THE EVOLUTION OF VENTURE CAPITAL INVESTMENT NETWORKS†

OLAV SORENSON
London Business School
Sussex Place, Regent's Park
London NW1 4SA
osorenson@london.edu

TOBY E. STUART
Columbia Graduate School of Business
3022 Broadway, Uris 710
New York City, NY 10027
toby.stuart@columbia.edu

December 11, 2005

† Both authors contributed equally to the development of this paper. We thank the UCLA Price Center for financial support, David Waguespack for research assistance, and Woody Powell and seminar participants at Harvard Business School, the Harvard-MIT Economic Sociology seminar, and UT Austin for comments on an earlier version of this paper.

ABSTRACT

Despite a wealth of research on the value of brokering and boundary-spanning relations, few have considered from where such relations arise. Indeed, most existing theories of network formation, whether based on homophily or structural constraint, imply that actors will form highly cohesive, homogenous clusters. Yet real interorganizational networks also include many 'distant' ties—isolated links between parties that vary on multiple social dimensions. To explain these patterns, we propose a theory of network formation based on the characteristics of 'events', or the places and times where actors meet. In particular, we argue that distant relations form when organizations participate in two types of events: unusually popular ones (e.g., fads), and those with little partner risk. In an empirical corroboration of our thesis in the formation of syndicate relations between venture capital firms, we find that the likelihood that socio-demographically distant connections form increases with several attributes of the target company investment 'event': (1) the recent popularity of investing in the target firm's industry, (2) investment syndicate size, (3) target company maturity, and (4) geographic proximity of the lead VC investor to the target company.

I. Introduction

Growth in the number of articles examining how networks affect organizational outcomes has been torrid. Twin engines appear to be driving the development of this literature: an increase in the availability of longitudinal network data of all kinds, and the arguments of Granovetter (1973; 1985), Coleman (1988), Burt (1992), and others that have proposed social mechanisms linking particular network configurations to the attainment of desirable outcomes. Whether focusing on individual careers, such as the processes of searching for a job (Fernandez and Weinberg, 1997), negotiating a salary (Seidel, Polzer and Stewart, 2000), earning a promotion (Podolny and Baron, 1997) or receiving a bonus (Burt 1997), or on organization level outcomes, such as revenue growth (Ingram and Roberts, 2000), innovation rates (Ahuja, 2000), survival (Uzzi, 1996), the adoption of novel practices (Mizruchi, 1996), or the achievement of important performance milestones (Stuart, Hoang and Hybels, 1999), the positions of individuals and organizations in networks of relationships have been found to beget multifaceted consequences.

In our view, belying this rapid progress in the study of network effects is the comparative absence of theoretical and empirical work on how inter-organizational networks form. Although there have been a few influential articles on the evolution of interorganizational networks (e.g., Gulati, 1995; Powell, Koput and Smith-Doerr, 1996; Gulati and Garguilo, 1999; Powell, et al., 2005; for a review, see Brass, et al., 2004), and a growing body of research considers the mechanisms that govern the formation of networks among individuals (e.g., Bearman, Moody, and Stovel, 2004), we know relatively little about how particular configurations of relationships come into being. Indeed, the dynamic implications of many existing theories of network evolution appear only partially consistent with the shapes of interorganizational networks typically observed in empirical data. This apparent mismatch, we will argue, stems from the fact that micro-level theories of network dynamics—those that postulate mechanisms thought to regulate the likelihood that particular relationships materialize—often imply that networks crystallize around existing affiliations. Our research and reading has brought us in contact with longitudinal data describing numerous networks, and our experience suggests that this expectation of evolution toward stable, cohesive localized social structures is, at best, only somewhat consistent with observed patterns in alliance, syndicate, interlock, trading, and other types of interorganizational networks.

Three primary mechanisms have been featured in previous work on the evolution of interoganizational networks: reciprocity, transitivity, and homophily. Though potent and prevalent mechanisms of network generation, these forces also conspire to produce stability in a network—when alike organizations pair, when a past recipient of a sent tie conforms to the norm of reciprocity by returning an offer of exchange to the sender, and when a dyad repeats a past symmetric tie or a triad closes, it reinforces the local clusters within a network (Davis, 1967). Thus, although each of these mechanisms can account for the formation of many interorganizational ties, none can explain the emergence of relationships among dissimilar organizations that do not share common exchange partners. Throughout the paper, we will refer to relationships that connect heterophilous organizations lacking a prior connection as socio-demographically 'distant' ties.

The challenge in explaining distant ties resides in the difficulty of formulating arguments that, on the one hand, offer sufficient generality to provide explanatory traction across settings, and on the other, still provide insight into the processes that produce ties. One can always formulate an argument that rests on the idiosyncrasies of a given context to explain the emergence of selected relationships, but the lack of generalizability in such an approach limits its appeal. To avoid the inelegance and provincialism inherent in particularistic accounts, most scholars have instead devised theories that relate the structure of a network in one period to the likelihoods that ties among particular pairs of actors emerge in the next time interval. In effect, the explanation is self-contained within the network, or equivalently, the theory is one of endogenous (to the network) change.[1] This general approach, however, has thus far failed to provide satisfactory explanations of the process of network change. Specifically, existing studies leave unanswered questions such as, how do new actors gain admission

[1] Although not a theory of network evolution, Burt's (1992) formulation of 'structural hole' theory is an archetype of this approach. Burt defines social capital exclusively in terms of the pattern of relationships surrounding an actor. The theory has been applied broadly—across networks involving different types of actors, and to an extremely wide array of types of relationships.

to an established network?[2] And, when, where, and why do organizations form relationships with disconnected and dissimilar others?

Our objective in this paper is to examine empirically a few mechanisms capable of predicting the emergence of relationships outside of local clusters (i.e. distant ties). In doing so, we seek to avoid the problem of mechanisms that imply only local changes in network structure by focusing on conditions that one might regard as exogenous to the network, and we hope to eschew the limits to generalizability that result from the inclusion of exogenous factors by considering the repercussions of only relatively general types of external influences. As an attempt to address the question of who forms relationships with whom, our approach represents something of a compromise—our arguments offer less generality than those that rest exclusively on the shape of the existing network (and therefore may apply to any network), but we hope, they remain sufficiently encompassing to have predictive power in many settings.

We can envision at least two methodological approaches that one might employ to gain insight into the process of distant tie formation in an interorganizational network. One strategy, a 'nodal' approach, involves the construction of a theory rooted in either the heterogeneous preferences or the systematically differing contexts of the organizations in a network. A notable application of this approach appears in Podolny (1994): he argued that the strength of organizations' preferences for exchanging with similar alters decreases with the level of uncertainty in the market. Baum *et al.* (2004) provide another example: adopting an explicitly nodal approach, they argued that the performance of an organization relative to its firm-specific aspiration level influences its willingness to engage unfamiliar trading partners. We can certainly see the opportunity for this line of reasoning to contribute to our understanding of network formation processes, although it is not the direction we follow in this paper.

The second strategy we see for exploring the determinants of distant tie formation, and the avenue we pursue here, has its origins in Feld's (1981; 1982) work on social foci. Feld argued that human interaction typically revolves around foci, such as

[2] Although the recent work applying statistical mechanics to the study of social networks accommodates the formation of distant ties (Barabasi and Albert, 1999; Watts, 1999), it adopts the opposite extreme, treating these relations as products of an entirely random process. Though useful for understanding the macrostructures of networks, these techniques essentially sidestep the issue of the mechanisms involved in shaping network evolution.

workplaces and voluntary groups. In turn, many relationships emerge among individuals who jointly participate in the same foci. Similarly, many interorganizational relationships materialize in the context of joint involvement in activities. For ease of exposition, we will refer to foci that serve as the context for interorganizational interaction as 'events'. Examples of events that spawn associations among organizations include research consortia, trade associations, standard-setting bodies, boards of directors, business groups, and in the case we consider here, investment syndicates.

The insight that motivates our work is that the events providing the backdrop for interorganizational relationships have varying relative and absolute affinities within the organizational community. We posit that interactions between relationally or demographically distant organizations most commonly arise when—often for exogenous reasons—a particular class of events becomes especially appealing. In the clamor to participate in popular events, previously unacquainted organizations find themselves members of the same group. Thus, the polarity of fashionable events sometimes draws together dissimilar organizations, and hence contributes to the formation of non-local ties. Further, when a single organization, a 'host', controls invitations to participate in an event, we speculate that characteristics of the association between the host and the event will influence the identities of the others invited to join. We hypothesize that the host more likely pursues a network expansion strategy—to invite the participation of socio-demographically distant partners—in routine events and when it can spread the risk (however likely) of partner malfeasance across several participants. In routine pursuits and in large gatherings, the host depends less on the contributions of its collaborators, and thus may more willingly experiment with new partners.

We explore these predictions in an analysis of the formation of investment syndicates established by venture capital (VC) firms to finance early stage companies. We construe each portfolio company as an event, and build an industry-wide affiliation network from the recent history of relations created from VC firms' syndications of investments. Our models address the likelihood that a given pair of venture capital firms will jointly invest in the same target company; thus, we model the factors that influence the probability that VC firms form particular pair-wise relations. In this regard, the dependent variable in our paper does not differ from standard dyadic models of relationship formation. However, the data we analyze have a structure common to interorganizational affiliation networks: the data comprise events (the startup companies), hosts (the venture capital firms that build or 'lead' the syndicate), and a set of partner firms (the other VCs that participate in the syndicate). Analogously, in analyzing a director interlock network, one would have events (the boards), hosts (the firms whose boards are being studied) and partners (other firms that send representatives to boards). Our theorizing and modeling depart from that of previous work because, although our dependent variable is the formation of a dyadic tie, we explicitly *incorporate attributes of the relationship between actors and events* in our analysis of the probability that a lead VC firm selects a particular partner to invest in a given target company. Put in more general terms, we project a dual-mode, actor-event network into a one-mode, actor-by-actor network. When modeling the probability of actor-to-actor tie formation, however, we incorporate attributes of the event in which a tie forms, and of the relationships between actors and events.

II. Determinants of Change in Interorganizational Networks

Challenges in the governance of interorganizational relationships motivate the work on why established networks affect the creation of new relationships. Because the explicit contracts that govern complex intercorporate transactions often lack sufficient detail to preclude all opportunities for firms to violate the spirit of an exchange agreement (Williamson, 1975), participants in these transactions face the risk that their trading partners will behave opportunistically. According to structural sociologists, in response to this risk, actors turn to their social networks to select transaction partners that they believe will behave honorably, even in the event that such behavior deviates from the partner's near-term interests and the formal contract governing the relationship remains silent on the obligations of the partner (Granovetter, 1985; Powell, 1990; Uzzi, 1996).

Information access plays a central role in network-based theories of interorganizational relations. Existing ties affect patterns of affiliation because the paths in the network determine who has access to information circulating about the characteristics of particular potential partners, including fine-grained knowledge of would-be associates' reputations (see Granovetter, 1985 for a programmatic discussion;

Podolny, 1994; Gulati, 1995; Walker, Kogut, and Shan, 1997).[3] In Podolny's (2001) language, networks form the 'pipes' that transport information. This affects trading patterns because knowing about a potential partner reduces the perceived risk of transacting with that alter, and dealing only with known associates lowers the cost of searching for and screening potential partners. In effect, established networks serve to delineate patterns of trust—the subset of 'trusting' dyads—in an embedded system of relationships. Because the network aids in the identification of trustworthy partners in situations with a risk of partner malfeasance, the shape of the network in one time period constrains the pattern of subsequent affiliation. In short, actors use their social networks to overcome the uncertainty and distrust that beleaguer market transactions.

Many empirical studies have demonstrated how existing networks affect future transaction patterns. Contemporary studies typically utilize panel network data, which enable the researcher to examine how the configuration of the network at one point in time affects the probability that all, or selected, pairs of actors in the network choose to transact in a subsequent observation window. Much of this work has examined the network-based antecedents of strategic alliance formation, although the nexus of cross-equity holdings and the configuration of syndicates in securities underwriting and venture capital investing have also provided fruitful empirical venues. A sampling of the studies in this area include Podolny (1994), who posits that uncertain market conditions reinforce organizations' proclivity to transact with their previous trading partners; Gulati (1995) and Gulati and Gargiulo (1999), who argue that firms indirectly connected by a common third party more likely establish strategic alliances; Powell, Koput and Smith-Doerr (1996), who assert that the central firms in an industry's alliance network more frequently establish new alliances in the following period, particularly R&D partnerships; and Lincoln, Gerlach and Takahashi (1992), who investigate levels of reciprocity and homophily in Japanese inter-firm ownership, director interlock, and exchange networks.

[3] Of course, the information transmission function of networks is central to many arguments about the advantages of occupancy of particular network positions. Just in the interorganizational context, Strang and Soule (1998) review dozens of studies on the role of networks in transmitting information related to innovation adoption decisions; Mizruchi (1996) discusses research on the communication properties of board interlocks; Zuckerman (1999) elucidates the role of market intermediaries; Ingram and Roberts (2000) document the role of friendships between managers in communications between organizations; and this list barely scratches the surface.

Despite the success of these approaches in explaining some of the variance in who transacts with whom, the existing literature nonetheless has several shortcomings (similar observations are made in Podolny and Page, 1997; Baum *et al*. 2004). First, studies presupposing that partner risk leads to the formation of embedded transactions cannot account for the formation of relationships among disconnected organizations. If actors restricted their transaction partners to those about whom they could reasonably expect links in an existing network to convey thick information, then in a typical, sparsely connected interorganizational network, new ties could only emerge in a small subset of dyads. A second limitation is that exploiting the network structure at one time period to predict future exchanges is tantamount to treating the network's 'time zero' structure as an exogenous fact. If some existing network structure sits antecedent to a theory, that theory then cannot explain the origins of that structure (nor, typically, how new participants gain access to an existing network). Third, a great deal of work has been inspired by Granovetter (1973) and Burt (1992), who have established the central role of weak ties and relationships that bridge structural holes in determining outcomes of all types. As the theoretical importance of these ties rests in the significant relational distances they traverse, knowledge of the determinants of distant tie formation becomes vital for understanding network effects.

The weak ties and structural holes arguments suggest that organizations should pursue network expansion strategies. The embeddedness perspective meanwhile highlights the high cost of searching for new associates and of the risk that an unknown partner could prove unreliable. These contrasting views imply a tradeoff that demands resolution, and the existing literature has sought a reconciliation by theorizing about the conditions most likely either to lower organizations' search costs or to minimize their exposure to partner risks. Galaskiewicz and Shatin (1981), for example, found that in uncertain environments, organizational leaders favor the comfort of the familiar—they demonstrate a preference to strike deals with partners led by socio-demographically similar individuals. Podolny (1994) likewise found that market uncertainty induces investment banks to engage in transactions with past partners, and to favor similar status alters. Baum *et al.* (2004) extend the behavioral theory of the firm's focus on problem-driven search to argue that organizations' performances relative to their aspiration levels determine their willingness to bear the risk of collaborating with unfamiliar partners. Thus, some progress has been made in identifying outside-the-network conditions that influence patterns of relationship formation.

We propose a new approach in this study, which capitalizes on the fact that many interorganizational networks emerge from the participation of organizations in common events. Connections that surface when events organize social interactions are known as actor-event networks, sometimes also called affiliation, bipartite, dual-mode, or hyper networks (Breiger, 1974; McPherson and Smith-Lovin, 1982). Typical examples of events that spawn associations among organizations include research consortia, trade associations, standard-setting bodies, boards of directors, business groups, and investment syndicates. When one considers the long list of events whose occurrences give rise to inter-firm relationships, it becomes apparent that much of the scholarly literature on interorganizational networks in fact examines affiliation network data.

Considering actor-event data allows us to add a dimension to the literature on network formation. As our review of the existing literature indicates, thus far, researchers have developed either nodal (pertaining to organizational attributes and conditions) or relational embeddedness arguments to explain patterns in the evolution of interorganizational networks. Once we explicitly recognize that inter-firm networks evolve in the context of a landscape of events, it becomes possible to add a third dimension of explanatory focus—the role of the events, or contexts for interaction, on shaping the network of co-occurrence ties.

The sociological literature offers a precedent for taking into account the extra-network bases of social ties. In particular, Feld's (1981; 1982) pioneering work on social foci—locations in time and space around which individuals organize their social interactions—has been an influential perspective. While network-based studies typically conceive of social structure as being built from actors and relations, Feld argued for three essential building blocks: actors, relations, and social foci. In this view, each individual associates with some foci but not with others. Relationships emerge with greatest frequency among individuals who congregate in the same foci. The attraction of individuals to extra-network foci thus becomes a central—if rarely observed—explanatory factor in the process of network emergence.

We believe that the social focus idea has significant importance for the development and evolution of interorganizational networks. Of course, many firm-to-firm relations, such as most strategic alliance and buyer-supplier relations, represent direct interactions among exchange partners. Some—perhaps even a large percentage—of interorganizational ties arise from chance meetings between organizational members that result in business being conducted. But many interorganizational ties, including the syndicate relations we examine here, occur against a backdrop of events.

III. HYPOTHESES

The original work on social foci sought to explain why macrostructures often come to exhibit a partitioning of ties with a high density of connections among homophilous actors, and infrequent ties connecting socio-demographically diverse individuals. Although the prevailing theory has attributed the emergence of clusters to transitivity in tie formation, the social focus perspective offers a competing mechanism that could also generate clusters in networks; namely, dense clusters among homophilous actors might emerge from the preferences of similar actors to participate in the same foci. In other words, two potential explanations exist. On the one hand, two actors that share a connection to a common party might form a relationship because of transitivity. Alternatively, their shared preferences for common social foci might bring them together, and also may explain why they have a common third party in the first place.[4]

The existing work on social foci draws attention to the joint distributions of actors' preferences for involvement in events. We can nonetheless easily extend it in a number of directions that may improve our understanding of the origins of distant ties in a network. One avenue that strikes us as especially promising is exploring the implications of sharp changes in the popularity of events over time as an explanation for the formation of relations among disparate actors. Especially in the context we analyze,

[4] Although not expressed in these terms, a potential implication of the social foci argument is that the findings of many network studies may be suspect because of omitted variable bias. In effect, preferences for participation in foci of a given type are unobserved correlates of patterns of relations in a network. At a minimum, this work therefore suggests the need to account for the attraction of actors to events to produce reliable estimates of the effects of existing ties on the formation of subsequent relationships. This issue seems particularly important to structural accounts because a union formed as a result of overlapping preferences to participate in a particular event represents a substantially different explanation for relationship formation than a trust-related argument about the role of a common partner in brokering a tie.

the evolution of a network fashioned from joint participation in financial syndicates, the emergence of 'bubbles' or 'hot' periods may significantly affect the appeal of particular types of events, irrespective of actor types.

Many researchers across sociology, economics, and psychology have noted the prevalence and consequences of bandwagons (Banerjee, 1992), cascades (Bikhchandani, Hirshleifer, and Welch, 1992), fads (Strang and Macy, 2001), or more generally, instances in which actors exhibit rampant conformity in their behavior.[5] In Banerjee's (1992) herd model, the mechanism that drives mimicry is rational actors' reliance on the observed choices or actions of others, which they use to derive inferences about the private information available to other actors. Similarly, Abrahamson and Rosenkopf (1993) argue that bandwagons result from the influence others' revealed adoption decisions have on the choice of any given, at-risk individual. They find that social contagion can occur even if actors hold low individual assessments of the value of a practice or event. In a more recent piece, Strang and Macy (2001) propose a theory of fads specifically catered to the business community. They argue that organizations experiencing poor performance engage in 'adaptive emulation'—they mimic the behavior of more successful peers.

Clearly, the literatures on bandwagons, fads, and cascades differ in their intellectual origins and the social processes they invoke. Regardless of the underlying mechanisms that produce surges in the appeal of particular activities, processes, things, or events, we believe that the theories share a common implication for network formation. When the origins of inter-organizational ties rest in the joint participation of actors in the same events, the formation of ties among dissimilar organizations most likely occurs in the context of especially appealing events. Put differently, we assume as a baseline that distant organizations—regardless of whether one measures distances in geographic, social, or specialization-based terms—establish relationships less frequently than proximate ones. We nonetheless anticipate that this difference in baseline likelihoods diminishes for ties created in the context of 'hot' events. When bandwagons accelerate

[5] For rhetorical convenience, we refer to an instance of significant social conformity in decision making as a 'bandwagon'. Of the concepts in the literature that describe the general phenomenon of actors exhibiting herd-like behavior in decision making, a bandwagon comes closest to the behavior we have in mind.

the popularity of particular events, diverse actors find themselves considerably more likely to associate. We therefore predict:

> **Hypothesis 1**: The negative effect of socio-demographic distance on the likelihood that organizations establish economic exchange relations declines when ties form in the context of a bandwagon.

In addition to heterogeneity in the degree to which events attract organizations, a second feature that varies significantly across the events that give rise to interorganizational ties is the level of risk that an organization assumes from its involvement in a group. In most multilateral alliances, particularly those in which participation requires resource commitments, a nontrivial chance exists that members of the federation will incur significant losses. Much as Williamson (1975), Granovetter (1985), Uzzi (1996) and others call attention to the risk that counterparties to an exchange may engage in opportunistic behavior, similar uncertainty surrounds the integrity and competence of the organizational members of events. Just as transaction cost theorists have drawn attention to the characteristics of exchange relations that determine the ability of counterparties to use legal contracts as safeguards against partner malfeasance, so we argue that the characteristics of the events in which organizational relationships form can expose their participants to more or less partner risk.

In his formulation of an exchange theory of social structure, Blau (1964) recognized that a central problem for which structural theories must account is the process by which exchange relations emerge. Although he did not extensively develop the argument, Blau posited that unacquainted partners would initiate consequential exchanges only after a temporally unfolding period of experimentation. New trading partners would begin with minor transactions. Exchanges involving few resources serve as opportunities for exchange partners to demonstrate their trustworthiness in a context that does not expose them to the risk of a significant loss. As trust increases over a sequence of dyadic trades, so too does the magnitude (or value) of the resources partners will exchange.

This idea underpins our second prediction. Although the literature has considered the relationship between trust and network structure, the need for trust also varies across settings. In the context we examine, characteristics of the events in which organizations form relationships lead to variance in the amount of dependence that actors have on their co-participants. Actors prefer to begin exchange in the context of events where errors in their assessments of the trustworthiness of their exchange partners will not result in significant losses. Thus, analogous to Blau's description of the process by which unacquainted actors develop the confidence for significant resource-based exchanges, our second and final prediction states:

> **Hypothesis 2**: The negative effect of socio-demographic distance on the likelihood that organizations establish economic exchange relations declines when ties form in the context of events that do not entail significant risk to participants.

Put in different terms, our second prediction anticipates that organizations will exploit relational contexts with relatively limited transactional risk to experiment with network expansion strategies, in which they establish relationships with distant parties. In riskier settings, they rely upon familiar exchange partners.

IV. EMPIRICAL SETTING: THE SYNDICATE NETWORK IN VENTURE CAPITAL

Venture capital firms have emerged as a critical source of financing for high potential, fledging commercial enterprises. These firms serve as intermediaries between investors and entrepreneurs. Using funds primarily raised from institutional investors and wealthy individuals, they identify promising, yet risky, investment opportunities. Today, hundreds of VC firms collectively invest billions of dollars in the financing of young companies in many different industrial sectors and geographic regions.

For a number of reasons the venture capital industry serves as a compelling empirical context for this study. First, VC firms most commonly invest in target companies in groups, or syndicates, with other venture investors.[6] Many explanations have been offered for this practice, including that syndicated investments diversify risk by enabling VCs to invest smaller amounts in a greater number of companies (Wilson, 1968), and that syndication leverages the due diligence skills and domain-specific

[6] Of the firms in our data, roughly 60% receive financing from a syndicate (i.e., two or more venture capital firms invest in them). On average, 2.6 VCs invest in each target. Thus, the average investment leads to associations with 1.6 other venture capital firms.

expertise across coalitions of firms (Sah and Stiglitz, 1986; Lerner, 1994). Regardless of the particular motive for syndicating investments, the prevalence of this practice has given rise to an extensive, evolving actor-event network among the firms in the industry. Moreover, researchers can access longitudinal data describing this network.

The second reason to examine network formation in the venture capital sector is that scholars have both documented a number of significant performance consequences of occupancy of different positions in the industry's syndicate network and have developed a keen interest in how the industry works (e.g., Kaplan and Stromberg, 2003). Hochberg, Ljungqvist and Lu (2004) reported that target companies financed by VC firms central in the industry's network went public (i.e. IPOed) at higher rates, an important measure of success both for the firms and their investors.[7] Sorenson and Stuart (2001) showed that VC firms with axial positions in the syndicate network more frequently invested in target firms outside of their geographic regions and domain specializations than less advantageously positioned peers. Thus, well-networked firms ultimately could secure more diverse investment portfolios.

The third reason to examine the evolution of ties in this industry is that syndicate networks allow us to broaden the analysis to examine the role of events in shaping the evolution of the network. A syndicate in venture capital is simply a group of investors that agrees to finance the same target company. As such, the network derives from actors (VCs) meeting in events (target companies). Because organization theorists have increasingly studied actor-event networks, such as Podolny (1994) and Baum *et al.*'s (2004) work on relationship formation among investment banks participating in syndicates, as well as the myriad studies of the board interlock network (e.g., Mizruchi and Stearns, 1988; Kono et al., 1998), we believe that the approach developed here will have implications for much of the growing literature on interorganizational networks.

In the VC industry, syndication involves a lead investor.[8] The lead frequently makes a solo initial investment in a given target company, but then invites other investors

[7] Freeman (1999), however, finds the opposite relationship using data from a different data source and time window, so the exact nature of this relationship remains an open question.

[8] Our use of the term 'lead' differs from common parlance in the industry, in which lead refers to the investor that sets the price in each investment round. We use the term 'lead' to refer to the first and typically most active venture capital investor in a company. Gorman and Sahlman (1989) report that this lead spends roughly ten times as much time managing and monitoring the company as the non-lead

to join it in subsequent financing rounds for the target company. Thus, the process of building a syndicate involves a lead venture capitalist selecting partners to co-invest in a given target. Both making and accepting the offer requires a certain degree of trust. Invited firms face a great deal of uncertainty in the quality of the target company. Leads clearly have an incentive to overstate the value of the company to maximize the return on their prior investments. Similarly, leads may worry about the quality of syndicate partners: All VC investors typically play a role in advising and nurturing the target company. When the lead admits an investor into the syndicate that lacks the resources or skills to contribute to the target's success, it represents an opportunity cost—all investors would have benefited from the recruitment of a more able syndicate member. The context we examine therefore aptly represents the canonical transaction of interest to economic sociologists: given the uncertainties of the context, ample room exists for opportunistic behavior. Moreover, a thick social structure in the market appears central to facilitating non-authority-based mechanisms for overcoming these informational asymmetries. The question of where this thick network comes from and how it evolves is therefore of central importance.

V. Methodology and Data

A well-established research design (if not a commonly accepted approach to estimation) has emerged for analyzing relationship formation in a network: The researcher creates a dyad-level dataset in which, depending on whether the ties in a matrix are symmetric or directional, all ordered or unordered elements in an adjacency matrix become cases in a vector of 0s and 1s denoting whether or not the firms in the *ij*th dyad have established a relationship (e.g., Lincoln, 1984; Podolny, 1994; Gulati, 1995).[9] This general approach to

---

investors. Accordingly, we identify leads using two criteria: either those that invest uniquely (i.e. solo) in the first round, or those that invest in the first round and every subsequent round. Together, these two criteria identify unique lead investors in roughly 92% of our target companies. For the remainder, we randomly assign a lead from those matching the second test. In unreported robustness checks, our results remained consistent even when excluding these indeterminate cases.

[9] Other methods have been proposed for estimating the dynamics of network evolution. Snijders (2001), for example, offers a method based on Markov Chain Monte Carlo (MCMC) estimation. Although this model allows for more explicit treatment of the interdependence between dyads in relationship formation, it has several restrictions that limit its usefulness for many longitudinal datasets: (i) the model does not accommodate the entry and exit of nodes (actors); (ii) all dyads face a continuous risk of tie formation; and (iii) MCMC estimation techniques become computationally impractical with a large number of nodes.

modeling relationship formation allows the researcher to exploit all available information when organizations connect directly to each other. When relationships arise in the context of joint participation in an event, however, this dyadic approach is incomplete.

To investigate tie formation in an actor-event network, and to test our hypotheses concerning how heterogeneity across events results in different types of relationships being formed, we propose that the analysis of tie formation should include not just the two actors, but also the event in which the two actors meet—in this case, the investment in a target company. Moving to this form of analysis has at least two advantages over the more traditional dyadic analysis: 1) It allows us to examine how the rules of action governing tie formation (such as those anticipated by our hypotheses) depend on the event that precipitates the tie; and 2) By including measures of the attractiveness of the event (i.e., the likelihood that a given actor would choose to engage in the event regardless of the partner), we can control better for the baseline odds that two actors will interact, and hence obtain more reliable estimates of the importance of existing relationships and homophily in the tie formation process.

The basic idea behind our approach is that we model the probability that two organizations meet in a 'triangle' in which two nodes represent organizations and the third node represents an event. Figure 1 illustrates the idea and our sampling design. In all models, we analyze the probability that lead organization *i* chooses alter *j* to participate in event *z*. Thus, *the presence or absence of the ijth link in z determines the realization of the outcome variable*. In this regard, our dependent variable exactly parallels that used in most studies of the formation of exchange relations: the outcome variable is still the probability of a tie among particular pairs of organizations. We nevertheless depart from previous research by explicitly incorporating attributes of the events and characteristics of the relationships between both organizations and the event.

We investigate this process by analyzing the formation of private equity co-investment relationships (i.e. two VC firms investing in the same target). The data contain information on all private equity investments listed in the VentureXpert database (formerly Venture Economics) prior to February 2002. In the analysis, we only analyze investments that occur after 1986, as we have concerns about the completeness of the data prior to 1986. Because the formation of a co-investment relationship requires at least two investors, we exclude from the analysis all target firms that have a single investor. We also exclude all venture capital firms and target investment companies located outside of the United States (so that we have comparable geographic proximity information for all cases). We nevertheless use the entire dataset to create our independent variables.

We restrict the dataset to private equity venture capital firms. The VentureXpert database includes information on all investors in each syndicate round. These investors include private individuals (so called 'angel' investors), banks, insurance companies, university endowments, pension funds and corporate venture capital arms. These organizations differ in at least three respects from venture capital firms. First, not all of these investors engage in both the identification and financing of new ventures. Rather, some simply act as passive investors. Since these organizations play a limited role in extending venture capitalists' information networks, lead investors may treat them differently from venture capital firms when composing an investment syndicate. Second, these heterogeneous firms also sometimes have different goals from VCs, which renders their decisions incomparable to those of venture capital firms. Finally, these investment vehicles have typically not been established as partnerships with the managers acting as general partners. As a result, managers of these other types of firms may respond to different incentives then do venture capitalists (e.g., wishing to minimize risk).

To generate the dataset analyzed, we employed a case-control selection procedure (see Fig. 1 for a graphical representation: the solid lines indicate observed relations while the dotted lines denote potential, but unrealized links). In each case-control set, two of the members of the triangle remain constant: the lead venture capital firm and the target company. (Therefore, a solid line in Fig. 1 connects leads and targets in both cases and controls). Our case sample contains all of the realized ties—that is, every instance in which a lead actually invited another VC firm to invest in a target company and that VC firm accepted the invitation. Because VC firms often invest routinely in all subsequent rounds after their initial investment in a target company, we only consider the first round in which each non-lead invests. In total, our data include 13,335 realized ties (cases), representing investments in 4,887 U.S.-based target companies. We matched these cases on a 1:10 ratio with a set of controls—co-investment ties that could have occurred but that did not.[10] The control triangles matched the same lead VC (hereafter, we occasionally refer to the lead as 'leadVC') and target company ('targetCO') with a potential syndicate partner that did *not* join the syndicate (i.e. an unrealized tie). We chose these private equity investors from the set of all venture capital firms that invested in a syndicate to finance a different target company in the same quarter. These potential syndicate partners exhibited a propensity both to invest at the same calendar time and as a member of a syndicated investment; thus they likely account for most of the relevant risk set for tie formation. In total, then, our sample includes 146,685 observations of which 13,335 are actual cases and 133,350 are controls that potentially could have occurred, but did not.

Relative to generating a matrix of all potential dyads/triangles, the case-control method has at least two major advantages in analyzing tie formation: 1) It reduces the likelihood that the data violate the independence assumption (in our data, across case-control groups) of binary choice maximum likelihood regression models. On average, each target contributes only three sets of cases and controls to the sample. 2) Reducing the number of cases in the analysis also eases the computational tasks in analyzing the data. Although our sample appears large, one must recognize that it represents a mere 2% of the 6.2 million possible dyads that would result from a complete sampling of the affiliation matrix. Regardless of the small sampling proportion, because most of the information in a sparse affiliation matrix comes from the realized ties, this sampling procedure does not substantially reduce statistical power (Coslett, 1981; Imbens, 1982).

Adopting a case-control methodology also requires a modification of the estimation procedure to adjust for the potential bias introduced by sampling on the dependent variable. One solution to this problem involves weighting observations according to their probability of entering the sample (Manski and Lerman, 1977; cf. Sorenson and Stuart, 2001). Though such an approach produces consistent estimates of the average population level effect, it does not take full advantage of the matched nature of the sampling design. Failure to accommodate the clustering in the sampling design can

[10] No hard rule governs the optimal ratio of cases to controls: Breslow and Day (1980) promote the simplicity of 1:1 designs. Meanwhile, simulations suggest that researchers gain little efficiency beyond a 1:5 matching (Self and Prentice, 1988; King and Zeng, 2001). Our 1:10 ratio places us on the extremely conservative side in terms of the number of observations used for our analyses.

yield both attenuated and inefficient estimates (Breslow and Day, 1980). A preferred approach for the estimation of matched case-control designs is conditional logistic regression (also known as a McFadden choice model). By grouping cases and controls, this estimator effectively purges the data of the effects of the common elements shared by the cases and controls (in our case, the actor-level attributes of the lead VC firms and target companies, and the relational characteristics of the leadVC-targetCO match), producing unbiased and efficient estimates of the effects conditional on these unobserved factors.

MEASURES

Geodesic length: A geodesic is the shortest possible path connecting any two actors in a network.[11] We calculate the geodesic length using a five-year window preceding the year of the potential investment. A geodesic of length one, which we refer to as a *prior tie*, therefore indicates that two venture capitalists have invested together in another target company within the past five years. We label a geodesic of length two as an *indirect tie (1-step)*; in other words, these firms have not invested together in the last five years, but each of them has invested in some other target with a common third party. Although longer geodesics exist, our analysis focuses on these one- and two-step connections for two reasons, one theoretical and one practical: (i) We suspect that relatively little of the thick information required to feel confident in a potential transaction partner travels through longer chains of connections; and (ii) On average, our sample of venture capitalists can reach 48% of all other venture capitalists (73% when weighted by the number of investments) through either one or two steps, and nearly all potential investment partners reside within three degrees of separation. Hence, the community offers few instances of geodesic lengths of greater than three from which to estimate effects.

In addition to their degree of distance in the syndicate network, we measure the socio-demographic distance between venture capitalists on two dimensions: geography and industry. Prior research suggests that both dimensions play important roles in the

[11] For venture capitalists with multiple offices we treated all locations as a single firm for the purpose of computing geodesics. Hence, if the California office of firm A had co-invested with firm B, we would also consider future deals by the New York office of firm A to have a geodesic length of one with firm B.

industry, particularly in relation to the matching of investors to target companies. Because venture capitalists monitor and advise the managers of the companies in which they invest, close proximity dramatically reduces the costs associated with these post-investment activities. In addition, to the extent that local social networks connect VC firms to entrepreneurs seeking funding, propinquity may play an important role in allowing VCs to evaluate the quality of potential investment opportunities (Sorenson and Stuart, 2001). Similarly, specialization in particular industries enables venture capitalists to develop industry-specific knowledge that can assist them both in evaluating deals and advising companies. Consistent with these factors, Sorenson and Stuart (2001) demonstrate that both dimensions strongly structure the investment patterns of VC firms.

Though prior research has focused on the connections between VC firms and their target investments, given the importance of these dimensions in shaping the pattern of VC-targetCO relations, it seems reasonable that homophily on these dimensions might also influence VC firms' choices of syndicate partners. Consistent with this assumption, Piskorski and Anand (2003) find high levels of homophily on both dimensions in a dyadic analysis of VC co-investments. In this context, homophily on these dimensions might stem from two factors. On the one hand, similarity in geographic and industry space could increase the odds that two VC firms share relations with common third parties. On the other hand, social similarity might increase the level of trust between two firms because they feel that they have a better understanding of each other's worldviews. Because homophily serves as a baseline for us, we remain agnostic with regard to the precise mechanism driving its effects.

LeadVC-potential syndicate partner geographic distance (i-j property, Fig. 1): We used the logged distance in miles to measure the geographic distance between two venture capitalists. In practice, we assigned venture capitalists to precise locations by the latitudes and longitudes of the zip codes of their mailing addresses. For venture capital firms that operate more than one office, we assumed that the office closest to the target company would play the lead role in the investment and assigned its latitude and longitude as the location for that potential deal. After assigning latitudes and longitudes, we calculated the distance in miles using spherical geometry to account for the curvature of the surface of the planet.

LeadVC-potential syndicate partner industry distance (i-j property, Fig. 1): We also situated each venture capitalist in industry space by observing its distribution of investments across industries. In particular, we developed an investment profile for each firm by calculating the proportion of investments each venture capitalist made in ten broad industry categories over the preceding five years.[12] The choice of a five-year window represented a balance between allowing venture capitalists to adjust their positions over time and minimizing the measurement error associated with our estimates of position. To assess the distance between two venture capitalists we calculated the squared deviations between these vectors:

$$IndDist_{ij} = \sum_k \left(p_{ik} - p_{jk}\right)^2,$$

where *i* and *j* index leads and venture capitalists respectively, *k* indexes 1-digit industries, and *p* indicates the proportion of investments a lead or venture capitalist made in industry *k*. The resulting measure ranges from zero, for two venture capitalists with identical investment patterns, to one, for two firms that have no overlap in their investing patterns.

Potential syndicate partner-targetCO geographic distance (j-z property, Fig. 1): One of the important distinctions of our actor-event approach to estimation is that we control for the preferences of actors to participate in the events in which their joint involvement creates actor-to-actor relationships. In this way, we explicitly incorporate the dual modes of the data in our analysis. Specifically, our models include measures of the extent to which the target company (event) falls within the geographic and industry profile of the VCs in each triangular observation. We assume that matches along these dimensions increase the probability that a particular target company attracts a given VC. Although other factors also influence venture capitalists' decisions to invest (e.g., the reputation of the target company's founding team), as noted above, the preference for geographic and industry proximity likely represents a rational response to the need for a rich exchange of information and skills in both the pre- and post-investment periods (Sorenson and Stuart, 2001).

[12] The 1-digit industries are biotechnology, consumer related businesses, communications and media, computer hardware, computer software and services, energy or industrial businesses, health/medical, Internet specific businesses, semiconductors and other miscellaneous businesses.

Our measure of the geographic distance between the potential syndicate partner and the target company parallels the construction of our measure of the geographic distance between the lead venture capitalist and the syndicate partner. Again, we situate both venture capitalists and target companies in space by assigning them to the longitudes and latitudes corresponding to the zip codes of their mailing addresses. When defining the locations of multi-office venture capital firms, we again use the address of the closest office to the target firm. We then calculate the distance between each potential syndicate partner and each target company using spherical geometry.

Potential syndicate partner-targetCO industry distance (j-z property, Fig. 1): To assess the distance between a potential investor's profile and the target company, we computed the proportion of the venture capitalists' investments in the prior five years that went to firms in *different* industries from the target in question (again using the 1-digit classifications listed in footnote 12).

Although the conditioning in the estimates removes the need to control for factors related to the lead VC, the target company and the relations between them (the *i-z* relationship in Fig. 1), our models do include several measures of these attributes that we include in the regressions as components of interaction terms with leadVC-targetCO (*i-z*) geographic and industry proximity measures to test our hypotheses.[13] In essence, we look for the factors that cause matches to form among geographically, industry, and relationally distant elements of each lead VC-syndicate partner-target company triangle.

Target Company's Industry Heat: To assess exogenous shifts in the attractiveness of target companies (events), we calculated a 'heat' measure based on the distribution of IPOs in the year before the potential investment in targetCO *z*. The ability of a venture capitalist to liquidate its holdings in a company on the public equity markets is crucial to its performance. Venture capitalists therefore must constantly assess the appetites of investors for particular types of companies when choosing investments. The willingness

[13] Effectively, one can think of the regressions as including a dummy variable for each leadVC-targetCO pair. This is because the (conditional) fixed effects correspond to the case-control observation sets, and the leadVC-targetCO pairing remains constant across all eleven observations in each case-control set. We therefore cannot include properties of the *i-z* relationship (Fig. 1) in the regressions (e.g., the geographic distance between leadVC and targetCO), but we can and do interact these properties with other covariates to explore how leadVC-targetCO relational attributes affect the probability that distant ties will form along the other two (*i-j; j-z*) legs of the triangle.

of capital markets to purchase the equity of new ventures varies substantially over time (Ritter, 1984); for example, Gompers and Lerner (2000) find that a doubling of values for existing stock offerings corresponds to a 15% to 35% higher expectation of IPO value. When an industry is “hot”, investors appear to exhibit strong preferences for new offerings in the same industry.

These preferences often come in waves. The most salient example of this phenomenon may have been the Internet bubble. Beginning with the Netscape IPO, investors demonstrated vigorous demand for companies that offered infrastructure technology for the Internet or plied services via this distribution channel. Not surprisingly, venture capitalists adjusted to this surge in demand by allocating ever greater amounts of capital to these ventures in the hopes of bringing them public quickly. To reflect these spikes in investor demand and test our hypothesis that exogenous changes in the popularity of events stimulate new associations among actors, we computed a variable, *Industry heat,* which represents the proportion of venture-backed firms that went public in the prior year that operated in the same 1-digit industry as each target company. As a proportion, our heat measure could theoretically range from zero to one (though in our data, no industry ever accounted for more than 39% of IPOs). We expect that VC firms’ preferences for proximate investments—both in geographic and industry space—weaken when considering a potential investment in a ‘hot’ industry. Per our first hypothesis, we expect industry heat, a property of the z in each triangle observation and a measure of the degree to which the event belongs to a bandwagon, to increase the likelihood that more distant ties form in the context of the event.

Our second hypothesis claims that actors more frequently experiment with new partners when the relationship comes about through events that pose minimal relational risk. We have measures of four factors that we expect will correlate with the leadVC’s exposure to relational risk in investment syndicates. In particular, we expect that a leadVC will perceive less risk concerning a syndicate partner’s performance when, (i) the syndicate size is large, (ii) the investment is at a late stage of development, (iii) leadVC is geographically proximate to targetCO, and (iv) leadVC is a specialist in targetCO’s industry. As we explain below, we expect that all of these proxies of (minimizing) exposure to risk will weaken leadVC's preference for teaming with homophilous partners.

Syndicate size simply counts the number of investors involved in a financing round. As the number of investors rise, the risks associated with uncertainty regarding the future contributions of any one of them decline. Hence, we anticipate that VC firms' willingness to co-invest with more demographically distant partners rises with the size of the syndicate. Because syndicate size is highly skewed in the data, we split the sample at the median (4 investors) to test the effects of syndicate size.

Round provides a measure of the uncertainty surrounding the investment target. VC firms typically stage their financing of new ventures. In other words, in a first round of financing, venture capitalists only contribute a portion of the funds the target company expects that it will need to execute its business plan. If the company progresses satisfactorily, investors will raise a second round of financing, and so on, until the company either ceases to exist or reaches the point that it no longer depends on venture capital financing to continue to operate. Staging limits the risks associated with an investment by delaying a portion of the financing until a later date when less uncertainty surrounds the potential of the business (Sahlman, 1990). Since both the uncertainties concerning the investment target and the probable need for future resource contributions from syndicate members decrease in later financing rounds, the creation of late round syndicates offer VC firms more conducive events in which to expand their networks. In the data, the distribution of rounds is also highly skewed, so we again construct our variables by splitting the sample around the median round number (round two).

In addition to these characteristics of the investment (event), we also consider interactions between the relational attributes of leadVC-targetCO pairing (*i-z* relations in Fig. 1) and the socio-demographic distance observed between leadVC and potential co-investment partners (*i-j* relations in Fig. 1). As with the other relations along the leadVC-targetCO-syndicate partner triangle, our measures assess the proximity between the lead VC and the target company on the two dimensions of geography and industry specialization. To the extent that geographic proximity to and specialization in the industry of the investment target eases the tasks associated with selecting, monitoring and advising their portfolio companies, lead investors should perceive less risk inherent in syndicates spatially and industry-proximate to them. Therefore, we expect that a leadVC will exhibit a greater willingness to explore possible distant connections in their co-investment relations in syndicates formed to finance a proximate targetCO.

VI. RESULTS

Table 1 reports descriptive statistics for our sample. The table breaks out variable means according to whether an actual tie formed between the lead investor and syndicate partner ("cases") and randomly drawn potential ties that did not materialize ("controls"). Unsurprisingly, the mean value for whether or not the *ij*th leadVC-syndicate partner pairing had a prior tie is much higher for the cases than for the control. So too is the mean value for whether or not one or more indirect ties connect the leadVC and syndicate partner. In addition, as we would expect, leadVC-syndicate partner industry and geographic distances are lower for the cases than the controls, as are the *j-z* (syndicate partner-target company) industry and geographic distances. In other words, the descriptive statistics uniformly indicate that *all* of our measures of distance (social, geographic, and industry) between actors are lower in the observed syndicates than in the potential syndicates formed through random pairing. This is true along both legs of the triangular data structure that vary: leadVC-syndicate partner relations, and syndicate partner-targetCO ties.

Although the descriptive statistics show evidence of homophilous interaction, the overall syndicate network does not appear to be evolving toward dense, local clusters of interaction. One could illustrate the macrostructure of the (actor-to-actor) VC syndicate network in many ways. In Figure 2, we report one simple network statistic over time: in any given year, the figure plots the proportion of triads (of three VCs) eligible to close, that have in fact closed.[14] In other words, of all existing triads in which an indirect tie links two VCs through a third VC firm, what percent of the triads have actually formed the third and final link? For the 16-year interval of our data, approximately 14% of possible triads have closed. Thus, despite the evidence of homophilous interaction at the

[14] To be very clear, we use the term 'triangle' to refer to the LeadVC-targetCO-syndicate partner pairings that serve as our units of analysis. We follow convention in using the term 'triad' to refer to three-way connections (A↔B↔C↔A) among venture capitalists. Thus, triangles reflect both of the dual modes of the syndicate (actor-event) network, whereas triads denote patterns in the one-mode VC-to-VC network projection of the dual mode data.

micro level, Figure 2 (and other, unreported evidence) does not suggest that the macrostructure of the industry has evolved toward tightly connected cliques. The open question, therefore, is what micro-mechanisms counterbalance the apparent preference for socio-demographically proximate interactions?

The results of our analyses begin in Table 2. Since our methodology involves a substantial departure from previous studies of tie formation, we began by replicating the dyadic approach to estimation in our sample. Model 1, therefore, simply estimates the odds of a co-investment relationship forming between two venture capitalists only on the basis of their relational characteristics to each other. The results appear consistent with the descriptive statistics and with prior studies that find strong evidence both for structural constraints on partner selection (in terms of proximity in the affiliation matrix) and for homophilous sorting on geography and industrial specialization. In particular, model 1 shows that leadVC(*i*) is more likely to form a syndicate relationship with potential partner(*j*): (i) if the two have a previous, direct tie, (ii) if a common third party connects them, (iii) if they are geographically proximate; and (iv) if their investment profiles share common industry foci.

By comparing the results of model 1 to those of model 2, which introduces measures of VC firms' preferences for particular types of target companies, one can see the importance of explicitly accounting for the relationship of the venture capitalists to the target company that forms the context for their relationship. The first thing to note is the dramatic improvement in the model: The log-likelihood increases by more than 4,000 and the pseudo-R^2 indicates that the inclusion of measures of the syndicate partner-targetCO (*j-z*) relationship more than doubles the amount of variance explained by the model. Next, our attention is drawn to the fact that the coefficients for the dyadic measures shift substantially. The importance of prior direct and indirect ties to the likelihood of a future co-investment relation increases by 21% and 163% respectively. Similarly, the magnitude of the coefficient for homophily on industry specialization increases by 37% in the actor-event analysis. But the effect sizes do not uniformly increase. After accounting for VC firms' preferences for investing locally in industries in which they have expertise, the estimated effect of homophily on geographic proximity *declines* by 70%. It therefore appears that failing to account for actor preferences when estimating tie formation in dual mode data (*i.e.*, affiliation networks) can lead to substantial omitted variable bias.

Recall that our primary purpose is to examine the origins of new, distant ties. Though prior relations clearly play an important role in structuring future partnering, as noted earlier, to the extent that these relations remain exogenous to our analysis they limit our ability to understand fully the evolution of the network. The existence of a prior tie moreover may fundamentally alter the dynamics of tie formation. To assess this possibility, we split the sample in models 3 and 4 according to whether or not the two venture capital firms have invested together in the preceding five years. Splitting the sample allows the geographic and industry proximity effects across the elements of each triangle to vary with the relational history of the leadVC-syndicate partner (*i-j*) pairing. The number of observations in these two models do not sum to the total number of observations in the sample because sets of cases and controls in which the dependent variable does vary within these selected groups drop out of the conditioned logit estimates; in other words, those observations in which the unrealized ties (controls) do not match the realized tie (case) on the existence of a prior affiliation do not contribute to the estimates. Two interesting, though unsurprising, facts appear when we split the sample. First, both homophily and preferences for particular targets exhibit stronger effects on tie formation when two actors have not co-invested in the previous five years. Second, our models explain a much larger degree of the variance in partner selection among those without a prior connection. Although the next two tables only report estimates across the entire sample, we will return to this issue below.

The tests of our hypotheses begin in Table 3. Model 5 interacts the VC firms' preferences for proximate investments with industry heat, our measure of investor enthusiasm for the industries in which each target company participates. Recall that the models do not include the 'main effects' of the variables that we use to assess the attractiveness of and risk associated with particular social foci (targetCOs); because these terms do not vary within matched sets of cases and controls, they drop out of the model. To test hypothesis 1, we focus on how the level of industry heat influences the relationship between the syndicate partner-targetCO (*j-z*) proximity variables. In particular, we interact the industry heat of targetCO(*z*) with the geographic and industry distance of syndicate partner(*j*) to the target company. As discussed in the theory section above, we expect that popular events (bandwagons) attract actors that would not normally engage in them, thus diverting actors from their ordinary group affiliations and contributing to the emergence of heterophilous relationships.

Consistent with hypothesis one, when an industry experiences a large number of IPOs in the preceding year, the strength of the negative effect of distance between a syndicate partner's industry focus and the industry of the target company declines. In other words, target companies in hot industries attract investors that normally focus their investment activity in industries that differ from the target company. Though this effect does not directly form distant attachments, the weakening of industry preferences increases the odds that a VC will connect with another VC specializing in a different industry. The magnitude of this effect is large; a one standard deviation increase in industry heat reduces the importance of a potential syndicate partner's specialization in targetCO's industry by 19%. And at the height of the observed IPO waves, the strength of preferences for industries in which investors have prior experience drops by more than 90%. Thus, exogenous shifts in investor demand that affect the IPO market in particular areas of technology do appear to result in the formation of otherwise unlikely relationships among VCs.

Though consistent with our expectations, one might worry that these effects reflect the unusual (and potentially anomalous) period surrounding the Internet bubble. Many new venture capital firms began investing during this period in response to the dramatic rise in investor interest in private equity and venture capital in the late 1990s. Hence, one might expect these fledgling firms with short track records to exhibit less structured investing patterns. To address this issue, in model 6, we therefore re-estimated model 5 excluding all cases in which targetCO operated an Internet specific business. As one can see, the results remain robust to the exclusion of these triangles.

Model 7 introduces our first of many tests of hypothesis two, which anticipates that lead VCs will more likely partner with socio-demographically distant syndicate partners when target company and syndicate characteristics minimize the level of partner risk. Since these factors moderate the perceived partner-specific risks involved in co-investing, we test their effects (and hypothesis two) by interacting each of these event characteristics with leadVC-syndicate partner distance (*i-j*) measures. Our hypothesis is that our multiple proxies for low targetCO and syndicate risk will diminish the importance of leadVC-potential syndicate partner distance on reducing the likelihood of a relationship. In other words, leadVC's more likely select socio-demographically distant investment partners in relatively less risky syndicates and LeadVC-targetCO pairings.

As we had expected, the strength of homophilous sorting in co-investment relationships, at least on geography, declines with the size of the syndicate. As more investors become involved with the financing round, the risk associated with an errant assessment of any one of them declines. In model 8 (Table 4), VC firms similarly show a willingness to partner with more distant associates, both in terms of the location and industry specialization of potential syndicate partners, in later financing rounds when less uncertainty surrounds the targetCO investment. And finally, models 9 and 10 test the interactions between leadVC's proximity to targetCO (*i-z* relational characteristics) and its tolerance for distant investment partners (*j*). When the lead is closer to the target in either geographic or industry specialization terms, it more frequently pairs with more geographically distant co-investors.

Collectively, with four proxies for uncertainty and two measures of distance, we have eight independent tests of hypothesis 2. Although the hypothesis is not supported in all eight of the interactions, our expectation is supported in more than half of these independent tests. Focusing on the individual coefficient significance levels, moreover, understates the true significance level of the support for our hypothesis since the odds of finding support at a $p < 0.05$ significance level by chance in five of eight independent tests is less than 1 in 2.4 million.

One might nonetheless worry that our effects tested one at a time simply capture common variance. Table 5 therefore provides joint tests of all of the interactions. In general, the results remain robust, but the simultaneous estimation of effects reveals three differences. First, though the sign remains in the expected direction, the interaction effect between industry heat and the lead VC-syndicate partner industry distance falls to a significance level of $p \sim .10$. Second, the interaction between industry proximity and the lead's geographic proximity to the target unexpectedly flips positive. This positive coefficient suggests that the difference in investment patterns between co-investors increases with the lead's geographic distance from the target. The effect size, however, is small and not robust (see models 12 and 13). Finally, the effect of specialization in the target company industry on homophily shifts from considering more distant geographic partners to affiliating with firms with different industry investment patterns. Hence, when tested simultaneously our eight independent tests support hypothesis two in three cases at the $p<.05$ (or four cases at $p<.10$) level. The joint odds against such simultaneous support exceed 2688 to 1. On the whole, then, it appears that leadVCs do connect to more distant co-investors in the context of events with less relational risk.

As noted above, we have a particular interest in our ability to predict new, distant ties. Since a history of prior interactions can engender the formation of trust, homophilous tendencies and the deviations from homophily described in hypotheses one and two should operate most strongly in situations in which the two actors have not previously co-invested. In models 12 and 13, therefore, we again split the sample according to whether or not potential co-investment partners have a prior relationship to see if these patterns differ across the groups. The results strike us as quite interesting and consistent with our overall theory. When VC firms have a prior co-investment, they exhibit no significant homophily. Most of the explained variance in the matching of co-investment partners stems from their potential partners' preferences for particular events (target investments). Once VC firms have built trust through prior interactions they exhibit no homophilous preferences among their prior associates. The situation looks much different, however, among VC firms that have not partnered recently. Lead VC firms exhibit strong preferences for working with similar others. Consistent with hypothesis two, however they relax these constraints (i) when working in larger syndicates, (ii) in later rounds, and (iii) when they either have greater expertise in the target company's industry or reside closer to its headquarters.

VII. Discussion and Conclusion

One could frame our results in at least two different ways. The first, which we use to introduce the paper, considers the larger issue of how networks evolve. Existing theories of tie formation have highlighted two primary explanations of who forms relationships with whom. One argues that the structure of the network itself influences subsequent tie formation (e.g., Gulati and Gargiulo, 1999). The other maintains that actors prefer to interact with similar others (e.g., Lincoln, Gerlach and Takahashi, 1992). Though both of these rules of action undoubtedly account for a substantial portion of the variance in network evolution, they imply long-range structures incompatible with our empirical observations. Indeed, both of these logics of action imply an evolution toward static clique-like structures of similar individuals. Yet, real interorganizational networks exhibit dynamism and numerous distant connections across actors.

Critical to moving beyond the rigid structures implied by existing theory is recognition that factors exogenous to the network also drive tie formation. Here, our analysis highlights two such factors. First, actors' preferences for events shift over time. The emergence of new and/or highly popular events can therefore push previously unconnected parties into forming relations. Though the popularity of these events may soon decline, at least a portion of the relations formed during these periods likely endures, thereby forming the basis for new connections. Second, the strength of homophilous sorting varies by context. In high-risk events, actors exhibit strong preferences for interacting with similar individuals. In lower cost and risk settings, however, actors can and do appear to explore new social relations.

Our results therefore offer micro-level dynamics of tie formation consistent with the global structure of observed large-scale interorganizational networks. In the risky situations that characterize many types of events, firms interact primary with known partners or with highly similar ones. As a result, networks exhibit a high degree of local clustering. Bridging ties nonetheless emerge from two types of activities: the attractiveness of unusually popular events and the experimentation of firms with distant partners in low risk situations. The former strikes us as particularly interesting. Research on 'small worlds' has had relatively little to say so far in respect to why these network patterns emerge. One possibility suggested here is that the arrival of one or more popular events catalyzes the creation of a critical mass of distant ties linking previously unconnected groups of actors.

A second perspective for interpreting our results involves thinking about the problem more specifically from the point of view of the venture capitalist. VC firms face two competing forces in selecting investment partners. On the one hand, both making and accepting invitations to co-invest require a certain level of trust. Invited firms face substantial uncertainty regarding the quality of the target company, and leads clearly have an incentive to overstate the value of the company to maximize their returns on prior investments. Similarly, leads may doubt the ability and willingness of syndicate partners to bring critical resources to bear. Given the uncertainties inherent in these non-market transactions, one might expect private equity firms to limit their exchanges to trusted partners—those with whom they share prior interactions or a common milieu. On the other hand, investors might also wish to maximize the reach of their social networks. To the extent that these networks transmit valuable, private information on potential investments, those in axial positions have access to a greater quantity and higher quality of information when choosing opportunities (Sorenson and Stuart, 2001).

How do VCs manage these competing demands? Our results suggest that venture capitalists cope with this tradeoff by using different rules of action depending on the situation. Investments differ in the degree of uncertainty inherent in the transaction. On average, early stage investments, those with fewer syndicate members and those where the lead knows less about the target company have the highest level of uncertainty. The need for trust to mitigate these risks will virtually require venture capital firms to interact with known partners. When investing in areas they know better, or in later rounds when the uncertainty regarding the investment's value declines, VC firms can afford to assume more relational risk, thereby allowing them to explore distant connections.

In addition to its theoretical implications, we also believe that our approach makes an important methodological contribution. By introducing actor-event relations into the estimation, we not only allow for contingency in the rules of action governing tie formation, but also critically control for the interests of actors in events. In our own data, the absence of these controls produces substantial omitted variable bias. Indeed, these actor-level preferences have a larger effect on tie formation than the relational attributes of the two actors. Researchers may therefore wish to revisit their estimates of tie formation in cases where these ties form not directly but rather in the context of events.

Our analysis has at least two limitations: The first concerns the potential endogeneity of the attributes of the events. Syndicate size, for example, may depend on the decision to include unknown firms in the syndicate rather than serving as a precondition for the selection of these firms. Though this possibility suggests caution in interpreting the effects of syndicate size on partner selection, our other covariates should vary exogenously to partner choice. For instance, because leads choose investment companies in earlier rounds, their positions vis-à-vis the targets do not vary with respect to subsequent co-investment relations.

Second, our data include a type of selection bias: we only observe accepted offers. In other words, if a lead invited another VC to join in an investment syndicate and that firm declined the offer, we would have no record of the invitation in our data. One should really think of our results therefore as estimates of the joint probability that a lead invites a particular VC firm to the syndicate and that the VC accepts. Though this framing shifts the locus of decision making, we do not believe that it should alter our central conclusion. An alternative framing of our hypotheses, for example, would simply restate the actor as the invitee. Invited firms more likely accept invitations to popular events and when those events require them to assume less relational risk as well.

Finally, we would like to conclude with one suggestion for future research. As researchers become increasingly interested in theories of network formation capable of predicting the emergence of socio-demographically distant or bridging ties, the question emerges: Do distant ties differ from local ties in how they contribute to the subsequent evolution of the network? In an examination of the stability of network ties, Burt (2002) shows that relations that span structural holes 'decay' more rapidly (see also, Rowley, et al., 2005). With respect to our project, this work raises questions such as, to what extent do the distant ties that form in the context of faddish or low-risk events become part of the social fabric that structures the social network in its next iteration? And, can we identify types of circumstances that both create distant ties and differentially impact the probability that these ties survive to contribute to the rewiring of the network in later periods?

VIII. References

Abrahamson, E., and L. Rosenkopf
1993 "Institutional and competitive bandwagons: Using mathematical modeling as a tool to explore innovation diffusion." Academy of Management Review, 18: 487-517

Ahuja, G.
2000 "Collaboration networks, structural holes and innovation: A longitudinal study." Administrative Science Quarterly, 45: 425-455

Banerjee, A.V.
1992 "A simple model of herd behavior." Quarterly Journal of Economics, 107: 797-817

Barabasi, A.-L., and R. Albert
1999 "Emergence of scaling in random networks." Science, 286: 509-512

Baum, J.A.C., T. Rowley, A.V. Shiplov, and Y.-T. Chuang
2004 "Dancing with strangers: Aspiration performance and the search for underwriting syndicate partners." Working paper, University of Toronto

Bearman, P.S., J. Moody, and K. Stoval
2004 "Chains of affection: The structure of adolescent romantic and sexual networks." American Journal of Sociology, 110: 44-91

Bikhchandani, S., D. Hirshleifer and I. Welch
1992 "A theory of fads, fashion, custom, and cultural change as informational cascades." Journal of Political Economy, 100: 992-1026

Blau, P.
1964 Exchange and Power in Social Life. New York: John Wiley & Sons

Brass, D.J., J. Galaskiewicz, H.R. Greve, and W.P. Tsai
2004 "Taking stock of networks and organizations: A multilevel pespective." Academy of Management Journal, 47: 795-817

Breiger, R.L.
1974 "The duality of persons and groups." Social Forces, 53: 181-190

Breslow, N.E., and N.E. Day
1980 Statistical Methods in Cancer Research: Volume 1 -- The Analysis of Case-Control Studies. Lyon: IARC Scientific Publications

Burt, R.S.
1992 Structural Holes. Cambridge, MA: Harvard University Press
1997 "The contingent value of social capital." Administrative Science Quarterly, 42: 339-365
2002 "Bridge decay." Social Networks, 24: 333-364.

Coleman, J.S.
1988 "Social capital in the creation of human capital." American Journal of Sociology, 94: S95-S120

Coslett, S.R.
1981 "Maximum likelihood estimator for choice-based samples." Econometrica, 49: 1289-1316

Davis, J.A.
1967 "Clustering and structural balance in graphs." Human Relations, 20: 181-187

Feld, S.L.
1981 "The focused organization of social ties." American Journal of Sociology, 86: 1015-1035
1982 "Social structural determinants of similarity among associates." American Sociological Review, 47: 797-801

Fernandez, R.M., and N. Weinberg
1997 "Sifting and sorting: Personal contacts and hiring in a retail bank." American Sociological Review, 62: 883-902

Freeman, J.
1999 "Venture capital as an economy of time." Pp. 460-482 in S. Gabbay and R. Leenders (Eds.), Corporate Social Capital and Responsibility. Boston: Kluwer.

Galaskiewicz, J., and D. Shatin
1981 "Leadership and networking among neighborhood human service organizations." Administrative Science Quarterly, 26: 434-448

Gompers, P., and J. Lerner
2000 "Money chasing deals? The impact of fund inflows on the valuation of private equity investments." Journal of Financial Economics, 55: 281-325

Gorman, M., and W.A. Sahlman
1981 "What do venture capitalists do?" Journal of Business Venturing, 4: 231-248

Granovetter, M.S.
1973 "The strength of weak ties." American Journal of Sociology, 78: 1360-1380
1985 "Economic action and social structure: The problem of embeddedness." American Journal of Sociology, 91: 481-510

Gulati, R.
1995 "Social structure and alliance formation pattern: A longitudinal analysis." Administrative Science Quarterly, 40: 619-642

Gulati, R., and M. Gargiulo
1999 "Where do interorganizational networks come from?" American Journal of Sociology, 104: 1439-1493

Hochberg, Y., A. Ljungqvist, and Y. Lu
2004 "Whom you know matters: Venture capital networks and investment performance." Journal of Finance: forthcoming

Imbens, G.
1992 "An efficient methods of moments estimator for discrete choice models with choice-based sampling." Econometrica, 60: 1187-1214

Ingram, P., and P.W. Roberts
2000 "Friendships among competitors in the Sydney hotel industry." American Journal of Sociology, 106: 387-423

Kaplan, S.N., and P. Stromberg
2003 "Financial contracting theory meets the real world: An empirical analysis of venture capital contracts." Review of Economic Studies, 70: 281-315

King, G., and L. Zeng
2001 "Logistic regression in rare events data." Political Analysis, 9: 137-163

Kono, C., D. Palmer, R. Friedland, and M. Zafonte
1998 "Lost in space: The geography of corporate interlocking directorates." American Journal of Sociology, 103: 863-911

Lerner, J.
1994 "The syndication of venture capital investments." Financial Management, 23: 16-27

Lincoln, J.R.
1984 "Analyzing relations in dyads." Sociological Methods and Research, 13: 45-76

Lincoln, J.R., M.L. Gerlach, and P. Takahashi
1992 "Keiretsu networks in the Japanese economy: A dyad analysis of intercorporate ties." American Sociological Review, 57: 561-585

Manski, C., and S. Lerman
1977 "The estimation of choice probabilities from choice-based samples." Econometrica, 45: 77-88

McPherson, J.M., and L. Smith-Lovin
1982 "Women and weak ties: Differences by sex in the size of voluntary organizations." American Journal of Sociology, 87: 883-904

Mizruchi, M.S.
1996 "What do interlocks do? An analysis, critique and assessment of research on interlocking directorates." Annual Review of Sociology, 22: 271-298

Mizruchi, M.S., and L.B. Stearns
1988 "A longitudinal study of the formation of interlocking directorates." Administrative Science Quarterly, 33: 194-210

Piskorski, M.J., and B. Anand
2003 "Resources, power and prestige: Formation of structural inequality in social exchange networks." Working paper, Harvard Business School

Podolny, J.M.
1994 "Market uncertainty and the social character of economic exchange." Administrative Science Quarterly, 39: 458-483
2001 "Networks as pipes and prisms of the market." American Journal of Sociology, 107: 33-70

Podolny, J.M., and J.N. Baron
1997 "Resources and relationships: Social networks and mobility in the workplace." American Sociological Review, 62: 673-693

Podolny, J.M., and K.L. Page
1998 "Network forms of organization." Annual Review of Sociology, 24: 57-76

Powell, W.W.
1990 "Neither market nor hierarchy: Network forms of organization." Research in Organizational Behavior, 12: 295-336

Powell, W.W., K.W. Koput and Smith-Doerr
1996 "Interorganizational collaboration and the locus of innovation: Networks of learning in biotechnology." Administrative Science Quarterly, 41: 116-145

Powell, W.W., D.R. White, K.W. Koput and J. Owen-Smith
1996 "Network dynamics and field evolution: The growth of inter-organizational collaboration in the life sciences." American Journal of Sociology, 110: 1132-1205

Ritter, J.R.
1984 "The hot issue market of 1980." Journal of Business, 57: 215-240

Rowley, T.J., H.R. Greve, H. Rao, J.A.C. Baum, and A.V. Shiplov
2005 "Time to break up: Social and instrumental antecedents and consequences of firm exits from exchange cliques." Academy of Management Journal, 48: 499-520

Sah, R.K., and J.E. Stiglitz
1986 "The architecture of economic systems: Hierarchies and polyarchies." American Economic Review, 76: 716-727

Sahlman, W.A.
1990 "The structure and governance of venture capital organizations." Journal of Financial Economics, 27: 473-521

Seidel, M.-D., J.T. Polzer, and K.J. Stewart
2000 "Friends in high places: The effects of social networks on discrimination in salary negotiations." Administrative Science Quarterly, 45: 1-24

Self, S.G., R.L. Prentice
1988 "Asymptotic distribution theory and efficiency results for case-cohort studies." Annals of Statistics, 16: 64-81

Snijders, T.A.B.
2001 "Syndication networks and the spatial distribution of venture capital investments." In M.E. Sobel and M.P. Becker (eds.), Sociological Methodology: 361-395. Boston: Basil Blackwell

Sorenson, O., and T.E. Stuart
2001 "Syndication networks and the spatial distribution of venture capital investments." American Journal of Sociology, 106: 1546-1588

Strang, D., and M.W. Macy
2001 "In search of excellence: Fads, success stories and adaptive emulation." American Journal of Sociology, 107: 147-182

Strang, D., and S. Soule
1998 "Diffusion in organizations and social movements: From hybrid corn to poison pills." Annual Review of Sociology, 24: 265-290

Stuart, T.E., H. Huang, and R.C. Hybels
1999 "Interorganizational endorsements and the performance of new ventures." Administrative Science Quarterly, 44: 315-349

Uzzi, B.
1996 "The sources and consequences of embeddedness for economic performance of organizations." American Sociological Review, 61: 674-698

Walker, G., B. Kogut and W.J. Shan
1997 "Social capital, structural holes and the formation of an industry network." Organization Science, 8: 109-125

Watts, D.
1999 Small Worlds. Princeton, NJ: Princeton University Press

Williamson, O.
1975 Markets and Hierarchies. New York: Free Press

Wilson, R.
1968 "The theory of syndicates." Econometrica, 36: 119-132

Zuckerman, E.W.
1999 "The categorical imperative: Security analysts and the illegitimacy discount." American Journal of Sociology, 104: 1398-1438

Table 1: Descriptive statistics†

	All	Cases (tie = 1)	Controls (tie = 0)
N	146,695	13,335	133,350
Prior tie	.247 (.432)	.474 (.499)	.225 (.417)
Indirect tie	.728 (.445)	.818 (.386)	.719 (.450)
Lead-target distance (*i-z* link, Fig. 1)			
Geographic	4.93 (2.30)	4.93 (2.30)	4.93 (2.30)
Industry	.765 (.175)	.765 (.175)	.765 (.175)
Lead-VC distance (*i-j* link, Fig. 1)			
Geographic	6.12 (2.28)	5.25 (2.68)	6.21 (2.21)
Industry	.232 (.246)	.166 (.179)	.239 (.251)
VC-target distance (*j-z* link, Fig. 1)			
Geographic	6.34 (1.87)	5.30 (2.26)	6.45 (1.80)
Industry	.832 (.180)	.728 (.205)	.843 (.174)
Industry heat	.132 (.082)	.132 (.082)	.132 (.082)
Syndicate size	4.21 (2.68)	4.21 (2.68)	4.21 (2.68)
Round	3.12 (2.46)	3.12 (2.46)	3.12 (2.46)

† Means and standard deviations; standard deviations reported in parentheses.

Table 2: Conditional logit estimates of tie formation†

	Dyadic analysis	Actor-event analysis		
	Model 1 All cases	Model 2 All cases	Model 3 Prior tie	Model 4 No prior tie
Prior tie	**1.29** **(.041)**	**1.56** **(.045)**		
Indirect tie (1-step)	**.175** **(.036)**	**.460** **(.039)**		
Lead-VC (*i*-*j*) distance				
Geographic	**-.130** **(.004)**	**-.039** **(.006)**	**-.023** **(.008)**	**-.053** **(.009)**
Industry	**-1.43** **(.086)**	**-1.96** **(.088)**	**-2.29** **(.269)**	**-2.42** **(.097)**
VC-target (*j*-*z*) distance				
Geographic		**-.241** **(.007)**	**-.176** **(.011)**	**-.289** **(.009)**
Industry		**-4.39** **(.071)**	**-4.19** **(.175)**	**-5.20** **(.085)**
Log-likelihood	-28,904.0	-24,973.7	-6566.2	-12,183.1
Pseudo-R^2	.098	.219	.127	.214
N	146,685	146,685	23,996	65,667

† Standard errors reported in parentheses. Coefficients with $p < .05$ (two-tailed) highlighted in bold.

Table 3: Actor-event conditional logit estimates of tie formation†

	Model 5 All	Model 6 All (excluding Internet)	Model 7 All
Geodesic = 1	**1.53 (.045)**	**1.55 (.051)**	**1.57 (.045)**
Geodesic = 2	**.422 (.039)**	**.431 (.046)**	**.459 (.039)**
Lead-VC (*i*-*j*) distance			
Geographic	**-.039 (.006)**	**-.035 (.007)**	**-.072 (.008)**
Industry	**-2.05 (.091)**	**-2.11 (.103)**	**-1.98 (.106)**
Lead-VC (*i*-*j*) distance interactions with syndicate size (>3)			
Geographic			**.060 (.010)**
Industry			.073 (.147)
VC-target (*j*-*z*) distance			
Geographic	**-.242 (.007)**	**-.247 (.009)**	**-.242 (.007)**
Industry	**-4.51 (.071)**	**-4.81 (.084)**	**-4.37 (.071)**
VC-target (*j*-*z*) distance interactions with industry heat			
Geographic X industry heat	-.110 (.071)	-.280 (.154)	
Industry X industry heat	**10.4 (.702)**	**7.72 (1.47)**	
Log-likelihood	-24,817.9	-20,020.3	-24,947.6
Pseudo-R^2	.224	.234	.220
N	146,685	119,900	146,685

† Standard errors reported in parentheses. Coefficients with p < .05 (two-tailed) highlighted in bold.

Table 4: Actor-event conditional logit estimates of tie formation†

	Model 8 All	Model 9 All	Model 10 All
Geodesic = 1	**1.57** **(.045)**	**1.58** **(.045)**	**1.57** **(.045)**
Geodesic = 2	**.458** **(.039)**	**.465** **(.039)**	**.461** **(.039)**
Lead-VC (*i*-*j*) distance			
Geographic	**-.074** **(.007)**	**-.031** **(.006)**	**-.105** **(.026)**
Industry	**-2.07** **(.114)**	**-1.95** **(.089)**	**-1.59** **(.357)**
Lead-VC (*i*-*j*) distance interactions with round (>2)			
Geographic	**.072** **(.010)**		
Industry	**.278** **(.132)**		
Lead-VC (*i*-*j*) distance interactions with lead-target (*i*-*z*) distance			
Geographic X lead geo dist		**-.022** **(.003)**	
Industry X lead geo dist		.055 (.033)	
Geographic X lead ind dist			**-.084** **(.032)**
Industry X lead ind dist			-.494 (.446)
VC-target (*j*-*z*) distance			
Geographic	**-.243** **(.007)**	**-.287** **(.009)**	**-.287** **(.007)**
Industry	**-4.37** **(.071)**	**-4.37** **(.071)**	**-4.37** **(.072)**
Log-likelihood	-24,935.6	-24,933.1	-24,967.7
Pseudo-R^2	.220	.220	.219
N	146,685	146,685	146,685

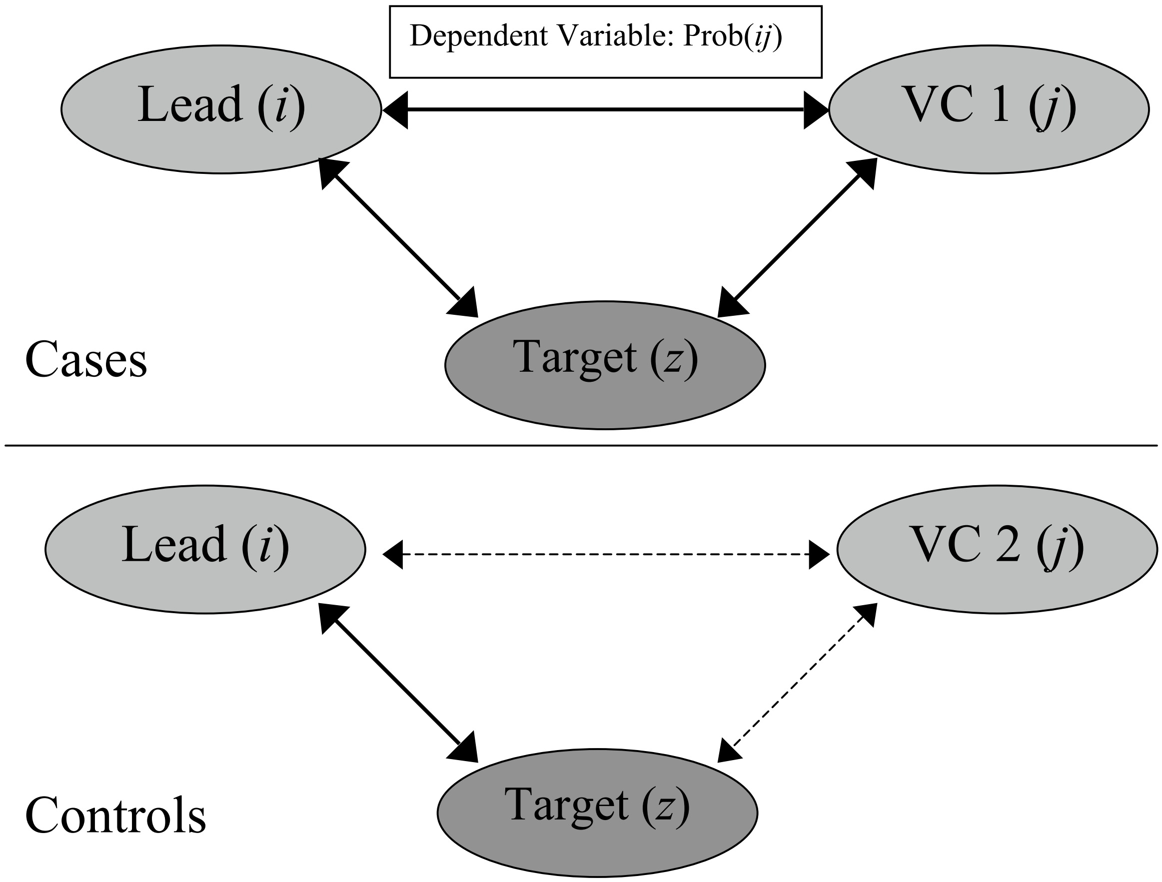
† Standard errors reported in parentheses. Coefficients with $p < .05$ (two-tailed) highlighted in bold.

Table 4: Actor-event conditional logit estimates of tie formation[†]

	Model 11 All	Model 12 Prior tie	Model 13 No prior tie
Geodesic = 1	**1.52 (.045)**		
Geodesic = 2	**.417 (.039)**		
Lead-VC (*i*-*j*) distance			
Geographic	**-.120 (.025)**	.019 (.051)	**-.134 (.033)**
Industry	**-1.31 (.322)**	-1.61 (1.51)	**-1.13 (.340)**
Lead-VC (*i*-*j*) distance interactions			
Geographic X syndicate size	**.045 (.010)**	**.033 (.015)**	**.054 (.015)**
Industry X syndicate size	.016 (.152)	.359 (.519)	-.123 (.180)
Geographic X round (>2)	**.056 (.010)**	.022 (.015)	**.059 (.015)**
Industry X round (>2)	.242 (.149)	.918 (.501)	-.312 (.178)
Geographic X lead (*i*-*z*) geo dist	**-.022 (.003)**	**-.020 (.005)**	**-.021 (.004)**
Industry X lead (*i*-*z*) geo dist	**.074 (.033)**	.214 (.111)	-.013 (.039)
Geographic X lead (*i*-*z*) ind dist	-.051 (.032)	-.078 (.063)	-.049 (.041)
Industry X lead (*i*-*z*) ind dist	**-1.21 (.413)**	-1.96 (1.83)	**-1.47 (.443)**
VC-target (*j*-*z*) distance			
Geographic	**-.288 (.009)**	**-.225 (.015)**	**-.333 (.012)**
Industry	**-4.60 (.073)**	**-4.55 (.179)**	**-5.18 (.091)**
VC-target (*j*-*z*) distance interactions			
Geographic X industry heat	-.066 (.071)	.028 (.125)	-.055 (.089)
Industry X industry heat	**10.7 (.699)**	**11.5 (2.13)**	**11.4 (.805)**
Log-likelihood	-24,718.7	-6529.0	-12,010.9
Pseudo-R^2	.227	.132	.225
N	146,685	23,996	65,667

[†] Standard errors reported in parentheses. Coefficients with p < .05 (two-tailed) highlighted in bold.

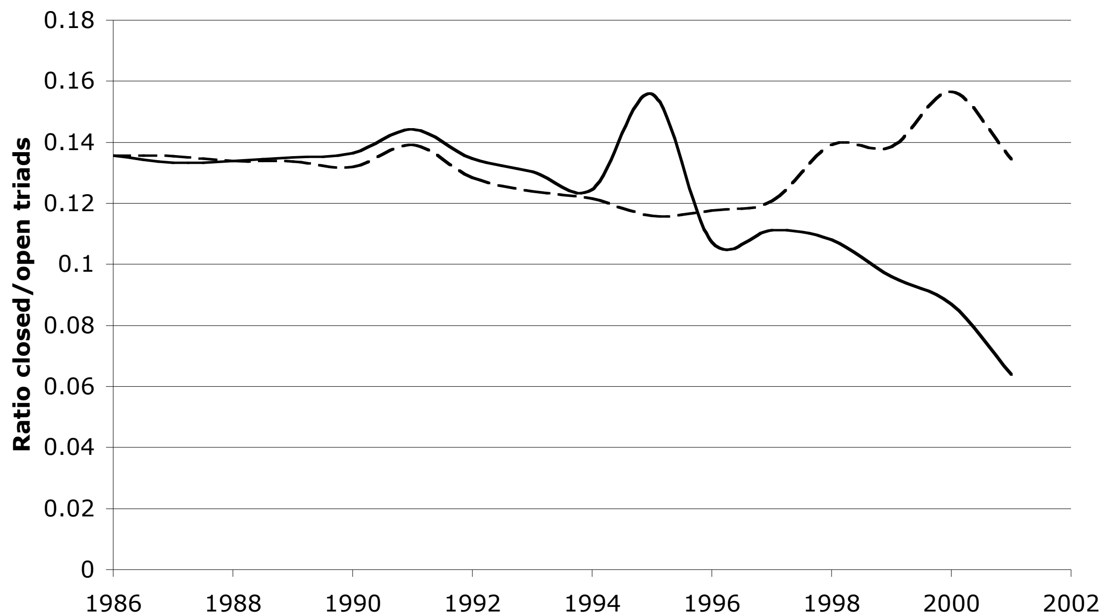
Figure 1: Actor-event analysis



Legend: The triangles illustrate the data structure. We index lead VCs with *i*, syndicate partners with *j*, and target companies with *z*. For each actual lead VC-syndicate partner (*ij*) pair, we draw ten of the syndicate partners that *i* could have chosen in place of the actual *j*. We therefore have eleven observations per actual case. The lead and target remain constant across all eleven observations, but each has a different syndicate partner (*j*), only one of which actually participated in the syndicate.

Consider an actual case in the data. Crosspoint Ventures (*i*), a venture capital firm located in Silicon Valley, took a lead position in Protolite (*z*), a manufacturer of display panels. In constructing our sample, we matched Crosspoint and Protolite with eleven potential co-investors: Emerging Growth, 530 Funds, Arete, El Dorado Ventures, Glenn Capital, Oak Investment, Phillips-Smith, Prime Capital, Seidman, Jackson, Fishser & Co., Southwest Venture Capital, and Technology Funding. Of these, only Emerging Growth actually co-invested in Protolite.

Figure 2: Triad closure



Legend: The solid line depicts the ratio of closed triads (i.e. all three possible connections present) to open triads (i.e. two of the three possible ties in a triad) among VC firms over time. To adjust for changes in the mix of VC experience over time (due to entry) he dotted line follows this trend for the subset of VC firms that entered the industry in or before 1986.