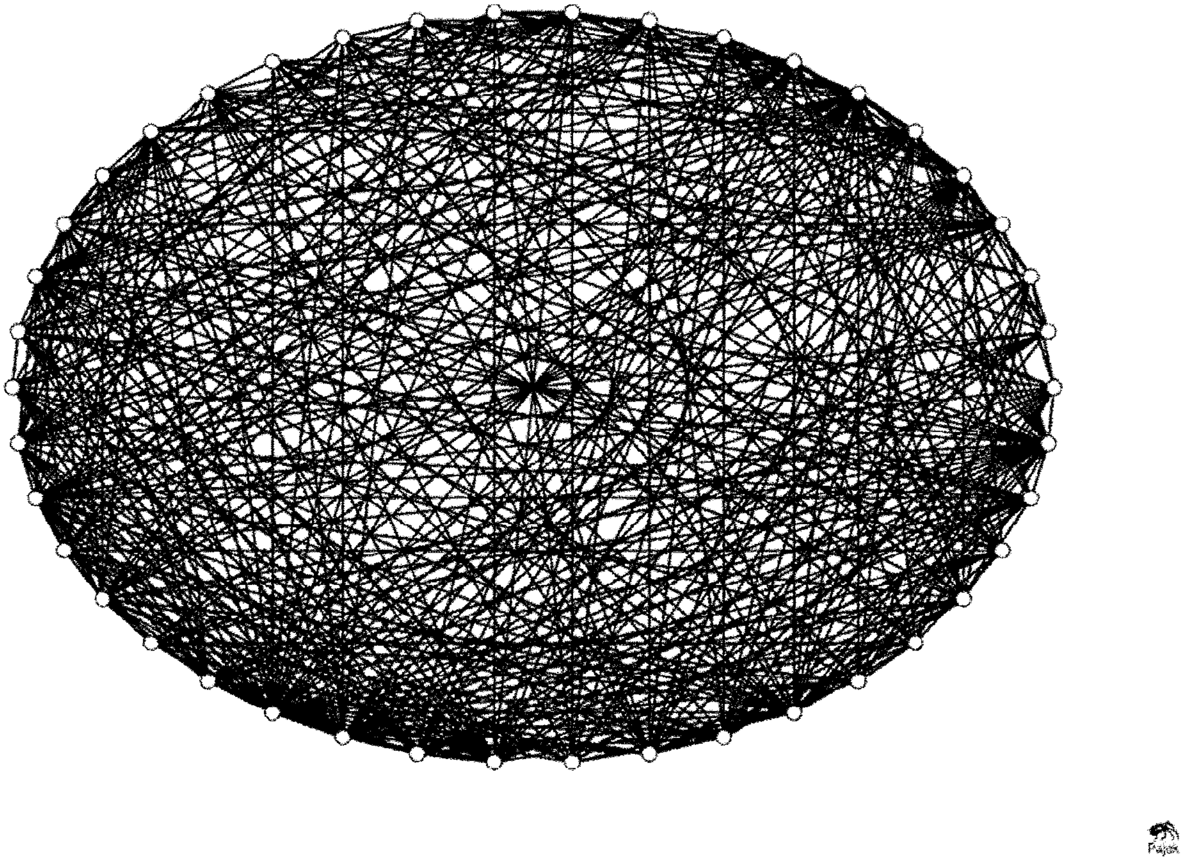
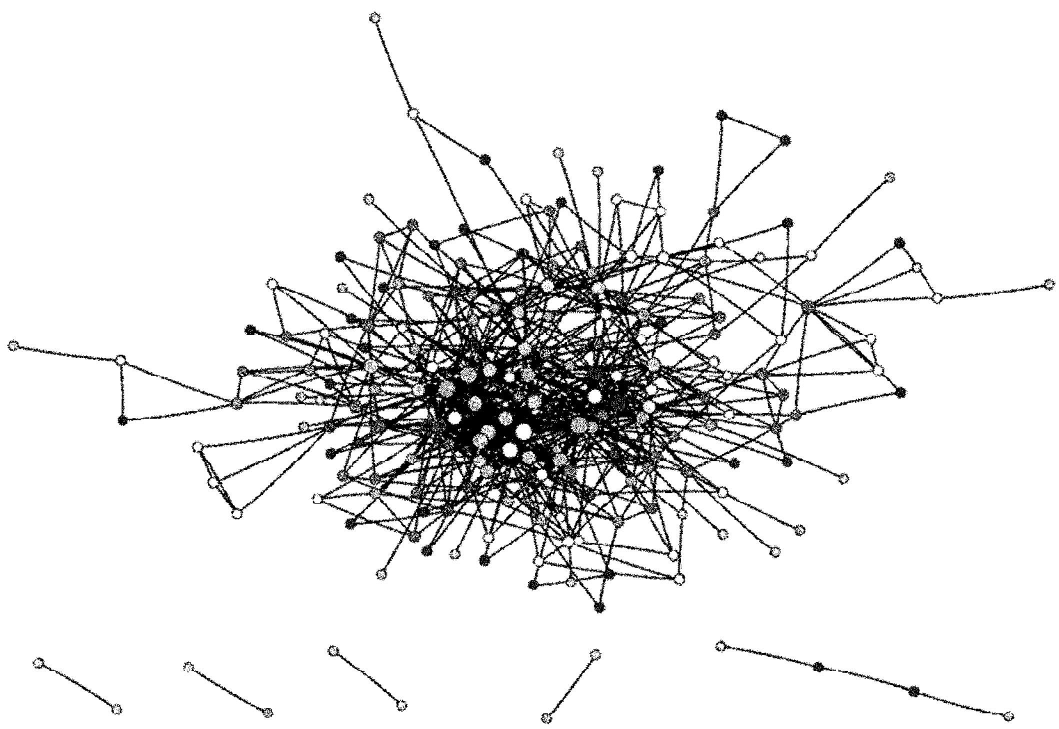


Figure 4.1, continued

Net2



The larger the node circle, the more ties the VC firm has with other VC firms. The colors are consistent across circle size.

Hypotheses Results

The hypotheses were tested using regression using SAS, PROC GLM, which uses least squares to fit the linear model. PROC GLM is not ideally designed for categorical dependent variables. A logistic regression (PROC CATMOD) would have been the better choice. When this was attempted, every previously discussed limit of the program was encountered. As a result the tests of the hypotheses, using regression, should be viewed as preliminary and exploratory.

The dependent variable, escalation of commitment, is a categorical variable with three categories. Successful outcomes (IPO, merger, acquisition) were dummy coded 1 and represents good decision-making. Another good decision, dummy coded 2 was the decision to stop funding a failing company after 1 or 2 rounds of funding. Dummy coded 3 was the escalation of commitment case. These are the companies that received more than 2 rounds of funding and ultimately failed.

The analyses were only performed using the VC firms in the large component. The VC firms in either network who where not included in this component were so few in number that there was not enough statistical power to contrast these small clusters of VC firms against the main component. In addition, including VC firms disconnected from the main component makes no theoretical sense because they would not be involved in any information flow that took place in the main component.

Hypothesis 1a: VC firms connected to primarily inexperienced or very experienced VC firms will escalate more than those with a higher number of connections to VC firms with 12–15 years of experience.

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This hypothesis predicted a curvilinear relationship between the experience of the advice network VC firms and escalation. Shepherd, et al. (2002) found that additional experience improved inexperienced venture capitalists' decision-making processes up to a point. They documented that venture capitalists' decision accuracy increased over time, with decision accuracy peaking at 12–15 years of experience. After this time period, good decision-making decreased somewhat. Although these researchers were looking at the experience level of the focal VC firm rather than the kinds of advice a VC firm would give based on their experience level, their results do have some bearing on the advice network. Presumably a VC firm's decision-making quality would influence the quality of the advice they could give others. As a result it is expected that there would be a curvilinear relationship between quality of advice as inferred from the experience level of the advice network VC firm and the tendency to escalate commitment. When the advice network VC firms had a midrange of experience, they were expected to escalate commitment less than the advice networks made up of VC firms with more experienced or less experience.

The experience level of the focal VC firm was also included because of the direct effect of experience on focal VC firm decision-making quality. In the regression equation the variable *VCAge1* is the years of experience the focal VC firm had at the time of the first round of funding of the focal start-up company. *VCAge2* is the years of experience of each VC firm in the focal VC firm's advice network. The number of companies that a VC firm funded prior to 1990, *VCNumCompaniesHist1*, the number of companies that a VC firm funded prior to 1990, is another measure of experience for the VC firms.

Although the model was significant (Net1 F=39.32, p<.0001 and Net2 F=25.40, p<.0001), the hypothesis was not supported in either analysis due to the lack of a curvilinear relationship. With both Net1 and Net2, it appears that what is of primary importance is the collective experience level of the VC firms as measured by the number of companies funded in the past (*VCNumCompaniesHist1*). In addition, this variable interacted with the age of the focal VC firm (*VCAge1*) but not with the age of the VC firms in the advice network (*VCAge2*). The more companies a focal VC firm had funded in the past slightly increased the tendency to escalate (Net1 beta coefficient = -.00039 and Net2 beta coefficient = -.00513). That effect went away, however, when this variable was combined with the actual age of the focal VC firm. The older the VC firm was and the more companies it had funded in the past, the less likely it was to escalate. VC firm age in years was not significant, nor was the age of the VC firms in the advice network. The amount of variance explained is very small: 0.0126% in Net1 and 0.0169 in Net2. (See Table 4.8).

Table 4.8

Ho: 1a, VC Firm experience and escalation

Net1 The GLM Procedure

Dependent Variable: CoEscalate

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	7	193.74962	27.67852	39.32	<.0001
Error	21509	15139.42489	0.70386		
Corrected Total	21516	15333.17451			

R-Square	Coeff Var	Root MSE	CoEscalate Mean
0.012636	53.13487	0.838966	1.578938

Source	DF	Type III SS	Mean Square	F Value	Pr > F
VCAge1	1	0.46683179	0.46683179	0.66	0.4154
VCAge2	1	0.01354246	0.01354246	0.02	0.8897
VCNumCompaniesHist1	1	20.18151966	20.18151966	28.67	<.0001
VCAge1*VCAge2	1	1.48817709	1.48817709	2.11	0.1459
VCAge1*VCNumCompanie	1	19.13695855	19.13695855	27.19	<.0001
VCAge2*VCNumCompanie	1	0.03821903	0.03821903	0.05	0.8157
VCAge1*VCAge2*VCNumC	1	0.31390810	0.31390810	0.45	0.5043

Parameter	Estimate	Standard Error	t Value	Pr > |t|
Intercept	1.569424475	0.03675455	42.70	<.0001
VCAge1	-0.002192334	0.00269198	-0.81	0.4154
VCAge2	-0.000303364	0.00218706	-0.14	0.8897
VCNumCompaniesHist1	-0.003908855	0.00072999	-5.35	<.0001
VCAge1*VCAge2	0.000234302	0.00016114	1.45	0.1459
VCAge1*VCNumCompanie	0.000216992	0.00004162	5.21	<.0001
VCAge2*VCNumCompanie	-0.000010562	0.00004532	-0.23	0.8157
VCAge1*VCAge2*VCNumC	-0.000001689	0.00000253	-0.67	0.5043

Table 4.8, continued

Net2 The GLM Procedure

Dependent Variable: CoEscalate

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	7	126.309328	18.044190	25.40	<.0001
Error	10333	7341.972850	0.710536		
Corrected Total	10340	7468.282178			

R-Square	Coeff Var	Root MSE	CoEscalate Mean
0.016913	52.85455	0.842933	1.594817

Source	DF	Type III SS	Mean Square	F Value	Pr > F
VCAge1	1	3.04657264	3.04657264	4.29	0.0384
VCAge2	1	1.85641459	1.85641459	2.61	0.1060
VCNumCompaniesHist1	1	11.92503789	11.92503789	16.78	<.0001
VCAge1*VCAge2	1	5.38917154	5.38917154	7.58	0.0059
VCAge1*VCNumCompanie	1	13.30853831	13.30853831	18.73	<.0001
VCAge2*VCNumCompanie	1	0.00821165	0.00821165	0.01	0.9144
VCAge1*VCAge2*VCNumC	1	1.46529677	1.46529677	2.06	0.1510

Parameter	Estimate	Standard Error	t Value	Pr > |t|
Intercept	1.684568756	0.06633566	25.39	<.0001
VCAge1	-0.009702098	0.00468547	-2.07	0.0384
VCAge2	-0.005924533	0.00366530	-1.62	0.1060
VCNumCompaniesHist1	-0.005132731	0.00125289	-4.10	<.0001
VCAge1*VCAge2	0.000722218	0.00026224	2.75	0.0059
VCAge1*VCNumCompanie	0.000304779	0.00007042	4.33	<.0001
VCAge2*VCNumCompanie	0.000007697	0.00007160	0.11	0.9144
VCAge1*VCAge2*VCNumC	-0.000005640	0.00000393	-1.44	0.1510

VCAge1 = age of the VC firm
VCAge2 = age of the VC firm's advice network (direct tie)
VCNumCompaniesHist1 = the number of companies the VC firm has funded in the past

Hypothesis 1b: Syndicates with more VC firms with more industry relevant experience will escalate less than those with less past experience in that industry.

De Clerc (2002) found that it was a venture capitalist's knowledge of a specific industry and previous investment history that affected future outcomes. These results were attributed to the added value a venture capitalist brings to an entrepreneurial company with regards to VC oversight, involvement with entrepreneur's strategic decisions, connections, and credibility. The absorptive capacity literature has documented that the greater the overlap of the knowledge base of parties involved in a project the greater the learning and the greater the new knowledge creation (Cohen & Levinthal, 1990). The logical extension would be to expect that the greater the knowledge the better the advice and the greater the industry relevant experience the better the advice. As a result greater industry relevant experience was expected to decrease escalation.

This hypothesis is mostly supported. Experience in the same industry, as measured by the number of companies funded and the percentage of total companies funded, was significant (Net1 $F=65.96$, $p<.0001$ and Net2 $F=38.54$, $p<.0001$). For Net 1 greater experience in the same industry, as determined by a count of the number of past companies funded in that industry, decreased escalation (beta coefficient is .008, $0<.0001$) as expected. Unexpectedly when looking at the percent of companies funded in the same industry (percentage out of the total number of companies funded in the past), the higher the percentage funded in the industry the greater the escalation (beta coefficient is -.0011).

When looking at related industry experience, the more related industry experience a VC firm had, the greater the escalation of commitment (beta coefficient is -0415, $p<.0001$). Again, unexpectedly the greater percent experience in the related industry decreased escalation of commitment (beta coefficient is .0026, $p<.0001$). The opposite was true with experience in unrelated industries. Unexpectedly the greater the unrelated industry experience the less the escalation of commitment (beta coefficient is .0167, $p<0001$). As expected, the higher the percentage of unrelated experience the greater the escalation of commitment (beta coefficient is -.00107).

The Net2 had exactly the same pattern of results and the beta coefficients were almost identical. In both networks the amount of variance explained was small, In Net1 the R squared was .01257 and for Net2 it was .01685. (See Table 4.9).

Table 4.9

Ho: 1b, VC firm industry and escalation

Net1 The GLM Procedure

Dependent Variable: CoEscalate

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	6	282.73536	47.12256	65.96	<.0001
Error	31080	22204.31163	0.71442		
Corrected Total	31086	22487.04700			

R-Square	Coeff Var	Root MSE	CoEscalate Mean
0.012573	53.39103	0.845236	1.583105

Source	DF	Type III SS	Mean Square	F Value	Pr > F
VCSameHist1	1	188.6869292	188.6869292	264.11	<.0001
VCSameHistPct1	1	17.3950651	17.3950651	24.35	<.0001
VCRelatedHist1	1	205.4880753	205.4880753	287.63	<.0001
VCRelatedHistPct1	1	11.2076471	11.2076471	15.69	<.0001
VCUnrelatedHist1	1	103.5972452	103.5972452	145.01	<.0001
VCUnrelatedHistPct1	1	3.4150062	3.4150062	4.78	0.0288

Parameter	Estimate	Standard Error	t Value	Pr > |t|
Intercept	1.606384586	0.01047540	153.35	<.0001
VCSameHist1	0.008215528	0.00050553	16.25	<.0001
VCSameHistPct1	-0.001104806	0.00022390	-4.93	<.0001
VCRelatedHist1	-0.041526156	0.00244854	-16.96	<.0001
VCRelatedHistPct1	0.002621012	0.00066174	3.96	<.0001
VCUnrelatedHist1	0.016764087	0.00139214	12.04	<.0001
VCUnrelatedHistPct1	-0.001071695	0.00049018	-2.19	0.0288

Table 4.9, continued

Net2 The GLM Procedure

Dependent Variable: CoEscalate

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	6	163.428117	27.238020	38.54	<.0001
Error	13488	9531.725199	0.706682		
Corrected Total	13494	9695.153316			

R-Square	Coeff Var	Root MSE	CoEscalate Mean
0.016857	53.02153	0.840644	1.585476

Source	DF	Type III SS	Mean Square	F Value	Pr > F
VCSameHist1	1	123.5960054	123.5960054	174.90	<.0001
VCSameHistPct1	1	25.3504827	25.3504827	35.87	<.0001
VCRelatedHist1	1	119.4582578	119.4582578	169.04	<.0001
VCRelatedHistPct1	1	16.4158975	16.4158975	23.23	<.0001
VCUnrelatedHist1	1	44.0156727	44.0156727	62.28	<.0001
VCUnrelatedHistPct1	1	0.5066038	0.5066038	0.72	0.3972

Parameter	Estimate	Standard Error	t Value	Pr > |t|
Intercept	1.634446940	0.01723263	94.85	<.0001
VCSameHist1	0.009881483	0.00074719	13.22	<.0001
VCSameHistPct1	-0.002182501	0.00036440	-5.99	<.0001
VCRelatedHist1	-0.047930144	0.00368649	-13.00	<.0001
VCRelatedHistPct1	0.005452628	0.00113132	4.82	<.0001
VCUnrelatedHist1	0.015724178	0.00199240	7.89	<.0001
VCUnrelatedHistPct1	-0.000671996	0.00079368	-0.85	0.3972

Hypothesis 1c: Syndicates with at least one VC firm with 12–15 years experience with fewer escalation outcomes and more experience in the industry of investment will escalate less.

This hypothesis built on the previous two, except that it is looking at the advice coming from other syndicate members rather than from the pre-1990 advice network. Combining Ho 1a and Ho1b, It is expected that a venture capitalist with 12-15 years of experience, with a deep knowledge of the investment's industry and one that had fewer investments that resulted in escalation of commitment may give more valuable advice than a venture capitalist with less than 12 or more than 15 years of experience or with more experience in another industry than the target industry or one with a poorer record of controlling escalation. Thus the best advice would be expected from VC firms with 12-

15 years of experience, with most of that experience in the industry, and who had few past escalation outcomes. This is a three way interaction hypothesis.

The hypothesis is significant in the sense that the three-way interaction of experience (except it is not a curvilinear relationship as hypothesized), industry related experience, and fewer escalation outcomes was found to decrease escalation of commitment (Net1 $F=113.82$ $p<.0001$ and Net2 $F=60.46$, $p<.0001$). However the same problem with age and experience was present here. Again the curvilinear relationship with age is not present; instead, it is it a straight linear relationship. The greater the VC firm's experience in years (*Age1*), the more experience in the industry as measured by number of companies funded in the past (*VCSameHist*) and the fewer escalations (*VCEscalate*) the less the syndicate escalates. The three-way interaction accounts for more of the variance than any of the other significant terms (Net1 mean square is 173.72, parameter $t = 15.91$, $p<.0001$ and Net2 mean square is 103.02, parameter $t = 12.25$, $p<.0001$). The amount of variance explained is small (Net1 R squared is .0435 and Net2 R squared is .0515). (See Table 4.10).

Table 4.10

Ho: 1c, Experience, industry, and escalation

Net1 The GLM Procedure

Dependent Variable: CoEscalate

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	11	859.49338	78.13576	113.82	<.0001
Error	27560	18919.14389	0.68647		
Corrected Total	27571	19778.63728			

R-Square	Coeff Var	Root MSE	CoEscalate Mean
0.043456	52.33655	0.828536	1.583092

Source	DF	Type III SS	Mean Square	F Value	Pr > F
VCAge1	1	58.5652372	58.5652372	85.31	<.0001
VCSameHist1	1	12.7616384	12.7616384	18.59	<.0001
VCSameHistPct1	1	1.4287737	1.4287737	2.08	0.1491
VCEscalateHist1	1	2.5813271	2.5813271	3.76	0.0525
VCEscalatePctHist1	1	16.3048578	16.3048578	23.75	<.0001
VCAge1*VCSameHist1	1	26.4111261	26.4111261	38.47	<.0001
VCAge1*VCEscalateHis	1	36.7932835	36.7932835	53.60	<.0001
VCSameHis*VCEscalate	1	98.8082505	98.8082505	143.94	<.0001
VCAge1*VCEscalatePct	1	22.0188928	22.0188928	32.08	<.0001
VCSameHis*VCEscalate	1	62.6495652	62.6495652	91.26	<.0001
VCAge1*VCSame*VCEsca	1	173.7244988	173.7244988	253.07	<.0001

Parameter	Estimate	Standard Error	t Value	Pr > |t|
Intercept	1.451933454	0.02136760	67.95	<.0001
VCAge1	0.015603043	0.00168928	9.24	<.0001
VCSameHist1	-0.008563664	0.00198618	-4.31	<.0001
VCSameHistPct1	0.000423227	0.00029336	1.44	0.1491
VCEscalateHist1	0.007985739	0.00411817	1.94	0.0525
VCEscalatePctHist1	-0.003512388	0.00072070	-4.87	<.0001
VCAge1*VCSameHist1	-0.000465711	0.00007508	-6.20	<.0001
VCAge1*VCEscalateHis	-0.002071018	0.00028289	-7.32	<.0001
VCSameHis*VCEscalate	-0.000603533	0.00005031	-12.00	<.0001
VCAge1*VCEscalatePct	0.000464464	0.00008201	5.66	<.0001
VCSameHis*VCEscalate	0.000520338	0.00005447	9.55	<.0001
VCAge1*VCSame*VCEsca	0.000048368	0.00000304	15.91	<.0001

Table 4.10, continued

Net2 The GLM Procedure

Dependent Variable: CoEscalate

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	11	456.738766	41.521706	60.46	<.0001
Error	12231	8399.411851	0.686731		
Corrected Total	12242	8856.150617			

R-Square	Coeff Var	Root MSE	CoEscalate Mean
0.051573	51.89873	0.828693	1.596749

Source	DF	Type III SS	Mean Square	F Value	Pr > F
VCAge1	1	35.2899680	35.2899680	51.39	<.0001
VCSameHist1	1	3.1810746	3.1810746	4.63	0.0314
VCSameHistPct1	1	0.2378251	0.2378251	0.35	0.5562
VCEscalateHist1	1	2.3618070	2.3618070	3.44	0.0637
VCEscalatePctHist1	1	1.2711950	1.2711950	1.85	0.1737
VCAge1*VCSameHist1	1	19.4374738	19.4374738	28.30	<.0001
VCAge1*VCEscalateHis	1	22.8101877	22.8101877	33.22	<.0001
VCSameHis*VCEscalate	1	52.8773207	52.8773207	77.00	<.0001
VCAge1*VCEscalatePct	1	9.6772277	9.6772277	14.09	0.0002
VCSameHis*VCEscalate	1	18.8047187	18.8047187	27.38	<.0001
VCAge1*VCSame*VCEsca	1	103.0161545	103.0161545	150.01	<.0001

Parameter	Estimate	Standard Error	t Value	Pr > |t|
Intercept	1.409219751	0.03896860	36.16	<.0001
VCAge1	0.020687871	0.00288592	7.17	<.0001
VCSameHist1	-0.006446930	0.00299543	-2.15	0.0314
VCSameHistPct1	0.000257817	0.00043810	0.59	0.5562
VCEscalateHist1	0.011076749	0.00597288	1.85	0.0637
VCEscalatePctHist1	-0.001615999	0.00118776	-1.36	0.1737
VCAge1*VCSameHist1	-0.000613910	0.00011539	-5.32	<.0001
VCAge1*VCEscalateHis	-0.002416399	0.00041927	-5.76	<.0001
VCSameHis*VCEscalate	-0.000662829	0.00007554	-8.77	<.0001
VCAge1*VCEscalatePct	0.000471299	0.00012555	3.75	0.0002
VCSameHis*VCEscalate	0.000444374	0.00008492	5.23	<.0001
VCAge1*VCSame*VCEsca	0.000056474	0.00000461	12.25	<.0001

Hypothesis 2a: VC firms with less dense networks or with clique-like networks will be more likely to escalate.

This hypothesis looked at where the venture capitalist was situated in the network and whether or not this affected escalation. Previous research documented that groups with more ties outperform those with fewer ties (Baldwin, Bedell, & Johnson, 1997; Reagans & Zuckerman, 2001). In addition, groups which have ties to other actors external to themselves gain access to useful information (Mizurchi, 1996; Anacona & Caldwell, 1992). Hansen (1999) documented that tie strength and information complexity interact with each other and affect group performance. When complex information is needed, a number of redundant strong ties transmitting that information are necessary in order for a group to actually use that information. Taken together the literature suggests that network centrality indices of a VC firm should affect escalation. It should follow that when a VC firm is situated in a less dense area of the network there would be less information available and therefore a higher probability of escalation. The reverse should hold true when a VC firm is located in a denser, more interconnected part of the network.

This was analyzed using the network measure k-plex, which takes into consideration both the density of ties around the focal VC firm and clique-like properties of clusters of VC firm ties. The descriptive statistics documented that there were no clique like properties within the main component of this network, therefore what effectively is being tested is the value of the local VC density around any given VC firm. The unit of analysis is at the VC firm tie level. The lower the k-plex rank, the denser the network is where the VC firm is located and, presumably, the easier it is for the VC firm to access a greater quantity of advice. The variable k-plex was normalized and then ranked to try to artificially increase the variance between the VC firms.

For Net1 this hypothesis was not supported ($F = 0.12$, $p<.05$, adjusted R squared is 0.000). This means that being located in a dense area of the network where nearly everyone locally is interconnected with each other and has connections to others does not (because there is no clique-like tendencies identified in the main component) decrease a VC firm's tendency to escalate commitment to a failing company.

For Net2 the hypothesis was supported ($F=24.83$, $p>.05$, adjusted R squared is 0.001). When a VC firm is located in a less dense area of the network, there is a slight tendency to increase escalation of commitment. The explanatory value of the k-plex variable is very small: only 0.1% of the variance is explained. Because a higher k-plex value means being located in an area of relative lower density, the beta coefficient is negative (-0032). (See table 4.11).

Table 4.11

Ho: 2a, K-plex and escalation

Net1 The GLM Procedure

Dependent Variable: CoEscalate

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	1	0.12140	0.12140	0.17	0.6821
Error	31082	22486.23798	0.72345		
Corrected Total	31083	22486.35938			

R-Square	Coeff Var	Root MSE	CoEscalate Mean
0.000005	53.72746	0.850558	1.583097

Source	DF	Type III SS	Mean Square	F Value	Pr > F
VCkplexRank1	1	0.12139666	0.12139666	0.17	0.6821

Parameter	Estimate	Standard Error	t Value	Pr > |t|
Intercept	1.595412188	0.03044726	52.40	<.0001
VCkplexRank1	-0.000123792	0.00030220	-0.41	0.6821

Net2 The GLM Procedure

Dependent Variable: CoEscalate

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	1	17.813878	17.813878	24.83	<.0001
Error	13485	9674.938550	0.717459		
Corrected Total	13486	9692.752428			

R-Square	Coeff Var	Root MSE	CoEscalate Mean
0.001838	53.41761	0.847030	1.585675

Source	DF	Type III SS	Mean Square	F Value	Pr > F
VCkplexRank1	1	17.81387794	17.81387794	24.83	<.0001

Parameter	Estimate	Standard Error	t Value	Pr > |t|
Intercept	1.768718484	0.03745151	47.23	<.0001
VCkplexRank1	-0.003237223	0.00064967	-4.98	<.0001

Hypothesis 2b: VC firms are located in a more densely interconnected portion of the network and they themselves are more densely connected to other VC firms, will be less likely to escalate.

This is an interaction hypothesis looking at the various measures of the interconnections (centrality measures) between the VC firms funding the company (in the regression these are variables with VC1 in them), the VC firms they are directly linked to in the network (these are the VC2 variables) and escalation of commitment.

As stated previously, the different measures of centrality measure slightly different aspects of the ease or difficulty of accessing information that is available in the network. These measures are based on the structural configuration of the network. Ideally it would have been possible to include all measures of centrality in the same regression equation. This would give the most complete information about the access an individual VC firm has to advice. Due to the colinearity problems referred to earlier, it was not possible to test all centrality measures in the same regression equation. Instead a number of regression equations were run, grouping together the centrality measures without colinearity problems.

Theoretically when a VC firm and the VC firm's advice network all have high actor degree centrality, high betweenness centrality, high information flow centrality, low closeness centrality (is an inverse score) and low k-plex rank centrality (low is denser) this would reduce escalation of commitment.

For Net1,all the regression equations were significant. Most of the measures of centrality were significant for the focal venture capital firm and to a lesser extent, for the VC firm's advice network. The interaction of the centrality measure between the focal VC firm and the advice network was generally significant. The directions were not always in the predicted direction. Sometimes the term was significant in one equation but not in another. Taken together, these results indicate that centrality in a network sometimes decreased escalation of commitment, in other cases it made no difference, and in yet other cases increased escalation of commitment. Net1 results were different than Net2 results. With Net2 there were fewer significant results.

The amount of variance explained was very small for either network (Net1R squared ranged from .09 to .005, Net2 R squared ranged from.017 to .005). The results also indicate that redefining the network to include only links for venture capitalists who are in Rounds 1 and 2 deletes important links that are present in the overall network. (See Table 4.12.)

For Net1, betweenness centrality was significant for the focal VC firm and explained most of the variance. It was not significant for the focal VC firm's advice network nor for the interaction of the VC firm and the advice network. Information centrality was significant, but in the wrong direction for the focal VC firm, in the right direction for the advice network, and the interaction term was significant in the wrong direction. Closeness centrality was not significant for the VC firm, was significant in the wrong direction for the network and significant in the right direction for the interaction. Degree centrality was significant in the wrong direction for the VC firm, was not significant for the advice network and was significant in the right direction for the interaction. K-plex was not significant for the VC firm, was significant in the wrong direction for the advice network, and significant in the right direction for the interaction.

For Net2 there were far fewer significant results. Betweenness centrality was significant in the right direction only for the VC firm. Information flow centrality and

Closeness centrality were generally not significant. Degree centrality was significant in the wrong direction for the VC firm, was not significant for the advice network and was significant in the right direction for the interaction. K-plex was not significant for the VC firm, was significant in the wrong direction for the advice network and in the right direction for the interaction.

Table 4.12

Ho: 2b, Network centrality, VC firm connections, and escalation

Net1

Net1 The GLM Procedure

Dependent Variable: CoEscalate

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	9	386.43264	42.93696	60.38	<.0001
Error	31077	22100.61436	0.71116		
Corrected Total	31086	22487.04700			

R-Square	Coeff Var	Root MSE	CoEscalate Mean
0.017185	53.26878	0.843301	1.583105

Source	DF	Type III SS	Mean Square	F Value	Pr > F
VCbetween1	1	297.8888232	297.8888232	418.88	<.0001
VCbetween2	1	0.3530195	0.3530195	0.50	0.4811
VCInfocentrality1	1	6.0614577	6.0614577	8.52	0.0035
VCInfocentrality2	1	0.5176696	0.5176696	0.73	0.3936
VCCloseness1	1	2.3893511	2.3893511	3.36	0.0668
VCCloseness2	1	5.3676919	5.3676919	7.55	0.0060
VCbetween*VCbetweenn	1	1.0268825	1.0268825	1.44	0.2295
VCInfocen*VCInfocent	1	0.8409017	0.8409017	1.18	0.2769
VCClosene*VCClosenes	1	6.1362893	6.1362893	8.63	0.0033

Parameter	Estimate	Standard Error	t Value	Pr > |t|
Intercept	1.75303265	0.42573785	4.12	<.0001
VCbetween1	7.62668082	0.37264139	20.47	<.0001
VCbetween2	-0.37436791	0.53135145	-0.70	0.4811
VCInfocentrality1	0.82679746	0.28319998	2.92	0.0035
VCInfocentrality2	-0.27531793	0.32269393	-0.85	0.3936
VCCloseness1	-2.44472662	1.33374544	-1.83	0.0668
VCCloseness2	3.99427341	1.45387353	2.75	0.0060
VCbetween*VCbetweenn	12.64375963	10.52200476	1.20	0.2295
VCInfocen*VCInfocent	0.36996885	0.34023202	1.09	0.2769
VCClosene*VCClosenes	-9.17099882	3.12209673	-2.94	0.0033

Table 4.12, continued

Net1 The GLM Procedure

Dependent Variable: CoEscalate

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	6	88.22807	14.70468	20.40	<.0001
Error	31080	22398.81893	0.72068		
Corrected Total	31086	22487.04700			

R-Square	Coeff Var	Root MSE	CoEscalate Mean
0.003924	53.62437	0.848930	1.583105

Source	DF	Type III SS	Mean Square	F Value	Pr > F
VCdegree1	1	7.16331039	7.16331039	9.94	0.0016
VCdegree2	1	9.41415485	9.41415485	13.06	0.0003
VCInfocentrality1	1	0.00844387	0.00844387	0.01	0.9138
VCInfocentrality2	1	0.00000140	0.00000140	0.00	0.9989
VCdegree1*VCdegree1	1	12.48090716	12.48090716	17.32	<.0001
VCbetween*VCbetweenn	1	18.91065614	18.91065614	26.24	<.0001

Parameter	Estimate	Standard Error	t Value	Pr > |t|
Intercept	1.73266848	0.08517129	20.34	<.0001
VCdegree1	-0.00851391	0.00270050	-3.15	0.0016
VCdegree2	-0.00214123	0.00059244	-3.61	0.0003
VCInfocentrality1	0.01587334	0.14664576	0.11	0.9138
VCInfocentrality2	0.00006056	0.04337926	0.00	0.9989
VCdegree1*VCdegree1	0.00010853	0.00002608	4.16	<.0001
VCbetween*VCbetweenn	41.07981830	8.01949959	5.12	<.0001

Net1 The GLM Procedure

Dependent Variable: CoEscalate

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	6	80.12415	13.35403	18.52	<.0001
Error	31077	22406.23523	0.72099		
Corrected Total	31083	22486.35938			

R-Square	Coeff Var	Root MSE	CoEscalate Mean
0.003563	53.63611	0.849112	1.583097

Source	DF	Type III SS	Mean Square	F Value	Pr > F
VCdegree1	1	4.35081723	4.35081723	6.03	0.0140
VCdegree2	1	0.00271208	0.00271208	0.00	0.9511
VCkplexRank1	1	0.38516906	0.38516906	0.53	0.4648
VCkplexRank2	1	3.21808629	3.21808629	4.46	0.0346
VCdegree1*VCdegree1	1	14.84620963	14.84620963	20.59	<.0001
VCkplexRa*VCkplexRan	1	5.74811868	5.74811868	7.97	0.0048

Parameter	Estimate	Standard Error	t Value	Pr > |t|
Intercept	1.591828038	0.07987894	19.93	<.0001
VCdegree1	-0.004812004	0.00195887	-2.46	0.0140
VCdegree2	0.000027075	0.00044145	0.06	0.9511
VCkplexRank1	0.000707033	0.00096734	0.73	0.4648
VCkplexRank2	0.002149748	0.00101755	2.11	0.0346
VCdegree1*VCdegree1	0.000088484	0.00001950	4.54	<.0001
VCkplexRa*VCkplexRan	-0.000028566	0.00001012	-2.82	0.0048

Table 4.12, continued

Net1 The GLM Procedure

Dependent Variable: CoEscalate

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	6	343.48084	57.24681	80.34	<.0001
Error	31077	22142.87854	0.71252		
Corrected Total	31083	22486.35938			

R-Square	Coeff Var	Root MSE	CoEscalate Mean
0.015275	53.31997	0.844107	1.583097

Source	DF	Type III SS	Mean Square	F Value	Pr > F
VCbetween1	1	41.2116319	41.2116319	57.84	<.0001
VCbetween2	1	0.1470120	0.1470120	0.21	0.6497
VCkplexRank1	1	0.0816404	0.0816404	0.11	0.7350
VCkplexRank2	1	1.2720207	1.2720207	1.79	0.1815
VCbetween*VCbetweenn	1	124.9772523	124.9772523	175.40	<.0001
VCkplexRa*VCkplexRan	1	2.1188566	2.1188566	2.97	0.0846

Parameter	Estimate	Standard Error	t Value	Pr > |t|
Intercept	1.66267613	0.07894774	21.06	<.0001
VCbetween1	-5.56858897	0.73220510	-7.61	<.0001
VCbetween2	-0.12512147	0.27545649	-0.45	0.6497
VCkplexRank1	-0.00028391	0.00083874	-0.34	0.7350
VCkplexRank2	0.00132992	0.00099535	1.34	0.1815
VCbetween*VCbetweenn	93.45024741	7.05606324	13.24	<.0001
VCkplexRa*VCkplexRan	-0.00001729	0.00001003	-1.72	0.0846

Table 4.12, continued

Net2

Net2 The GLM Procedure

Dependent Variable: CoEscalate

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	9	69.338094	7.704233	10.79	<.0001
Error	13485	9625.815222	0.713816		
Corrected Total	13494	9695.153316			

R-Square	Coeff Var	Root MSE	CoEscalate Mean
0.007152	53.28851	0.844877	1.585476

Source	DF	Type III SS	Mean Square	F Value	Pr > F
VCbetweenness1	1	45.22499942	45.22499942	63.36	<.0001
VCbetweenness2	1	0.00577909	0.00577909	0.01	0.9283
VCInfocentrality1	1	1.57256720	1.57256720	2.20	0.1378
VCInfocentrality2	1	1.75281226	1.75281226	2.46	0.1171
VCCloseness1	1	1.38082493	1.38082493	1.93	0.1643
VCCloseness2	1	0.55946033	0.55946033	0.78	0.3760
VCbetween*VCbetweenn	1	2.30285668	2.30285668	3.23	0.0725
VCInfocen*VCInfocent	1	1.78005383	1.78005383	2.49	0.1143
VCClosene*VCClosenes	1	0.31651730	0.31651730	0.44	0.5055

Parameter	Estimate	Standard Error	t Value	Pr > |t|
Intercept	1.55210230	0.21909535	7.08	<.0001
VCbetweenness1	3.48602607	0.43796019	7.96	<.0001
VCbetweenness2	0.05025729	0.55855086	0.09	0.9283
VCInfocentrality1	0.34259998	0.23082137	1.48	0.1378
VCInfocentrality2	0.40331583	0.25737766	1.57	0.1171
VCCloseness1	-1.29080479	0.92807814	-1.39	0.1643
VCCloseness2	0.91270751	1.03095632	0.89	0.3760
VCbetween*VCbetweenn	-16.64677621	9.26808421	-1.80	0.0725
VCInfocen*VCInfocent	-0.43425258	0.27499141	-1.58	0.1143
VCClosene*VCClosenes	-1.97230424	2.96188686	-0.67	0.5055

Table 4.12, continued

Net2 The GLM Procedure

Dependent Variable: CoEscalate

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	6	115.196895	19.199483	27.03	<.0001
Error	13488	9579.956421	0.710258		
Corrected Total	13494	9695.153316			

R-Square	Coeff Var	Root MSE	CoEscalate Mean
0.011882	53.15551	0.842768	1.585476

Source	DF	Type III SS	Mean Square	F Value	Pr > F
VCdegree1	1	33.03484356	33.03484356	46.51	<.0001
VCdegree2	1	2.14212324	2.14212324	3.02	0.0825
VCInfocentrality1	1	3.72473406	3.72473406	5.24	0.0220
VCInfocentrality2	1	0.58958140	0.58958140	0.83	0.3623
VCdegree1*VCdegree1	1	53.40924325	53.40924325	75.20	<.0001
VCInfocen*VCInfocent	1	1.78005383	1.78005383	2.49	0.1143

Parameter	Estimate	Standard Error	t Value	Pr > |t|
Intercept	1.639651959	0.08354481	19.63	<.0001
VCdegree1	-0.050807578	0.00744990	-6.82	<.0001
VCdegree2	-0.002978933	0.00171533	-1.74	0.0825
VCInfocentrality1	0.380114347	0.16598721	2.29	0.0220
VCInfocentrality2	0.064745600	0.07106346	0.91	0.3623
VCdegree1*VCdegree1	0.001281868	0.00014782	8.67	<.0001
VCInfocen*VCInfocent	-0.43425258	0.27499141	-1.58	0.1143

Table 4.12, continued

Net2 The GLM Procedure

Dependent Variable: CoEscalate

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	6	154.277640	25.712940	36.34	<.0001
Error	13480	9538.474788	0.707602		
Corrected Total	13486	9692.752428			

R-Square	Coeff Var	Root MSE	CoEscalate Mean
0.015917	53.04938	0.841191	1.585675

Source	DF	Type III SS	Mean Square	F Value	Pr > F
VCdegree1	1	0.79140832	0.79140832	1.12	0.2903
VCdegree2	1	0.00085272	0.00085272	0.00	0.9723
VCkplexRank1	1	2.09332082	2.09332082	2.96	0.0855
VCkplexRank2	1	10.31978033	10.31978033	14.58	0.0001
VCdegree1*VCdegree1	1	11.94333212	11.94333212	16.88	<.0001
VCkplexRa*VCkplexRan	1	11.20084414	11.20084414	15.83	<.0001

Parameter	Estimate	Standard Error	t Value	Pr > |t|
Intercept	1.683565669	0.08856616	19.01	<.0001
VCdegree1	-0.005837664	0.00551993	-1.06	0.2903
VCdegree2	-0.000048655	0.00140157	-0.03	0.9723
VCkplexRank1	-0.003254814	0.00189236	-1.72	0.0855
VCkplexRank2	0.008166902	0.00213854	3.82	0.0001
VCdegree1*VCdegree1	0.000479203	0.00011664	4.11	<.0001
VCkplexRa*VCkplexRan	-0.000149828	0.00003766	-3.98	<.0001

Net2 The GLM Procedure

Dependent Variable: CoEscalate

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	6	115.828979	19.304830	27.17	<.0001
Error	13480	9576.923450	0.710454		
Corrected Total	13486	9692.752428			

R-Square	Coeff Var	Root MSE	CoEscalate Mean
0.011950	53.15619	0.842884	1.585675

Source	DF	Type III SS	Mean Square	F Value	Pr > F
VCbetweenness1	1	5.72671527	5.72671527	8.06	0.0045
VCbetweenness2	1	0.90029519	0.90029519	1.27	0.2603
VCkplexRank1	1	0.30584233	0.30584233	0.43	0.5118
VCkplexRank2	1	4.94481592	4.94481592	6.96	0.0083
VCbetween*VCbetweenn	1	22.09430014	22.09430014	31.10	<.0001
VCkplexRa*VCkplexRan	1	5.38574094	5.38574094	7.58	0.0059

Parameter	Estimate	Standard Error	t Value	Pr > |t|
Intercept	1.65832358	0.08811721	18.82	<.0001
VCbetweenness1	-2.66185131	0.93755997	-2.84	0.0045
VCbetweenness2	-0.35138950	0.31215075	-1.13	0.2603
VCkplexRank1	-0.00110681	0.00168692	-0.66	0.5118
VCkplexRank2	0.00553021	0.00209621	2.64	0.0083
VCbetween*VCbetweenn	44.81002335	8.03531872	5.58	<.0001
VCkplexRa*VCkplexRan	-0.00010107	0.00003671	-2.75	0.0059

Hypothesis 2c: VC firms that are not tightly and exclusively connected with only a small number of other VC firms (i.e., are not in a clique) will escalate less.

Consistent with previous research, this hypothesis presumes that the lack of information variety that exists in a small clique is a disadvantage (Bert, 1992). Performance is higher when groups have more ties to others that are external to the focal group (Baldwin, et. al., 1997; Regans & Zuckerman, 2001) because useful information is gained when groups have ties to external actors (Mizurchi, 1986; Anacona & Caldwell, 1992). As a result it was expected that those VC firms who were not in a clique would escalate less than those who were tightly and exclusively connected with only a few others. This hypothesis cannot be tested. There are too few VC firms that are not part of the main component, and, therefore, not enough power to do any statistical tests.

Hypothesis 3a: When VC firms work with other VC firms they have worked with in the past, they will, up to a point, escalate less than if they have never worked together. When they work exclusively with each other they will escalate more.

There is a significant amount of small group research documenting that experience working together is required for smooth group functioning, for productive use of conflict over ideas, and for members to be able to take advantage of the skills and knowledge of their members. The result of greater experience working together is increased group performance, except in cases of overly cohesive groups where performance decreases (Arrow & McGrath, 1993; Jenh, 1995, 1997; Birmingham & Michaelsen, 1993, Watson, et. al., 1993, 1991). This hypothesis suggests a curvilinear result, presuming some syndicate groups experience group think when they work exclusively with each other.

Although there are significant results, the hypothesis is not supported because the results are not curvilinear. In Net1, when venture capitalists worked together in the past they escalated less (F = 6.33, p>.05); the variance explained, however, is very small (adjusted R squared is less than 0.0002). In Net2 this was also true (F = 11.93, p>.05, adjusted R squared is .0009). The portion of the hypothesis that addressed working exclusively with each other was not tested because there was not enough power to test this (only three dyadic groups of venture capitalists in Net1 and three dyadic groups and one group of four in Net2). (See Table 4.13).

Table 4.13

<u>Ho: 3a, Working together in the past and escalation</u>

Net1 The GLM Procedure

Dependent Variable: CoEscalate

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	1	4.58173	4.58173	6.33	0.0118
Error	31085	22482.46526	0.72326		
Corrected Total	31086	22487.04700			

R-Square	Coeff Var	Root MSE	CoEscalate Mean
0.000204	53.72008	0.850446	1.583105

Source	DF	Type III SS	Mean Square	F Value	Pr > F
VC1VC2WorkedInPast	1	4.58173334	4.58173334	6.33	0.0118

Parameter	Estimate	Standard Error	t Value	Pr > |t|
Intercept	1.591204909	0.00579837	274.42	<.0001
VC1VC2WorkedInPast	-0.026296293	0.01044783	-2.52	0.0118

Table 4.13, continued

Net2 The GLM Procedure

Dependent Variable: CoEscalate

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	1	8.566870	8.566870	11.93	0.0006
Error	13493	9686.586446	0.717897		
Corrected Total	13494	9695.153316			

R-Square	Coeff Var	Root MSE	CoEscalate Mean
0.000884	53.44061	0.847288	1.585476

Source	DF	Type III SS	Mean Square	F Value	Pr > F
VC1VC2WorkedInPast	1	8.56687027	8.56687027	11.93	0.0006

Parameter	Estimate	Standard Error	t Value	Pr > |t|
Intercept	1.607921318	0.00976802	164.61	<.0001
VC1VC2WorkedInPast	-0.050728218	0.01468485	-3.45	0.0006

Hypothesis 3b: Larger groups made up of more venture capitalists who have worked together in the past will escalate less than larger groups made up of fewer venture capitalists who have worked together in the past.

Building on the theory used in hypothesis 3a this hypothesis adds group size. Larger VC syndicates have other problems with decision-making and problem solving (D'Amico, 2002). Previous research on VC firms and escalation documented that larger syndicate groups had a tendency to escalate more than smaller syndicate groups (Birmingham, et. al.2003). As a result it is expected that large groups with less experience working together in the past will be more likely to escalate their commitment. Therefore it is expected that the interaction term will be significant.

Although the results are significant, this hypothesis is not supported because in both cases the interaction term is not significant. In Net1 the interaction term has an F of 0.07 and in Net2 F it is 1.89. In both cases, working together in the past decreased escalation (although Net1 p<.06, beta coefficient = -.028012 and Net2 p<.0001, beta coefficient = -.072863). In both cases, as the number of VC firms investing in the company increased, so did escalation (Net1 beta coefficient is .025035 and Net2 beta coefficient is .024093). The amount of variance for these results is small (Net1 R squared is .0896 and Net2 .0936). (See Table 4.14.)

Table 4.14

<u>Ho: 3b, Group size and working together in the past</u>

Net1 The GLM Procedure

Dependent Variable: CoEscalate

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	3	2015.96612	671.98871	1020.34	<.0001
Error	31083	20471.08088	0.65859		
Corrected Total	31086	22487.04700			

R-Square	Coeff Var	Root MSE	CoEscalate Mean
0.089650	51.26242	0.811538	1.583105

Source	DF	Type III SS	Mean Square	F Value	Pr > F
VC1VC2WorkedInPast	1	2.257295	2.257295	3.43	0.0641
CoNofVCs	1	1377.488542	1377.488542	2091.56	<.0001
VC1VC2Worke*CoNofVCs	1	0.047323	0.047323	0.07	0.7887

Parameter	Estimate	Standard Error	t Value	Pr > |t|
Intercept	1.300165370	0.00843287	154.18	<.0001
VC1VC2WorkedInPast	-0.028012188	0.01513080	-1.85	0.0641
CoNofVCs	0.025035759	0.00054743	45.73	<.0001
VC1VC2Worke*CoNofVCs	0.000263278	0.00098217	0.27	0.7887

Table 4.14, continued

Net2 The GLM Procedure

Dependent Variable: CoEscalate

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	3	907.635852	302.545284	464.48	<.0001
Error	13491	8787.517464	0.651361		
Corrected Total	13494	9695.153316			

R-Square	Coeff Var	Root MSE	CoEscalate Mean
0.093617	50.90393	0.807070	1.585476

Source	DF	Type III SS	Mean Square	F Value	Pr > F
VC1VC2WorkedInPast	1	7.8323951	7.8323951	12.02	0.0005
CoNofVCs	1	478.8471231	478.8471231	735.15	<.0001
VC1VC2Worke*CoNofVCs	1	1.2327195	1.2327195	1.89	0.1689

Parameter	Estimate	Standard Error	t Value	Pr > |t|
Intercept	1.329266293	0.01386341	95.88	<.0001
VC1VC2WorkedInPast	-0.072863895	0.02101242	-3.47	0.0005
CoNofVCs	0.024093317	0.00088861	27.11	<.0001
VC1VC2Worke*CoNofVCs	0.001862999	0.00135423	1.38	0.1689

VC1VC2WorkedIn Past – VC firms worked together in the past
CoNofVCs – number of VC firms investing in the current start-up company

Summary

In summary, the venture capital firm advice network is very dense and information flows freely though out the network.

Hypothesis 1a: VC firms connected to primarily inexperienced or very experienced VC firms will escalate more than those with a higher percentage of connections to VC firms with 12–15 years of experience.

This hypothesis was not supported, instead there was a linear effect.

Hypothesis 1b: Syndicates with more VC firms with more industry relevant experience will escalate less than those with less past experience in that industry.

This hypothesis was mostly supported.

Hypothesis 1c: Syndicates with at least one VC firm with 12–15 years experience with fewer escalation outcomes and more experience in the industry of investment will escalate less.

This hypothesis was mostly supported.

Hypothesis 2a: VC firms with less dense networks or with clique-like networks will be more likely to escalate.

This hypothesis was not supported for Net1 but was supported for Net2.

Hypothesis 2b: VC firms located in a more densely interconnected portion of the network, where they themselves are more densely connected to other VC firms, will be less likely to escalate.

This hypothesis received mixed and conflicting results.

Hypothesis 2c: VC firms that are not tightly and exclusively connected with only a small number of other VC firms (i.e., are not in a clique) will escalate less.

This hypothesis could not be tested.

Hypothesis 3a: When VC firms work with other VC firms they have worked with in the past, they will, up to a point, escalate less than if they have never worked together. When they work exclusively with each other they will escalate more.

This hypothesis was not supported.

Hypothesis 3b: Larger groups, when made up of more venture capitalists who have worked together in the past, will escalate less than larger groups made up of fewer venture capitalists who have worked together in the past.

This hypothesis was not supported.

While some of the hypotheses concerning advice networks were supported, the effect size was small (generally between .01% and 9% of the variance explained). To some degree, the support of the various hypotheses, and to a small extent the effect size, varied between Net1 and Net2. This indicates that how a network is defined affects network outcomes. When a network is very dense the network measures have very little variance which makes it hard to find significance or much in the way of effect size. In addition, with a network as interconnected and dense as this one, the current network tools available cannot adequately handle these kinds of analyses (Newman, Watts and Strogatz, 2002).

Discussion

This study examined the advice networks of venture capital firms that funded new high-technology start-up companies. The source of the data was Thompson Financial's VentureXpert database, which contains information about which VC firms funded each start-up company. When the focal VC firm worked with another VC firm prior to 1990, the latter VC firm formed part of the focal VC firm's advice network. Characteristics of the VC firm and the various advice network indices attached to the VC firm's position in the network were used to predict escalation of commitment in new high-technology start-up companies where the first round of funding was between 1990 and 1995. Some of the variables were statistically significant predictors of escalation of commitment.

There were three major findings. First, the network of VC firms that invest in high technology start-ups has become far more interconnected and dense over the last 15 or so years. Second, these dense interconnections allow information to flow freely throughout the VC network. Third, determining the boundaries of a network and defining its membership affect the representation of the underlying network structure. The decision to delete ties should be made with caution. A major limitation of this study is that the large size and incredibly dense nature of this network overwhelmed the capabilities of the existing network analytic tools. Since this potentially compromised the ability to credibly analyze the data, the results should be viewed with caution.

Findings

The initial steps in analyzing the network were to create the network from the ties observed and then to describe the network. One unexpected finding was that the VC firm advice network was extremely dense and that the network had, for all practical purposes, only one giant component. Earlier mappings of the VC firm funding network had documented regional hubs, such as Silicon Valley and the greater Boston area, with limited ties between hubs (Bygrave, 1987; Bygrave & Timmons, 1992). These earlier mappings showed a network comprised of many locally dense, almost clique-like components. One explanation for the regional nature of network hubs was that venture capitalists generally had a very "hands-on" management style with their investments and therefore preferred to be physically located near their investments. Another explanation was that when a VC firm was located in the same general vicinity as the new start-up and of other VC firms it was easier to determine the reputation both of the entrepreneur and of other potential investment partners (Bygrave 1987; Bygrave & Timmons, 1992; Castilla, 2003; De Clerc, 2002; Ferrary, 2003). Now, nearly 20 years later, the network documented in the early research is so dense that regional hubs cannot be statistically identified. Instead, the network is composed of one giant, interconnected component. In fact, only about 2% of VC firms are not connected to the main component. Clearly, in an industry that relies heavily on reputation and trust (Castilla, 2003; De Clerc, 2002; Sorenson & Stuart, 2001; Ferrary, 2003), this dense interconnectivity allows information about reputation and trustworthiness to flow freely throughout the network.

Changes in communication technology over the last 20 years may explain why this network has become more highly interconnected. The easier it is to communicate, the easier it is to have long distance relationships (Licoppe & Smoreda, 2005). Advances in communication technology may be partly responsible for the increased number of connections between physically distant VC firms. In the past, due to the hands-on nature of venture capitalists' management of new start-ups, VC firms preferred to fund companies within a 60–100 mile radius (Bygrave 1987; Bygrave & Timmons, 1992; Castilla, 2003; De Clerc, 2002; Ferrary, 2003). Long-distance partnerships may have been originally created due to the need to have a "local" partner for a new-startup when the start-up was not in the same geographical vicinity as the focal VC firm. Over time, technological changes made these kinds of long distant relationships easier, more practical, and therefore more frequent.

As new VC firms join the network, they also may be following the pattern noticed in other affiliation networks. New actors tend to attempt to establish ties with the most connected actors in the existing network (Davis, Yoo, & Baker, 2003; Barabasi & Albert, 1999). Certainly the scale-free property of the two networks implies that this holds true for the VC networks studied. The largest consequence of the change from regional hubs with few cross-hub connections to one large, densely interconnected component is that the later configuration allows information to flow freely throughout the network. When there is one very dense component, most network variables have little variance. The interconnectedness and therefore lack of variance make it harder to predict escalation of commitment and may explain why the findings explain very little of the variance.

Due to the generally weak findings and other problems associated with analyzing such a dense network, a second approach of modeling the advice network was made. Since the decision to fund Round 3 was made by the VC firms in Rounds 1 and 2, the advice networks of VC firms funding only the first two rounds were examined. The findings for each network were similar but not identical. Although Net2 was less dense and interconnected than Net1, it was still a dense, single-component network. However, the periphery of the Net2 was more spread out and thus more visible.

The significance of various network measures differed depending on which advice network was being examined. This raises another issue concerning network structure. Clearly, the definition of the network is critical when trying to make inferences about network independent variables.

Despite these problems, however, the analyses the hypotheses analyzed using Net1 and Net2 did reveal some relationships between the advice networks of VC firms and escalation of commitment. Results for the first set of hypotheses based on VC firm experience were not unexpected in the sense that past experience has been found to be significant in other studies. Past research has documented an inverted U-shaped curve for experience and new start-up company outcomes (Shepherd, Zacharakis, & Baron , 2003).This research, in contrast, found (hypothesis 1a), a linear relationship in both Net1 and Net2. This find implies that decision quality does not drop as VC firms reach a certain age level.

One specific finding (hypothesis 1a) was that the more companies that were funded in the past by the advice network VC firms, the more escalation of commitment by the focal VC firm. Yet that effect went away when the variable was combined with the age of the focal firm. Instead escalation of commitment dropped. It may be that experience over time allows for better judgment and so the combination of the two factors results in less escalation of commitment. Also, a relatively young VC firm that funded a number of companies concurrently would not benefit from the deep learning by experience that can develop over a number of years. An older company, provided it has funded a number of companies in the past, presumably has a greater pool of wisdom to draw upon, which should increase the value of its advice. Age in years also tends to select for the more successful firms, which may also explain why age combined with number of companies funded helped decrease escalation.

Another explanation for these finding is biases in the database. More successful outcomes than unsuccessful ones are in the database, yet the collective VC firm experience is the other way around. Because success is over-represented and presumably VC firms which are repeatedly unsuccessful go out of business, the VC firms in the network may be a group of firms that has been selected for because they have been successful in the past and are continuing to be successful in the present.

Experience in the same and in related industries (hypothesis 1b), as measured by the number of companies invested in previously, was also predictive of escalation of commitment. Greater experience in unrelated industries was inversely related. This finding makes sense, given that experience in the same or related industries would increase a VC firm's knowledge of industry-specific issues, and thereby increasing its absorptive capacity in that industry. The VC firm would have deeper knowledge in the industry helping it pick better start-up companies to fund and give better product related advice while funding the new start-up. In both networks, greater experience in the same industry, as determined by the number of companies funded, was linked to decreased escalation. By contrast, there was an increase in escalation when experience was measured by the percentage of companies funded. One explanation for this finding might be that VC firms could have a similar percentage without having similar experience. For example, one VC firm could have funded one company in a particular industry and two companies overall, while another firm might have funded ten companies in a particular industry and twenty overall. Clearly, while the percentage of companies funded is identical, the latter VC firm has greater industry experience.

When looking directly at VC syndicates funding current companies, a three-way interaction was found between the syndicate's age, the number of companies funded in the past in the same industry, and past escalation history (hypothesis 1c). As noted previously, while this research did not find the expected curvilinear relationship with age, it appears that the combination of greater age, more experience in the same industry, and fewer past escalation outcomes decreases escalation. As mentioned earlier, these surviving older, based on founding date, VC firms tend to be firms that are more likely to have funded a higher number of successes rather than failures. It is likely that these older VC firms have learned how to manage escalation of commitment, as Ross & Staw (1993) speculated could happen, which in turn contributed to their survival. Of course, VC firms that had escalated substantially in the past were probably under-represented in this study since they would be more likely to be out of business. Further research into how VC firms recognize that they are funding a failing company and act to terminate the investment without escalating would be useful.

The next set of hypotheses (2a, 2b, and 2c) used network indices to predict escalation of commitment. Jaaskelainen (2001) found that the different measures of centrality in a small VC network measured different aspects of information flow through the network. He demonstrated the importance of knowing not just who was in the most central unit but also what the centrality score values were. In general, the outcome for Net1 and Net2 were not consistent with the Jaaskelainen results. In these advice networks, most of the centrality scores' values (hypotheses 2a and 2b) had only small differences and there was only one component, so Net1 and Net2 centrality had little predictive value. Each of the measures of centrality measures different aspects of the same thing. All but VC degree and VC k-plex had little variance. Together, the results for Net1 indicate that a number of factors—including the number of direct ties between the focal VC firm and other VC firms, the degree to which the focal VC firm is the link between other firms, the ease with which the focal firm can reach other network members, and the number of more distant VC firms the focal firm can reach via a short "path"—all slightly increased the ability to predict escalation of commitment.

Hypothesis 2a, that venture capitalists with less dense networks or with clique-like networks would be more likely to escalate, was supported for Net2 but not for Net1. Net2, although dense, was less so than Net1, and it was easier to visually see a difference in the density between its core and periphery. As a result, Net2 offered more of an opportunity for a VC firm to be located in an area of the network which, although densely interconnected, would be comparatively less so than another area such as the core. A certain level of differentiation in dense interconnectivity for communication flows may be needed to have significant findings. Since Net2 had fewer than half the average number of direct ties than Net1, it may demonstrate that a VC firm's location near a dense part of the network makes more of a difference where fewer ties exist. Furthermore, the difference between Net1 and Net2 suggests that the advice network of the Round 1 and 2 VC firms makes the difference in recognizing escalation of commitment early in the process. By the time other VC firms enter in later rounds of funding, the original VC firms may be entrapped into escalation by too many sunk costs and the psychological processes outlined by Ross and Staw (1993) in their model utilized in this research.

A significant problem associated with hypothesis 2b, which tested all the centrality measures, was the extent of the correlation between the various centrality measures. Some of the results were conflicting or in the wrong direction. It may be that the network is so densely interconnected, with so many alternative paths for information to reach any given VC firm, that none of the centrality measures can meaningfully isolate particular kinds of centrality effects. Moreover, the measures may all be contaminated by the multiple paths information can take to arrive at a particular node and the ease with which information travels through the network. The problem could also stem from the fundamental difficulty of getting accurate network index values when the program creating these values cannot accurately handle a network this large and dense. In either case, some of the measures of central location in a network do affect information flow and have predictive value.

That the for Net2 differed from those for Net1 in some analyses may be due to the consequences of changing the underlying network structure by changing the decision rule governing which ties to count. In addition, because Net2 VC firms had, on average, far fewer ties than Net1 VC firms, there were fewer paths for information to flow through. The problem with this explanation is that it is likely that some active ties used in decision-making were deleted. For example, Net2 VC firms may consult with some VC firms present in Net1 that are not present in Net2 when Net2 VC firms make decisions. Perhaps venture capitalists in Round 3 are consulted and, because they agree to join the syndicate, their advice, presumably after due diligence, is to continue funding.

Unfortunately, there is no way to gather information on the VC firms contacted which advised the focal VC firm to cut its losses. The differences between the Net1 and Net2 results, along with the lack of consistency with the Jaaskelainen (2001) VC network results, should signal that the inclusion or exclusion of particular ties matters a great deal and that the manner in which a network, as well as an active tie, is defined is critical.

The last set of hypotheses (3 and 3b) had to do with the VC syndicates themselves. The number of VC firms investing in a company was predictive of escalation (hypothesis 3a). This confirmed the tentative finding ($p>0.1$) of an earlier study (Birmingham et al., 2003). Diffusion of responsibility is a likely explanation for this finding. Whether or not VC firms had worked with other VC firms in the syndicate in the past was significant. There was a linear relationship between the extent to which the VC firms had worked together in the past and escalation. Consistent with group research the more they had worked together in the past the less likely they were to escalate. Inconsistent with the group research was that there wasn't a curvilinear relationship. The decrease in escalation would have been expected if VC firms worked exclusively with each other and were overly cohesive. Because few VC firms in the data only worked with each other repeatedly there was probably no opportunity for these VC firms to develop an overly cohesive bond.

The interaction of working together in the past and size of the group investing in the new start-up was not significant (hypothesis 3b). It may be that the problems of working together in larger groups can overwhelm the advantages of having worked together in the past. Alternatively, it could mean that when only some of the firms in the VC syndicate had worked together in the past, most or all of the problems inherent in the management of new groups and their decision-making processes also afflicted VC syndicates.

Theoretically, this research contributes to understanding of advice networks and escalation of commitment. Decisions are not made in a vacuum. Advice networks are an important part of the venture capital decision-making process. Venture capitalists rely on their advice networks for information and advice concerning the viability of new venture funding proposals (Bygrave & Timmons, 1992). The dense networks and the resultant information flow through them contribute to improved decision-making by making public the private information about reputations of other venture capitalists, VC firms, and entrepreneurs (Castilla, 2003; Ferrary, 2003). This research documents another way advice networks influence investment outcomes. Access to experienced venture capitalists with significant industry-related experience that have escalated in the past and are central in the network gives access to advice that decreases the tendency for a VC syndicate to escalate its commitment to a failing venture. Discovering how experienced VC firms recognize the potential for escalation and cut their losses without escalating would be important in further understanding how people learn (or not) from escalation experiences. A related need is to discover what aspects of the advice from experienced VC firms help a VC syndicate to avoid escalation itself.

Several practical implications for VC firms come from this study. The first is that the tendency to escalate commitment to a failing new start-up is influenced, to a small degree, by the advice received from other VC firms. VC firms with more industry-related experience that had escalated commitment in the past gave better advice to prevent escalation of commitment than those firms with less experience or those which had not escalated their commitment in the past. Presumably market forces have, at least to some degree, selected for VC firms that have learned to manage escalation. The increased absorptive capacity of experienced VC firms operating in the same and related industries increases the value of their advice. Greater advice network's interconnectivity should facilitate the information flow. VC firms need to use this interconnectivity finding to their advantage when they choose their advice sources. Identifying which firms are located in the most advantageous network locations and creating ties to those firms should increase a focal VC firm's access to quality advice. The result should be that VC firms are then able to decrease the risk of escalating their commitment to a failing start-up.

Limitations

There are limits to using secondary data, even though using secondary data to document links between actors is a common practice in network analysis because of the likelihood of having fewer missing nodes and ties. For instance, secondary data does not make it possible to determine which historical ties are now "broken" and no longer in use. This study presumed that all ties from pre-1990 were still active for new start-ups that received their first round of funding between 1990 and 1995. This assumption was probably not accurate for some ties, although it is likely that most ties were still active. The data covered the period from about 1975 forward. As most VC syndicates last 10–12 years and the period of interest started in 1990, the 15-year time lag from the beginning of most of the historical advice network data to 1990 is, comparatively speaking, not very long, . Directly asking venture capitalists within a firm to identify which other VC firms they use for advice would solve that problem.

A second issue with using secondary data to infer active ties is that of actors' cognitive limits. It is not clear how many active ties one individual can maintain. This has been examined in the context of corporate board interlocks. The substantial costs associated with board membership and the costs of maintaining these ties create a practical limit on the number of active board ties an individual can maintain. There are time demands, frequent face-to-face meetings, and other social interaction requirements that represent a significant commitment of time, money and opportunity costs (Davis et al., 2003; Newman, Watts & Strigatz, 2002; Gifford, 1997). Newman et al. (2002), using the data of Davis et al. (2003), have documented how the number of ties between board members obeys the power law (i.e., data falls on a linear line on a logarithmic scale) and then drops off exponentially after about 10 ties. Whenever there are costs to adding or maintaining links, this cut-off to the power law trend is apparent. When the costs are high enough, this power law trend disappears completely (Amaral, Scala, Barthelemy & Stanley, 2000).

The power law is obeyed, although with less dramatic decay, in VC firm-to-firm network ties (see Table 4.3). The inclusion of broken links may contribute to the less dramatic decay of the power law trend. Maintaining the multiplex ties that are the norm in venture capitalist relationships is also very time consuming. Venture capitalist social and business ties are intertwined, and both are important (Castilla, 2003; De Clerc, 2002; Sorenson & Stuart, 2001; Ferrary, 2003). As a result, there may also be a practical limit to the number of current advice network ties an individual venture capitalist can keep active. For a small number of firms in the VentureXpert database, Thompson Financial lists the VC firms with which the focal VC firm partnered most often. It may be that these are the firms that make up the critical component of the VC advice network and that other VC firms in the network are consulted less frequently, or not at all.

Many of the unsuccessful start-ups are missing from the database entirely. This gap can be inferred from the outcome statistics. This group of 498 VC firms had 62.4% successful outcomes, whereas other research has documented approximately a 33.3% success rate in the VC industry (Grompers & Lerner, 2001). Presuming that Grompers & Lerner's percentage is correct, it means that approximately 239 unsuccessful start-ups are missing from Thompson Financial's VentureXpert database, a huge gap which obviously biases the sample towards success. If there really are 239 missing firms it also means that, as complete as this network is, there are still missing ties. The amount of presumed missing data (about 32.4% of what would have been an *n* of around 737) means that is not possible to determine which VC firms partnered most often with which other VC firms. This also suggests that the advice network under study is not complete, even though it is very dense and large.

Related to the issue of network definition is the issue of the level of analysis at which ties should be identified. For instance, the advice network of a specific venture capitalist employed by a VC firm may be more important than VC firm-to-firm ties. A focal venture capitalist who does not have any firsthand experience with a peer at another VC firm may be less likely to consult that VC firm for advice even when there is a firm-to-firm tie. In addition, the advice network internal to the particular VC firm may be critical in very large VC firms. Unfortunately, the database does not contain the information to create these intra- and inter-firm individual-to-individual ties.

Another issue with creating an advice network from affiliation ties is that the different kinds of advice obtained from different relationships may connect different people (Cross, Borgatti, & Parker, 2001).This study presumed that advice would be obtained by one class of actors, collectively measured as the VC firm. Be that as it may, the advice "rolodex" of venture capitalists includes others besides VC firms (Bygrave & Timmons, 1992).

A related limit is that the structural approach to an advice network only models the "pipes" (the ties) between venture capitalists and does not look at what "flows through the pipes" (the advice). While the value of the advice received can be inferred to some degree by the experience of the VC firm giving the advice, actually finding out which VC firms a venture capitalist goes to for which kinds of advice would be a more accurate way to model an advice network. Unfortunately this kind of information is very difficult to obtain.

Clearly, the criteria used and the information available affect the structure of the VC firm advice network. Ideally, asking all the venture capitalists in each VC firm to name not only their sources of advice (remembering that not all of these sources will be other venture capitalists) but also the individual venture capitalists and VC firms with whom they are affiliated would largely address these concerns. In addition, obtaining information missing from the database about those investments that failed would increase the accuracy of many of the variables used in this study. The networks created by addressing either of these concerns would look different, and as such, would result in different outcomes than those found in this study.

As previously stated, the primary reason that two versions of the VC firm advice networks were analyzed in this study had to do with the extreme interconnectivity of the networks. On one hand, the extreme interconnectivity of the network is an interesting finding. On the other hand, it also means there is insufficient power to contrast one part of the network against another. In addition, other analysis problems are associated with this extreme density. Most networks about which researchers have gathered information are relatively sparse compared to this network (Newman et al., 1999). As a result, the network analysis tools currently available are unable to handle, in a sophisticated or even an accurate way, networks of this density (Boyd, Fitzgerald, & Beck, 2006; Moody, 2001). Identifying local clusters/hubs/components becomes difficult using the available tools. When the network is so large and dense that most of the nodes are located close to each other, current tools are computationally inefficient, fail to identify clusters, or both. Only if these clusters are identified can previously developed measures be applied to analyze them (Boyd, Fitzgerald, & Beck, 2006; Moody, 2001).

The inability to identify clusters using available network analysis tools is exactly what happened when analyzing the VC advice networks. One giant component was identified. In the complete network (Net1), after tie reduction, about 15–18 local centers of density/clusters/hubs were visually identified. The centers could not be identified statistically, however, because they were too interconnected with the rest of the network. In the smaller VC network (Net2), these 15 or so clusters were more apparent and the edges of the component were more spread out, but again there was no statistical identification of what might be smaller hubs. These smaller possible hubs might represent regional concentrations of VC firm/entrepreneur activity, such as Silicone Valley.

Unfortunately such identification is impossible because the database, while including addresses for most VC firms, generally did not include address for their satellite offices. Another possible explanation is that these clusters were driven by specific VC firm major players, since some VC firms are very large with projects all over the United States. Each cluster could represent a major VC firm and the physically local and more distant ties it created in order to more efficiently invest in new start-ups nationwide. Again, because multiple components were not identified, it is not possible to identify particular VC firms as centers embedded in the nexus of relationships.

Another approach might have been to compare the core of the network with the periphery. Unfortunately, this too has its problems. In a network of any size, there is no efficient way to determine the optimal way to partition the core relative to the periphery. The problem is akin to that of identifying clusters/components in a large, dense network. If no a priori reason exists for a decision rule to partition the network into specific definable components or a clearly defined core/periphery dichotomy, then the available techniques to do so are overwhelmed by the sheer size of the problem of trying to find the optimal core/periphery structure (Borgatti & Everett, 1999; Boyd, Fitzgerald, & Beck, 2006). In addition, UCINET is known to give incorrect answers when trying to identify components and core/periphery structure with large, dense networks (Boyd, et al., 2006; Moody, 2001). Furthermore, UCINET has no back-up valid statistical test in place to use when the first method encounters problems. Unfortunately, neither does any other established network analysis program (Boyd et al., 2006). Boyd et al. (2006) did use a modified Keringham-Lin algorithm using Mathematica with some success in smaller (twelve different 8 x 8 matrices) dense networks, however, Mathematica can not handle networks as large as the one in this study (a nearly 300 x 300 matrix).

A further issue with these findings is that the amount of variance explained is not large. The power of a large *n* may have made it possible to find statistical significance where, on a practical level, the amount of variance explained is quite small. Alternatively, the statistical problems encountered in analyzing the network to begin with resulted in network indices that were not very accurate. The issues raised by the problems encountered when analyzing a dense, large network casts a shadow on the usefulness of the values assigned to the network variables for each VC firm. On the other hand, the problems of successfully managing a new start-up and bringing the investment to a successful conclusion are complex; a whole host of variables are involved in nurturing a new venture from start-up to a successful IPO. This study examined only a small part of a very complex set of processes that unfold over time. The small amount of variance explained could be correct despite the analysis problems. Clearly more work remains to be done.

Further Research Questions

A number of questions are left unanswered by this research, and additional research questions are suggested by it. Some of the methodological questions have been discussed in detail previously. A more accurate way to uncover hubs/clusters/components in large, dense networks is needed. More work is needed on how network definition amongst the same set of actors affects the network structure and, therefore, the outcomes. At what point in time should a historical tie be considered to be "broken" and deleted from the network?

The extent of the current interconnectivity between VC firms is a useful finding. Further research into how and what information flows through these connections, and how this density makes information public to the VC firms, could shed light on the nature of the extensive cooperation between VC firms. Brander, Amit, and Antweiler (2002), for example, found that syndication helped VC firms make better initial investment decisions and find better investments than they could do on their own. Information sharing is also a major reason for syndication (Bygrave, 1897; Bygrave & Timmons, 1992). As a result, creating the advice networks of each VC firm using snowball sampling and then gathering information about what kinds of information flow through the network structure could be a useful way to approach studying the questions asked in this study.

Research with primary data is needed to define an advice network with venture capital firms. Such research should resolve whether the proxies used with secondary data accurately reflect important advice network considerations. What, if any, are the cognitive limits to the number of ties a VC firm can effectively manage? There appears to be a limit to the number of new start-ups a venture capitalist can affectively manage at once (Jaaskelainen, Maula, & Seppa, 2003). There is probably a limit to the number of active ties that can be effectively maintained as well.

While the VC firm advice network used prior to the decision to invest in a new start-up has been the subject of considerable research, the advice networks used after the decision to invest have not been subjected to as much scrutiny. To what extent is the advice network internal to the VC firm important? To what extent are the ties of individual venture capitalists within a firm more or less important than the more general firm to firm ties in influencing whether a given VC firm is consulted? If the specific individual making contact is unknown to the focal venture capitalist within the latter firm, does a consultation take place only after an internal network tie advises contact? What kinds of advice come from what sources? At what points in the process does a VC firm seek different sources of advice? How are those sources of advice found? Does one measure of centrality better predict the ability of a venture capitalist to find certain kinds of advice than other measures of centrality? Does finding different kinds of advice sources work in ways similar to the manner in which strategic partnership partners are found, or is there some other mechanism?

How can a new VC firm break into the existing network and quickly take advantage of information flow? Does it matter with whom the VC firm makes its initial contact and where that contact is located in the network? These later questions bring up the temporal nature of advice networks. What causes VC firms to become more densely interconnected or less densely interconnected over time? How do these issues affect new start-up company success and VC firm escalation of commitment? It would be of interest to see if newer, less experienced VC firms invite more established VC firms into later rounds of funding when they are funding a "winner" in order to try to create this kind of connection. If the more experienced VC firm agrees to join, the implied social contract of reciprocity may make it more likely that the established firm will later extend favors to the less experienced one. Since VC firms can fund only a small percentage of the proposals that cross their desks, one such favor might be offering the newer VC firm access to a promising proposal that the more experienced VC firm is unable to fund. Other benefits to the newer firm might include access to advice and assistance not only from the experienced VC firm but also from the experienced firm's other advice network members.

The questions related to escalation of commitment and advice networks can be better answered when some of the previously mentioned issues have been addressed. What actors are best positioned to give advice to help prevent escalation of commitment? This research implies that it would be an experienced VC firm that learns from its mistakes, has industry-specific experience, and has escalated in the past. How did the experienced VC firm learn to manage escalation? What signals does it now pay attention to that trigger it to terminate the investment? When it does escalate its commitment, is there anything different about that investment from the ones it terminated? Past research indicates that clearly and strongly negative information results in project termination (Ross & Staw, 1993). Do these experienced VC firms need less clear and less strongly negative feedback than less experienced VC firms to terminate?

The next set of questions pertains to exactly what kinds of advice help the focal VC firm needs to recognize that it is funding a failing venture. When in the process is the focal VC firm most receptive to this advice? What signals from the venture trigger searching for this kind of advice? Does the position of the advice-giver in the network imply that this advice-giver is especially credible? What other factors give rise to the inference of credibility? Does the timing of this advice affect the ultimate outcome? Clearly this research has just begun to scratch the surface of the kinds of questions that need to be asked to further the understanding of the role of the advice network in escalation of commitment. Finding answers would help VC firms make appropriate decisions to bail from an investment early rather than escalate their commitment to a failing course of action.

Summary

This research investigated the advice networks of venture capital firms and whether network variables and VC firm demographic information influenced the tendency to escalate commitment to failing start-up companies. There were three major findings. The first finding was that the network of VC firms that invest in new high-technology start-up companies has become far more interconnected and dense over the last 15 or so years. It was not possible to identify regional hubs based on VC firm funding ties. The second finding was that these dense interconnections between VC firms allow information to flow freely throughout the network. Some of the network variables and characteristics of the VC firms within the advice network were significant predictors of escalation of commitment. The third finding was that determining the boundaries of a network and defining membership in that network affect the underlying network structure and thus the research results. The decision to delete network ties should be made with caution. Future research directions were suggested.

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