EMBEDDING INTER-ORGANIZATIONAL RELATIONS IN ORGANIZATIONAL MEMBERS’ PRIOR EDUCATION AND EMPLOYMENT NETWORKS.*

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ABSTRACT

This paper proposes that organizations leverage members’ prior education and employment networks to identify and select new partners. Mechanisms related to embeddedness, homophily and focus theory imply that the likelihood of two organizations forming a new relationship increases with the number of prior education and/or employment affiliations shared by the organizations’ members. Analyses of U. S. private equity co-investments demonstrate that shared prior affiliations increase the likelihood of relationship formation. Consistent with embeddedness theory, this effect is strongest for organizations that previously formed few or no relationships. Implications for studying network evolution and the reproduction of socioeconomic inequalities are discussed.
INTRODUCTION

One of the most consistent findings of organizational research is that behaviors and outcomes vary with organizations’ positions in inter-organizational networks and also with the structural properties of those networks. Though tempting to attribute causal influences to position and structure, recent work voices caution and argues for studies of how network structures evolve and how actors come to occupy network positions (e.g., Brass, Galaskiewicz, Greve and Tsai, 2004; Stuart and Sorenson, 2007). It is increasingly clear that the relationships between position and outcome and between structure and behavior are better understood than the determinants of either network structures or organizations’ network positions; credible causal inferences necessitate a much clearer understanding of how structures and positions evolve (Stuart and Sorenson, 2007; Stuart, 2007). More specifically, the prevailing logic of endogenous network dynamics (Gulati and Gargiulo, 1999; Walker, Kogut and Shan, 1997; Ahuja, 2000), in which tomorrow’s networks are shaped by today’s network properties, can be complemented by accounts of network formation; of actors’ network entries, transitions and exits; of exogenous influences on network structure and of initial relationship formation between organizations.

In this spirit, recent research on inter-organizational networks offers provocative insights into new organizations’ assimilation into existing networks (e.g., Hallen, 2008; Rosenkopf and Padula, 2008), established organizations’ transitions between networks (Jensen, 2003, 2008) and environmental influences on inter-organizational interactions (e.g., Powell, White, Koput and Owen-Smith, 2005; Kogut and Walker, 2001; Kogut, Urso and Walker, 2007; Sorenson and Stuart, 2008). At least two important questions linger; both are addressed in this paper. First, if organizations tend to repeat relationships (Podolny, 1994; Gulati, 1995a, 1995b; Gulati and
Gargiulo, 1999) then what accounts for the formation of initial relationships between two established organizations? Second, if inter-organizational relationships – the voluntary commitment of resources by organizations to the pursuit of common objectives – often emerge out of inter-personal relations (Granovetter, 1985; Lincoln, Gerlach and Takahashi, 1992) then how and where were those relationships formed? Answers to the first inform our understanding of how endogenous network dynamics are set into motion. Answers to the second inform our understanding of how existing social structures, and their inherent constraints and opportunities, are reproduced by networks.

This study investigates new relationship formation between established organizations. There are at least two analytical approaches to this inquiry. One approach is to examine how the rate of new relationship formation varies with changes in organizational environments (e.g., Powell, et al., 2005; Kogut, et al., 2007). A second approach is to examine how connections between two organizations’ members influence the likelihood of new relationship formation (e.g., Rosenkopf, Metiu and George, 2001; Hallen, 2008). Ideally, one would construct a balanced panel of dyadic observations and combine these two approaches; however, collecting time-series data on both organizations and their members is extremely resource-intensive. Consequently, I leverage the second approach and examine relationship formation in the cross-section. Two primary reasons provide justification. First, recent work admirably advances the first approach by modeling the rate of relationship formation between “distant” organizations as the context for interaction changes over time (Sorenson and Stuart, 2008; Rosenkopf and Padula, 2008). By examining the formation of new inter-organizational relationships while holding contextual influences constant, this study complements recent work. Second, economic
sociology emphasizes inter-personal relations in facilitating market transactions (Granovetter, 1985; Portes and Sensenbrenner, 1993; Uzzi, 1996). As Burt (1992: 9) states, “the social capital of people aggregates into the social capital of organizations.” Examination of such cross-level influences (e.g., individual to organization) on networks (Brass, et al., 2004) requires systematic collection of individual data and the second approach permits collection of such data at reasonable cost. The inferential trade-offs between fine-grained data on organizational members versus panel data on organizations are acknowledged.

Departing from research that takes inter-personal relations as given, I treat the origins of such relations as empirically consequential and theoretically interesting. Although prior organizational research highlights the role of individuals’ career experiences in conditioning both organizational (e.g., Fligstein, 1987, 1990; Thornton and Ocasio, 1999; Rosenkopf and Almeida, 2003; Higgins and Gulati, 2003) and individual (e.g., Useem and Karabel, 1986; Ishida, Spilerman and Su, 1997; Higgins, 2005; Stuart and Ding, 2006) behaviors and outcomes, the link between individual careers and inter-organizational network evolution remains implicit. By explicitly linking network mechanisms to the social structures of both non-market (i.e., colleges and universities) and market (i.e., labor markets) settings, I aim to integrate the study of network evolution with theories of how social structures are reproduced (e.g., Bourdieu & Passeron, 1977; Fligstein, 2002).

I propose that organizations tend to embed new inter-organizational relationships in the prior education and employment networks of their members. Several sociological theories
motivate the prediction that two organizations will be more likely to form a new relationship the more prior education and/or employment affiliations are shared by the organizations’ members. Primarily, embeddedness theory (Granovetter, 1985) implies that two individuals who share prior affiliations can readily access information on a potential partner’s capabilities and reliability through either direct ties or common ties to third parties (i.e., indirect ties). If these ties generate trust and discourage malfeasance, then two organizations will be more likely to form a relationship the more prior affiliations are shared by their members. Importantly, this prediction is not exclusive to embeddedness theory. Focus theory (Feld, 1981, 1982) implies that individuals who share prior affiliations to higher education institutions or to employers will jointly participate in similar social activities that also facilitate the identification and evaluation of potential partners via social interaction. Homophily theory (Lazarsfeld and Merton, 1954; Blau, 1977) suggests that organizational members will prefer to form relationships with similar others. Therefore, at least three theories support the prediction that two organizations will be more likely to form a relationship the more prior affiliations are shared by their members. Seeking to differentiate these three mechanisms, I formulate hypotheses intended to disentangle the predictions of embeddedness, focus and homophily theories.

This argument is tested with data on U.S private equity investments. I analyze 7,112 inter-organizational relationships formed in 2006 by examining almost 4,000 rounds of investment involving 1,110 U. S. private equity firms with 8,800 members. Analyzing a sample of organizational dyads that do and do not form co-investment relationships (i.e., invest in the same round of a target company’s financing), I model the relationship between the number of prior education and employment affiliations shared by two organizations’ members and the
likelihood that their organizations co-invest. Mediation and moderation analyses explore theoretical mechanisms related to direct and indirect ties, joint participation in activities, and homophilous matching. Differentiating dyads based on their relational histories reveals that inter-organizational relationships are often embedded in organizational members’ prior education and employment networks and that this statement holds most true for organizations that formed few or formed no relationships in previous years. This study complements endogenous theories of network evolution by accounting for relationships that form between organizations that, lacking a history of exchange, face substantial uncertainty about the value of partnering.

THEORETICAL DEVELOPMENT

The Formation of Inter-organizational Relationships

Organizations cannot produce all of the resources necessary to support their operations, so they depend on the external environment – including other organizations (Aldrich and Pfeffer, 1976; Hannan and Freeman, 1977; Pfeffer and Salanick, 1978). Consequently, inter-organizational relationships have long drawn organizational theorists’ attention (c.f., Levine and White, 1961; Pfeffer and Salancik, 1978; Burt, Christman and Kilburn, 1980; Galaskiewicz, 1985; Baker, Faulkner and Fisher, 1998). Because resources are critical to organizational operations and there are many potential partners, “With whom?” is a recurring question in many organizations. The extant literature on inter-organizational relationships indicates that the answer to this question is largely determined by the availability of reliable information on the capabilities and behavioral tendencies of potential partners.
A voluminous body of research indicates that organizations often embed inter-organizational relationships in social structures that, by generating trust and discouraging malfeasance, facilitate the exchange of fine-grained, private information on potential partners (Granovetter, 1985; Portes and Sensenbrenner, 1993; Uzzi, 1996). Despite the substantial knowledge accumulated thus far, much remains unclear. Specifically, tendencies to repeat inter-organizational relations (e.g., Podolny, 1994; Gulati, 1995a; 1995b; Gulati and Gargiulo, 1999) offer no insight into the formation of initial relations; interaction may be inferred from proximity (e.g. Sorenson and Stuart, 2001) or similarity (e.g., Podolny, 1994; Stuart, 1998) but such identification strategies do not illuminate the social structures that facilitate relationship formation; and empirical concerns about social ties that span organizational boundaries (e.g., Ingram and Roberts, 2000; Rosenkopf, et al., 2001) cloud causal inference – it is unclear if the tie caused the organizational behavior or if behavioral intentions caused tie formation.¹ In short, extant theories of network evolution offer an incomplete account of how inter-personal relations influence the formation of new inter-organizational relationships.

The basic argument of this paper is that contacts formed prior to individuals’ participation in a given setting influence future inter-organizational relationships by conditioning the availability of information on potential organizational partners. Highlighting affiliations formed during individuals’ prior education and employment experiences, I propose that organizations leverage members’ prior education and employment networks to identify and select new partners by raising awareness of partnering opportunities and by shaping preferences

for forming relationships. Additionally, because inter-organizational relationships tend to be repeated once formed, I argue that organizational members’ prior affiliation networks are likely to be most instrumental in the formation of initial relationships between organizations. I first leverage embeddedness theory to generate two basic predictions regarding prior affiliation networks. Pursuing nuance, I then formulate more specific hypotheses designed to differentiate the embeddedness argument from other plausible theoretical mechanisms.

The Prior Education and Employment Networks of Organizational Members

Why might the prior education networks of organizational members influence the formation of inter-organizational relationships? First, shared prior education experiences facilitate the formation of inter-personal relations that generate trust. For example, two individuals are more likely to form a tie and to confide in each other if their educational backgrounds are similar (Marsden, 1988). A study of 800 MBA program graduates found that 80 percent named a classmate as a close friend and that this percentage declined at a rate of only 2 percent per year (Burt, 2001). Yet another longitudinal study found that individuals relied upon friends from their school days for support up to ten years after completing their education (Suitor and Keeton, 1997). So, direct ties form while individuals pursue higher education and these ties tend to persist over time.

Second, prior education affiliations among individuals who attended the same institution but at different times (i.e., indirect ties) may generate trust and discourage malfeasance because one’s affiliations with higher education institutions are often laden with sentimentality (Mael and
Ashforth, 1992). This identification with one’s college or university encourages prosocial behaviors like making charitable donations (O’Reilly and Chatman, 1986; Mael and Ashforth, 1992). Additionally, research on law firms (Parkin, 2006; Oyer and Schaefer, 2009) reveals firm- and office-level clustering of partners by law school attended beyond what one could reasonably attribute to geography or school prestige. Lawyers are also more likely to attain a partner position if a higher percentage of partners within their firm attended the same law school (Parkin, 2006). Whether lawyers favor graduates of their law schools in hiring and promotion decisions or leverage law school networks for information on potential hires, these findings indicate that shared prior education affiliations encourage prosocial behaviors.

The most specific evidence of information flowing through prior education networks comes from two recent studies of financial markets. First, mutual fund managers invest heavily in the stocks of companies whose executives attended the same educational institution as the fund manager and such “connected” investments outperform “unconnected” investments (Cohen, Frazzini and Malloy, 2008). Moreover, the authors find that the abnormal returns are concentrated around major corporate announcements, suggesting very strong informational advantages of shared prior education affiliations. Supplementary analyses reveal that although the effects of direct ties (i.e., same cohort) are stronger, indirect ties (i.e., same institution, different times) also exhibit strong effects on investment performance. Second, equity analysts provide better stock recommendations for companies whose senior managers attended the same college or university as the analyst, whether they were in the same cohort or not (Cohen, Frazzini and Malloy, 2009). These studies convincingly demonstrate the value of shared prior education affiliations in obtaining advantageous access to information.
If organizational members’ prior education networks channel valuable private information on potential partners, then two organizations should find information on each other more readily available and available at lower cost if the organizations’ members share more prior education affiliations. This should increase the likelihood that two organizations identify partnering opportunities and form a relationship. In short, organizations will embed inter-organizational relationships in members’ prior education networks.

Hypothesis 1a: The more prior education affiliations shared by two organizations’ members, the greater the likelihood that the organizations will form a relationship.

Why might the prior employment networks of organizational members influence the formation of inter-organizational relationships? Consider that many individuals learn of jobs, gain employment, get promoted and remain employed by leveraging networks (Granovetter, 1973; Podolny and Baron, 1997; Fernandez, Castilla and Moore, 2000; Peterson, Saporta and Seidel, 2001). Once hired, employers then structure opportunities for employees to form ties (Williams and O’Reilly, 1998). For example, the General Social Survey documents that nearly 50 percent of individuals report a co-worker as being among their closest friends (Marks, 1994). A study of Iowa state legislators found that individuals tended to form friendships with legislators who served on the same committees (Caldeira and Patterson, 1987). Given these friendships, it is not surprising that individuals consult former co-workers when making important decisions. For example, co-workers constitute large portions of managers’ core discussion networks (Carroll and Teo, 1996). Academic scientists were more likely to pursue entrepreneurial opportunities if their colleagues did, arguably because colleagues are valuable
sources of information on such career transitions (Stuart and Ding, 2006). Individuals form valuable relationships during prior employment. Many ties persist, as evidenced by the finding that mutual fund directors and advisory firms continue working with each other even after changing employers (Kuhnen, 2009).

Additional evidence of the value of individuals’ prior employment networks comes from studies inspired by Freeman’s (1986) portrayal of entrepreneurs as “organizational products.” Networks formed during employment experiences tend to help entrepreneurs to access information on market opportunities and to mobilize resources in pursuit of those opportunities (Freeman, 1986; Aldrich and Zimmer, 1986; Audia and Rider, 2005). For example, new footwear producers tend to be founded near existing plants because entrepreneurs rely upon existing employers for access to market information and industry contacts (Sorenson and Audia, 2000). Similarly, prior employment experiences help technology entrepreneurs assuage resource providers’ concerns (Burton, Sørensen and Beckman, 2002).

If two organizations’ members share more prior employment affiliations, then the organizations should find information on each other readily available and available at lower cost. Thus, inter-organizational relationships will tend to be embedded in members’ prior employment networks.

Hypothesis 1b: The more prior employment affiliations shared by two organizations’ members, the greater the likelihood that the organizations will form a relationship.
Differentiating Theoretical Mechanisms

The argument that prior education and employment networks channel information on potential partners and facilitate the formation of inter-organizational relationships is supported by embeddedness theory. However, the predictions above are not exclusive to the logic of embeddedness; other sociological theories motivate similar predictions that invoke slightly different mechanisms. Therefore, I consider how the arguments of focus and homophily theories may be differentiated, theoretically and empirically, from those of embeddedness theory.

Focus theory (Feld, 1981, 1982) also supports the prediction that two organizations will be more likely to form a relationship the more prior education and/or employment affiliations are shared by their members. The underlying mechanism involves joint participation of two organizations’ members in social activities and not social ties formed during prior education or employment experiences. Foci are organized activities like school, work, religious worship or volunteering that systematically constrain the formation and maintenance of social relationships (Feld, 1982). Feld (1981: 1016) states, “A group's activities are organized by a particular focus to the extent that two individuals who share that focus are more likely to share joint activities with each other than two individuals who do not have that focus in common.” For example, an examination of personal networks reported in the U. S. General Social Survey found that most non-kin ties are formed at work, school or voluntary organizations (Louch, 2000). An individual’s prior education and employment experiences are two foci that provide opportunities for individuals to form social ties that span future organizational boundaries. Importantly, ties between two individuals who share a prior affiliation might also form after graduation or after
the employment spell ends if they meet elsewhere. If two individuals who share prior affiliations to schools or employers form ties by participating in the same activities (e.g., alumni clubs, political interest groups, trade associations), then the causal logic shifts from prior education (or employment) to the activity. For example, private sector employees in South Korea meet regularly for dinner with individuals that attended the same high school – even if they were not enrolled at the same time – because they share similar hobbies and interests (Siegel, 2007). In this case, the relevant context is dinner (i.e., the activity) and not high school (i.e., the focus).

If shared prior affiliations merely proxy for joint participation in otherwise-unobserved activities, then the effects of shared affiliations will be mediated by variables that account for the total number of opportunities for interaction between two organizations’ members. Because inter-personal relations involve two people opportunities for interaction should increase with the number of people “at-risk” for interaction. Specifically, the more members of two organizations the more likely it is that the organizations’ members will both share prior affiliations and participate in social activities that facilitate relationship formation.

**Hypothesis 2:** The main effect of shared prior affiliations on inter-organizational relationship formation will be mediated by the total number of possible opportunities for two organizations’ members to jointly participate in social activities.

Embeddedness theory suggests that organizational members will obtain information on potential partners through prior education or employment networks. Importantly, as Granovetter (1985: 490) notes, first-hand experience is generally preferred to second-hand information on an actor’s capabilities and reliability and second-hand information is preferred to an actor’s
generalized reputation. This implies that the information gathered through prior education and employment networks will be most valuable in instances where the focal organizations lack first-hand, relational experience with each other. As two organizations form more and more relationships, the predominant source of information on a potential partner will be that gathered from first-hand partnership experience. Consistent with this logic, employees’ joint participation in industry committees increased the rate of alliance formation between telecommunications companies but this effect was weaker for companies that previously formed more alliances (Rosenkopf, et al., 2001). Therefore, the more times two organizations have formed a relationship, the less important prior affiliation networks should be in facilitating the formation of future relationships.

Hypothesis 3: The main effect of shared prior affiliations on inter-organizational relationship formation will be weaker for organizations that previously formed more relationships.

A potential complication of the theory developed thus far is that individuals who share prior affiliations may be similar on important unobserved dimensions that facilitate relationship formation independent of ties or interactions between them. Generally, sociological research on labor markets documents extensive race and sex segregation by occupation, industry and employer (Fernandez and Su, 2004; Fernandez and Sosa, 2005; Fernandez and Fernandez-Mateo, 2006) and many higher education institutions were explicitly established to educate individuals that are similar in terms of sex (e.g., the “Seven Sisters”), race (e.g., historically black colleges and universities), faith (e.g., Jesuit colleges and universities) or intellectual interest (e.g., institutes of technology). Homophily theory (Lazarsfeld and Merton, 1954; Blau, 1977) implies that relationships form between people who are similar on sociodemographic or behavioral dimensions and this general phenomenon is well-documented in prior research (see McPherson,
Smith-Lovin and Cook, 2001 for an extensive review). For example, individuals tend to form friendships with those of similar educational and occupational backgrounds (Marsden, 1988; Huckfeldt, 1983; Louch, 2000). Graduate students form ties with classmates of the same race (Mollica, Gray and Trevino, 2003) and employees form many same sex relationships with co-workers (Ibarra, 1992). Moreover, homophily is associated with enduring friendships between co-workers (Burt, 2000) and classmates (Suitor and Keeton, 1997). Importantly, organizational members that are similar tend to share understandings about appropriate organizational behaviors (e.g., Beckman, 2006) and such understandings facilitate the formation of inter-organizational relationships (e.g., Lincoln and McBride, 1985; Larson, 1992; Stuart, 1998).

If individuals who share prior education or employment affiliations are more similar those who do not, then any observed effects of shared prior affiliations on the formation of inter-organizational relationships could be driven more by homophily than by direct or indirect ties. However, if homophily is the primary causal influence, then observed effects of shared prior affiliations will not be moderated by the number of previous relationships formed by two organizations. In other words, homophily should not diminish as two organizations gain more first-hand experience with each other. Instead, similarity will continue to be the basis for repeated relationship formation.

**Hypothesis 4:** The main effect of shared prior affiliations on inter-organizational relationship formation will not be moderated by two organizations’ prior relationships.
EMPIRICAL SETTING AND ANALYSES

The empirical setting is the U. S. private equity investment market, defined as all “professionally managed equity investments in the unregistered securities of private and public companies” (Fenn, Liang, and Prowse, 1997: 4). Investments are primarily venture capital financing and leveraged buyout transactions but also include investments in companies that are neither considered early-stage nor publicly-traded; investments of hedge funds and angel investors are excluded. The defining characteristic of this market is that the securities purchased are not traded publicly, which renders access to private information extremely valuable. In 2006, approximately $107 billion was invested in the U. S. by private equity investors (PricewaterhouseCoopers, 2008).

Private equity investments often involve more than one firm (Fenn, Liang and Prowse, 1997). Groups of private equity firms typically form investment *syndicates* of firms – each termed a “co-investor” – for each round of investment that a target company receives. Syndication enables co-investors to diversify investment risk across a portfolio of investments and, by involving multiple firms in the due diligence and advising processes, facilitates theoretically better investment selection and management (Lerner, 1994; Gompers and Lerner, 2001). Capable and reliable firms must be identified for syndicate membership and their participation negotiated. Co-investment relationships are unlikely to be formed absent trust among syndicate members. As such, the co-investment relationship is a voluntary commitment of resources (i.e., capital) by organizations (i.e., private equity firms) to the pursuit of common objectives (i.e., return on investment).
With whom do private equity firms co-invest? Most scholarly accounts (e.g., Sorenson and Stuart, 2008; Trapido, 2007; Piskorski and Anand, 2007) follow Granovetter’s (1985) observation that co-investment relationships are embedded in the existing structure of relations among firms (i.e., the “co-investment network”) because this network serves both information and governance purposes (Sorenson and Stuart, 2001). The private equity investors included in this study attended 1,098 higher education institutions and worked at 12,745 unique employers (see Table 1). Where a private equity investor went to school and where she worked prior to joining her current firm is likely to influence her ability to identify and manage good investment opportunities. Perhaps most importantly, these prior education and employment affiliations were formed before individuals began investing on behalf of their firms and before they could reasonably be expected to appreciate the value of these affiliations in private equity investing. Consequently, prior affiliation networks are less likely to be compromised by the endogeneity and/or unobserved heterogeneity that clouds inferences about the causal effects of social relations on economic behaviors and outcomes (Manski, 2000; Mouw, 2006).

== INSERT TABLE 1 ABOUT HERE ==

Dependent variable: likelihood of co-investment

To construct a sample of potential co-investing firms, I started with data on all U. S. private equity deals reported in the SDC Thomson VentureXpert database in 2006 (Thomson Financial, 2007), a database commonly used to study the U. S. private equity industry (Podolny, 2001; Sorenson and Stuart, 2001, 2008; Trapido, 2007). This yielded 4,152 unique company-
rounds of investment involving 3,259 target companies and 1,672 private equity firms. I limited the sample to only those U. S.-based firms listed in either the 2006 Greyhouse Directory of Venture Capital and Private Equity Firms (Greyhouse, 2006) or the 2006 Galante Directory of Venture Capital and Private Equity Firms (Asset Alternatives, 2006) in order to isolate firms whose principal business activity is making equity investments in private companies. I also dropped another 12 firms because no data on firm members’ education or employment backgrounds was available. This yielded a sample of 1,110 unique U. S. private equity firms that participated in 3,944 rounds of investment in 3,111 companies in 2006. This sample covers approximately 95 percent of all investment rounds in over 95 percent of the companies reported as receiving private equity financing by VentureXpert in 2006. These investments were the basis for 7,112 co-investment relationships between U. S. private equity firms.

I constructed an actor-event matrix in which the rows represented each of the 1,110 unique private equity firms and the columns represented each of the 3,944 rounds of investment. The cells take a value of “1” if firm $i$ invested in company-round $r$ in 2006 and “0” otherwise. This matrix was then transformed into a firm-by-firm co-investment matrix in which the rows and columns consisted of the 1,110 unique private equity firms in the sample and the cells represented a count of unique company-rounds in which firm $i$ and firm $j$ both participated in 2006. From this matrix, I extracted 614,940 unique, undirected firm $ij$ dyads; 7,112 of these dyads co-invested at least once in 2006 and 607,828 dyads did not co-invest at all – an incidence
rate of 1.17 percent. The dependent variable co-invested is a dichotomous measure that takes a value of “1” if firms $i$ and $j$ co-invested in 2006 and “0” otherwise.

Choice-based sampling and estimation

Because co-investments are rare events, I constructed a choice-based sample. Starting with 7,112 dyads that co-invested in 2006, I then randomly sampled, with replacement, an additional 71,120 dyads from the 607,828 dyads that did not co-invest. The final sample is 78,232 dyads – 7,112 “cases” and 71,120 “controls.” This approach accounts for two statistical issues that are particularly challenging for dyadic analyses of inter-organizational relations: (1) non-independence of observations attributable to multiple occurrences of firms in the dyads and (2) rare events bias attributable to the 1.17 percent rate of co-investment in the full sample. First, non-independence of observations can result in systematically underestimated standard errors for firm-level attributes that are invariant from dyad to dyad; however, this form of autocorrelation can be accounted for by including a variable that is the mean of the dependent variable for each dyad containing $i$ or $j$ except the $ij^{th}$ dyad (Lincoln, 1984). Because this variable captures within-firm effects that would influence the likelihood of a co-investment relationship, but are not otherwise accounted for in the models, it also serves as a control for otherwise-unobserved heterogeneity (Stuart, 1998). Second, rare events bias can produce inflated standard errors for the coefficients that are most responsible for producing the infrequently-occurring positive outcomes (King and Zeng, 2001). Weighting observations to compensate for the differences in the frequency of positive outcomes in the full sample (1.17 percent) versus the choice-based

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2 All 1,110 firm $ii$ dyads were dropped because a firm’s co-investment relationship with itself is not meaningful.

3 This approach follows recent research (Sorenson and Stuart, 2001, 2008; Jensen, 2003; Hallen, 2008) that uses a conservative 10-to-1 unrealized-to-realized dyads ratio in constructing a choice-based sample.
sample (9.10 percent) corrects for the systematic tendency of logistic regression to underestimate the likelihood of a rare event occurring.\textsuperscript{4} For each of the 78,232 dyads in the choice-based sample, I estimate a cross-sectional logit model of the likelihood that firm \(i\) and \(j\) co-invest in the same company-round in 2006. I generate robust standard errors to adjust for rare events bias using King and Zeng’s (2001) \textit{relogit} procedure in Stata 10.

\textit{Independent variables: shared prior education and employment affiliations}

I created a proprietary, hand-collected database in order to identify the shared \textit{prior education} and \textit{employment affiliations} of private equity firm members. First, I recorded the full names and titles of all firm members listed in either the 2006 \textit{Greyhouse Directory of Venture Capital and Private Equity Firms} or the 2006 \textit{Galante Directory of Venture Capital and Private Equity Firms}. After identifying duplicates and reconciling name variations, the database consisted of 15,237 unique individual members of 2,345 U. S. private equity firms.

Prior education and employment data was collected for each unique individual identified in either directory. The \textit{Greyhouse Directory} lists school(s) and prior employer(s) for most of the approximately 6,250 individuals listed in the 2006; either I or a trained research assistant manually coded this information for approximately 5,700 individuals. The \textit{Galante Directory} does not list such information. For approximately 10,000 individuals, internet searches were performed to locate individuals’ biographies. Either I or a trained research assistant coded each

\textsuperscript{4} I did not use the prior correction technique because I analyze co-investments involving a large, representative sample of U. S. private equity firms (95 percent of deals in 2006) and not the full population. To ensure that results reported here are not sensitive to estimates of the true rate of co-investment, I estimated models using weights ranging from 0.5 to 1.5 percent and found the results reported here robust over that range.
individual’s degree-granting institution for all degrees listed and the names of all prior employers based on biographies listed on firm websites. Additional data was collected from ZoomInfo, a web-based business information company that has utilized internet search technology to aggregate professional information for over 45 million people at approximately 5 million companies since 1999\(^5\), and LinkedIn, an online network on which approximately 45 million people summarize their professional experiences and identify their professional contacts. News articles and other online content (e.g., press releases, speaker biographies) provided additional data. This process yielded prior education and/or employment affiliation data for 13,551 individuals employed by 2,345 U. S. private equity firms in 2006.

I manually reconciled all firm and school names using various text string-identification and sorting procedures. Aggregating all schools (e.g., Harvard Business School, Harvard College, Harvard Graduate School of Education) to the university level (e.g., Harvard University) and eliminating duplicate entries (e.g., Univ. of North Carolina, UNC, University of North Carolina) yielded 1,330 unique prior higher education institutions. Reconciling name variations (e.g., HP, Hewlett-Packard) produced a total of 18,231 unique prior employers. In the case of mergers and acquisitions, the actual company name listed in each individual’s biography was recorded (e.g., Credit Suisse, First Boston and Credit Suisse First Boston are treated as three unique prior employers). Therefore, the independent variables capture the most relevant prior employment affiliations in order to reduce the likelihood of capitalizing on spurious correlations

\(^5\) Biographical data from firm websites has previously been used by economists studying within-firm and within-office concentration of lawyers based on law school attended (Oyer and Schaefer, 2009). Data from ZoomInfo has previously been used to study effects of venture capitalists’ human capital, equity analysts’ social capital and executives’ prior experience (Zarutskie, 2008; Cohen, Frazzini and Malloy, 2009; Graffin, Wade, Porac and McNamee, 2008).
produced by subsequent mergers and acquisitions. Extracting prior education and employment affiliation data for the 1,110 private equity firms included in the dyadic co-investor sample produced a final database of 8,800 individual members of 1,110 firms that previously attended 1,098 educational institutions and worked for 12,745 prior employers.\(^6\)

I then constructed two affiliation matrices, one for prior education and one for prior employment. The first was a firm-by-school matrix in which the rows represented each of the 1,110 private equity firms and the columns represented each of the 1,098 prior educational institutions. The second was a firm-by-employer matrix in which the rows represented each of the 1,110 private equity firms and the columns represented each of the 12,745 prior employers. The cells of these affiliation matrices are counts of the number of unique prior affiliations that each firm has to each school or employer, respectively.\(^7\) This process yielded 14,684 unique prior education affiliations and 26,877 unique prior employment affiliations for the 8,880 private equity investors represented in the data. On average, each individual contributes 1.65 prior education affiliations and 3.03 prior employment affiliations to the database.

Table 1 lists the top 20 prior educational institutions of the 8,880 private equity investors represented in the data analyzed here. Table 1 reveals that the prior education network is highly concentrated in a few educational institutions while the prior employment network is much

\(^6\) These 1,110 firms participated in 95 percent of all deals reported in VentureXpert in 2006 so the 4,500 individuals and 1,235 firms dropped from the data are not particularly active private equity investors. It is common for private equity firms to appear in the directories despite an extended period of investment inactivity.

\(^7\) Although each individual can hold multiple degrees, I only recorded one affiliation for each prior school for each individual (e.g., a Yale JD/MBA graduate has only one affiliation to Yale).
sparser. For example, nearly 40 percent of the individuals in the sample hold a degree from Harvard, Stanford or Penn; in contrast, the top 26 employers in the sample sum up to a similar figure. The most common educational institution is Harvard University and the most common prior employer is McKinsey & Company. A total of 1,678 private equity investors are affiliated with Harvard University by at least one degree, which represents 18.9 percent of the 8,880 private equity investors in the sample. There are 251 ex-McKinsey & Co. employees represented in the data, which is 2.8 percent of the individual investors in the sample.

Next, I transformed these firm-by-school and firm-by-employer matrices into two separate firm-by-firm matrices in which the cells represented counts of the number of prior education or employment affiliations, respectively, shared by firms i and j. I produced the shared prior affiliation counts using the cross-products method in Ucinet (Borgatti, Everett and Freeman, 2002) for valued data to produce a dyad-level count of the events (i.e., schools or prior employers) in which actors (i.e., individual firm members) jointly participated. For example, if firm i has three members who hold degrees from Cornell University (or previously worked at Merrill Lynch) and firm j has two members who hold degrees from Cornell (or were previously employed by Merrill Lynch) then the two firms share six prior education (or employment) affiliations to Cornell (or Merrill Lynch). In other words, the three members of firm i each share a prior education (or employment) affiliation with both members of firm j.

For each of the 78,232 dyads in the sample, I constructed two independent variables to test Hypotheses 1a and 1b: the number of shared prior education affiliations and the number of
shared prior employment affiliations. No prior affiliation education data could be collected for at least one of the firms in 3,730 dyads (4.77 percent of sample) and no prior employment data could be collected for at least one of the firms in 688 dyads (0.88 percent of sample). In these cases, the shared affiliation count variables were set to zero. Figure 1 depicts a positive pairwise relationship between the number of prior education or employment affiliations shared by each of the 78,232 dyads and the frequency of co-investment in 2006. The next section details dyad-level covariates included in the models to control for alternative explanations for the formation of co-investment relationships.

== INSERT FIGURE 1 ABOUT HERE ==

Control variables

Previous studies of co-investment relationships (e.g., Sorenson and Stuart, 2008; Trapido, 2007) establish a baseline model of the likelihood that two private equity firms co-invest. Typically, properties of the industry co-investment network in one period predict co-investments in subsequent time periods. My identification strategy is to account for these factors in the dyadic analyses as control variables and to also include organizational members’ shared prior affiliations to examine the effects of prior education and employment networks. I assume that two randomly-selected private equity investors who share a prior education or employment affiliation are more likely to exchange information than are two individuals who do not.

The variable inter-personal interaction opportunities is included to ensure that any observed effects of two firms’ shared prior affiliations are due to common background and not
firm scale. If two firms employ many investors, then those firms’ members might be more likely to share prior affiliations and to participate jointly in activities that would increase the likelihood of inter-personal interactions that might facilitate relationship formation. This control variable is the product of firm \( i \)’s total number of employees and firm \( j \)’s total number of employees.\(^8\) These variables are used as controls and for the mediation tests related to Hypothesis 2. I constructed a measure *number of prior co-investments* which is the number of times over the previous five years that two firms invested in the same company. This variable is interacted with the number of shared prior education and employment affiliations to test Hypotheses 3 and 4.

Following Sorenson and Stuart (2008), I include two control variables to account for prior findings that the likelihood of a co-investment relationship declines with geographic and industry distance between two firms. The first measure is the *geographic distance* between the two firms in the dyad, which is the natural log-transformed distance in miles, computed using spherical geometry (Sorenson and Audia, 2000), between the main offices of firms \( i \) and \( j \). The second measure, *industry focus dissimilarity*, accounts for two firms’ overlapping investments by industry. This dissimilarity measure is constructed as follows:

\[
D_{ij} = \sum (p_i - p_j)^2
\]

where \( p_i \) and \( p_j \) represent the proportion of firm \( i \)’s or firm \( j \)’s total number of investments between 2001 and 2005 that were made in each of the following nine industry categories listed in

\(^8\) In analyses not reported here, I instead included a variable that equaled the product of all prior affiliations held by members of firm \( i \) and members of firm \( j \) (i.e., both shared and unshared affiliations). I also disaggregated this variable into separate education and employment variables. Inclusion of these variables in the models produced similar results in terms of the degree of mediation, coefficient magnitude and statistical significance. Because the product of the two firms’ employee counts is a parsimonious measure, I report models with this variable. Results are robust to multiple approaches to accounting for opportunities for two organizations’ members to participate jointly in activities on the basis of their prior education or employment experiences.
the VentureXpert database: biotechnology, communications, computer hardware, computer software, consumer products, energy, healthcare and pharmaceuticals, industrial products and other unclassified. The measure has a minimum value of zero for two firms that invest identical proportions in each of the nine categories and a maximum value of two for two firms that make 100 percent of their investments in two different categories.

Firm age similarity is the age ratio of the younger of firm $i$ and firm $j$ to the older of the two firms (Gulati & Gargiulo, 1999). Firm age was computed as the difference between a firm’s founding year, as listed in the Greyhouse or Galante directory, and the year of observation. If founding year was unavailable, then the year of the firm’s first recorded private equity investment was used to calculate age. This variable accounts for systematic co-investment tendencies related to dyad-level age differences. Network centrality similarity accounts for the tendency of firms to form relationships with those of similar status (Podolny, 1994; Gulati and Gargiulo, 1999). This variable is the Bonacich centrality ratio of the less central of firm $i$ and firm $j$ to the more central of the two firms. Using deals completed between 2001 and 2005, I computed Bonacich’s (1987) eigenvector centrality measure in the private equity co-investment network using the following formula:

$$C_i = \alpha \sum \beta^k R^{k+1} I$$

where $\alpha$ is a scaling factor that normalizes the measure by the mean value of $\{\sum \beta^k R^{k+1} I\}$ in a given year, $\beta$ is a weighting factor that is equal to $\frac{3}{4}$ of the maximum eigenvalue in the firm-by-firm co-investment matrix $R$ in which cell $ij$ equals “1” if firm $i$ and firm $j$ invested in the same
company in the previous five years and “0” otherwise and $I$ represents a column vector of ones.\(^9\) Each firm’s centrality is a weighted measure of its co-investors’ centralities so that the most central firms in the co-investment network are those that co-invest with other central firms.

Individual firms enter the sample between 96 and 270 times so the observations violate the assumptions of non-independence of observations. To address this statistical issue, I include a variable for the $ij^{th}$ dyad that is defined as the mean value of the dependent variable for all dyads in which either $i$ or $j$ appears, excluding the $ij^{th}$ dyad (Lincoln, 1984). This autocorrelation control variable also serves as an important control for otherwise unobserved heterogeneity at the firm level (Stuart, 1998). For example, if some firms prefer to invest with few firms while others prefer to invest with many, this measure accounts for such variance by controlling for firm-level baseline propensities to invest with a given firm. Table 2 presents summary statistics and correlations among the variables.

\[
\begin{align*}
\text{== INSERT TABLE 2 ABOUT HERE ==}
\end{align*}
\]

Results

Table 3 displays the results of cross-sectional logit models of the likelihood that firms $i$ and $j$ co-invest in 2006. Model 1 is the baseline model with only control variables. Firms that made more co-investments in the previous five years are likely to co-invest again. Firms are less likely to co-invest if they are geographically distant or invest in different industry sectors. Older firms tend to co-invest with younger firms and firms that occupy similarly-central positions in the industry co-investment network tend to co-invest. Two firms that employ more individuals

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\(^9\) A weighting factor of $\frac{3}{4}$ of the maximum eigenvalue is commonly used in studies of co-investment networks to account for a focal firm’s access to network-based resources (e.g., Podolny, 2001; Sorenson and Stuart, 2001).
are more likely to co-invest, suggesting that joint participation in activities increases the rate of inter-personal interaction among two organizations’ members. These effects are consistent across models, so I focus on the hypothesis tests.

*Model 2* offers preliminary support for *Hypothesis 1a*. The likelihood of two organizations forming a relationship increases with the number of prior education shared by the organizations’ members. *Model 3* presents results of the focus theory mediation analysis (*Hypothesis 2*). Note in *Table 2* that the shared affiliation and interaction opportunity variables are positively correlated with the dependent variable and with each other. *Model 3* demonstrates that when one accounts simultaneously for these variables, the main effect of shared prior education affiliations is partially mediated. Relative to the results of *Model 2*, the positive coefficient is smaller in magnitude but still statistically significant. These results support *Hypothesis 2*. Consistent with focus theory, the total number of opportunities for two organizations’ members to interact attenuates the main effect of shared prior education affiliations on the co-investment rate.

*Model 4* includes the interaction term associated with the embeddedness argument of *Hypothesis 3* and the homophily argument of *Hypothesis 4*. The main effect of shared prior education affiliations on the likelihood of co-investment is moderated by the two firms’ previous co-investments. Specifically, the coefficient on the interaction term is negative. The effect of shared prior education affiliations is weaker for firms that made more co-investments in the past than for those that made few. Moreover, the coefficient on the main effect – the main effect for dyads that did not co-invest in the previous five years – is greater in magnitude than in *Model 3*. 
Consistent with *Hypothesis 3*, the effect of shared prior education affiliations on the likelihood of co-investment is strongest for two organizations that made few or no co-investments in the previous five years. These results are also inconsistent with *Hypothesis 4*. The homophily argument implied that firms would continue to co-invest on the basis of educational similarity independent of the number of prior co-investments. These results offer strong support for *Hypothesis 1a*. Effects of shared prior employment affiliations are examined before fully saturating the model with covariates.

*Model 5* offers preliminary support for *Hypothesis 1b*. The likelihood of relationship formation between two private equity firms increases with the shared prior employment affiliations shared by their members. Note again in *Table 2* that the shared and total affiliation variables are positively correlated with the dependent variable and with each other. *Model 6* addresses the focus theory argument (*Hypothesis 2*) by demonstrating that two firms that employ more individuals are more likely to co-invest and that this effect fully mediates the main effect of shared prior employment affiliations on the likelihood of co-investment. The coefficient of shared prior employment affiliations is reduced in magnitude and, perhaps more importantly, it becomes statistically insignificant. These results strongly support *Hypothesis 2*. Accounting for the number of opportunities for two organizations’ members to interact through joint participation in activities mediates the main effect of shared prior employment affiliations on the likelihood of co-investment.

*Model 7* includes the interaction term associated with the embeddedness and homophily arguments (*Hypotheses 3* and *4*). The effect of shared prior employment affiliations on the
likelihood of co-investment is moderated by the two firms’ previous co-investments. Specifically, this effect is weaker for firms that made more co-investments in the past than for those that made few. Moreover, the coefficient on the main effect – the effect for dyads that did not co-invest in the previous five years – increases in magnitude and becomes statistically significant \((p < 0.05)\). Consistent with Hypothesis 3, the effect of shared prior employment affiliations on the likelihood of co-investment are strongest for two organizations that made few or no co-investments in the previous five years. Furthermore, these results are inconsistent with Hypothesis 4, which predicted that firms would continue to co-invest on the basis of similarity independent of their prior co-investments. These results offer strong support for Hypothesis 1b.

Last, Model 8 includes all covariates and interaction terms. These results strongly support the argument that new inter-organizational relationships are embedded in organizational members’ prior education and employment networks. Although the autocorrelation control variable is positive and significant – indicating that two firms that co-invest with many other firms are more likely to co-invest with each other than two firms that co-invest with few other firms – the results of Model 8 are consistent with Hypotheses 1a and 1b. The effects of shared prior education and employment affiliations are positive and statistically significant at conventional levels and so are the coefficients on the interaction terms. Moreover, the effects of interest are robust to simultaneously accounting for both prior education and employment affiliations as well as dyads’ prior co-investments. Inclusion of the autocorrelation control variable should assuage most concerns about non-independence of observations and unobserved heterogeneity.\(^{10}\) These results imply that the effects of shared prior education and employment affiliations

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\(^{10}\) There is some debate about the appropriate method for accounting for autocorrelation in dyadic analyses. While I followed recent research (Stuart, 1998; Jensen, 2003; Hallen, 2008) in utilizing Lincoln’s (1984) method, some
affiliations are strongest for firms that made few or no co-investments over the previous five years.\textsuperscript{11}

\begin{center}
\textbf{== INSERT TABLE 3 ABOUT HERE ==}
\end{center}

The effects of shared prior education and employment affiliations on the likelihood of co-investment for two firms that did not previously co-invest are depicted graphically in \textit{Figure 2}. The curves are based on the reported coefficients in \textit{Model 8 of Table 3} and generated using the \texttt{relogit} command in Stata 10. To generate predicted changes in the relative risk of co-investment, I set the number of prior co-investments (and the interaction terms) to zero, held all other control variables at mean levels and varied only the number of shared prior education and employment affiliations. The Y-axis in both graphs represents the change in the risk of co-investment relative to a baseline likelihood that equals 1.0 when shared prior affiliations equal zero. \textit{Figure 2} demonstrates that the relative risk of co-investment between two firms that did not co-invest in the previous five years increases by approximately 5.2 percent as the number of shared prior employment affiliations increases from the mean (0.6 shared affiliations) to one standard deviation above the mean (2.7 shared affiliations).\textsuperscript{12} Similarly, the likelihood of co-investment increases by approximately 4.7 percent as the number of shared prior education affiliations increases from the mean (3.9 shared affiliations) to one standard deviation above the mean (13.6 shared affiliations).

\textsuperscript{11} Researchers prefer Mizruchi’s (1989) method of using firm-level fixed effects. I did not estimate models using firm-level fixed effects because of the computational difficulty of performing dyadic analyses with dummy variables for each of the 1,110 firms in the sample.

\textsuperscript{12} Supplementary analyses used a ten-year (instead of the reported five-year) window to construct the number of prior co-investments variable. Results were similar in magnitude and significance to those reported here. The five-year window is preferred because a substantial number of firms in the sample are less than 10 years old.

\textsuperscript{12} Note that the calculations use mean and standard deviation figures for the sub-sample of dyads that did not previously co-invest.
To compute the interaction effects, I increased the number of prior co-investments from zero to one while holding all other variables at their means. I compared the predicted relative risk of co-investment when the interaction term was set to zero to the predicted relative risk when the interaction term was the product of the shared affiliation variable and one previous co-investment. For two dyads that share the mean number of shared prior employment affiliations for all dyads (0.7 shared affiliations), the relative risk of co-investment is approximately 2.1 percent lower for the dyad that previously co-invested than for the dyad that did not. For two dyads that share the mean number of shared prior education affiliations for all dyads (4.6 shared affiliations), the relative risk of co-investment is approximately 3.3 percent lower for the dyad that previously co-invested than for the dyad that did not. In summary, the results presented in Table 3 demonstrate that two firms that share more prior education and/or employment affiliations are more likely to co-invest and that this is most true for two firms that made few or no co-investments in the previous five years.

== INSERT FIGURE 2 ABOUT HERE ==

Robustness Checks

I conducted several supplementary analyses to check the robustness of these results. The first addresses sample definition. The choice-based sample includes 3,730 dyads (4.77 percent of observations) for which no prior education data was located for either firm i or j and 688 dyads for which no prior employment data was located for i or j (0.88 percent of observations). In such cases, I set the shared prior affiliation variables to zero. In analyses not reported here, I estimated models that included two dummy variables coded as “1” if no education or no employment data was collected, respectively, for either of the firms in the focal dyad and “0”
otherwise. I also estimated models in which I excluded these observations from the sample. In both cases, the effects of interest were in the predicted direction and of similar magnitude and statistical significance. I include observations with missing data in the reported models because inclusion merely raises the noise-to-true-variance ratio of the affiliation counts.

Second, I included all firm members reported as “key contacts” in the Galante and Greyhouse directories. In analyses not reported here, I ran identical models on sub-samples of individuals that produced similar results in terms of key coefficient magnitude and statistical significance. In one analysis I dropped all individuals whose titles connoted administrative responsibilities (e.g., Administrative Manager, Fund Administrator, and Research Assistant). In another analysis I dropped individuals whose job titles seemed junior or tangentially related to deals (e.g., Associate, Financial Analyst, Investor Relations Manager, General Counsel) and included only those individuals with executive titles (e.g., General Partner, Managing Director, President). Because exclusion policies necessitate a theory of a firm-level division of labor (e.g., raising versus investing capital, generating versus managing deals) and I lack insight into variance across firms along that dimension, I present the results of the full-sample analyses here. Moreover, as Granovetter (1985: 496) states, “It is not only at top levels that firms are connected by networks of personal relations, but at all levels where transactions must take place.”

DISCUSSION

Complementing prior research on endogenous network dynamics, this study focused on prior education and employment affiliations of organizational members as determinants of new inter-organizational relationships. Although organizations repeat prior relationships (Podolny,
1994; Gulati, 1995a; 1995b; Gulati and Gargiulo, 1999) the question of how initial relationships arise has remained open. To address this gap in the network evolution literature, I theorized how organizations leverage the prior education and employment networks of organizational members to identify and select new partners. Analyses of U. S. private equity investments demonstrated that two firms are more likely to form a relationship if their members share more prior education and/or employment affiliations. Moreover, consistent with embeddedness theory, these shared prior affiliations are most influential in the formation of relationships between organizations that formed few or no relationships in previous years.

The effect sizes reported here are quite meaningful; a one standard deviation increase in the number of shared affiliations increases the likelihood that two firms form a new relationship by approximately 5 percent. To put these figures in context, consider that the 1,110 firms analyzed in this study made, on average, 7.6 investments in 2006 (standard deviation = 10.6 investments). Over several years, small preferences for embedding deals in prior affiliation networks are likely to account for great variance in firms’ network positions. Simulation models would likely illuminate just how advantageous it is – in terms of occupying a central co-investment network position – for a private equity firm to employ investors who attended Harvard or Goldman Sachs instead of, say, Georgetown or J.P. Morgan (see Table 1).

There are limitations to this study. In addition to the cross-sectional nature of the data, it is not possible to isolate the effects of overlapping experiences from the effects of non-overlapping experiences because specific years of attendance and employment are unavailable
for the vast majority of individuals in the data. However, if one assumes that overlapping experiences are more influential than non-overlapping experiences in facilitating the sharing of information (as in Cohen, et al., 2008), then the effect sizes reported here can be considered conservative estimates. Of course, future studies that isolate the two effects would be insightful. Similarly, although prior employment networks exhibit stronger effects on the formation of initial inter-organizational relationships than prior employment, as depicted by Figure 2, most individuals’ educational experiences precede their employment experiences and, additionally, many employers hire from a restricted set of schools (e.g., Phillips and Zuckerman, 2001; Oyer and Schaefer, 2009). Therefore, caution is warranted in evaluating the relative importance of prior education and employment networks in facilitating inter-organizational relationships. Future studies might disentangle the relative strength of education versus employment affiliations in settings where the time decay of each can be accounted for or held constant.

This study partially rebuts “the endogeneity critique” often levied against organizational network research – that social relations must be formed prior to, and for reasons independent of, the phenomena being studied in order to produce credible causal inferences (see Manski, 2000 or Mouw, 2006 for more). The results demonstrate that networks formed prior (and, in many cases, many years prior) to an individual’s entry into the private equity industry influence firms’ co-investment behaviors. Studying prior affiliation networks enables researchers to credibly claim that the network was formed prior to the observed behavior and arguably claim that ties were formed independent of intended future behaviors. Similar future studies would likely stimulate more specific critiques of how effects of social relationships are potentially compromised by unobserved heterogeneity and how empirical analyses might usefully resolve conflicting
theoretical arguments. Such interactions seem essential to building “a reasonably rich understanding of how networks emerge and change” because barring a better understanding “the ground underneath the findings of network effects will always be at least a little shaky” (Stuart, 2007: 81).

Importantly, this study offers insight on how the social structures of non-market settings (e.g., higher education) are reproduced in markets and how social structures are likely reproduced across markets (e.g., labor markets to investment markets). As Fligstein (2002: 29) notes, in many markets “actors try to produce a ‘local’ stable world where the dominant actors produce meanings that allow them to reproduce their advantage.” Embedding inter-organizational relationships in the prior education and employment networks of organizational members is one way that actors might reproduce advantage. Although sociological research on stratification in higher education or labor markets was not extensively integrated with the emerging literature on network evolution, longitudinal data and/or simulation models would permit more explicit connections. For example, work in the sociology of education documents how demographic characteristics affect the sorting of students into types of higher education institutions, fields of study and occupations as well as how such sorting processes condition individuals’ future professional achievements (see Stevens, Armstrong or Arums, 2008 and/or Grodsky, Warren and Felts, 2008 for extensive reviews). These sorting processes likely restrict opportunities to form diverse network ties (Feld, 1982; McPherson and Smith-Lovin, 1987). Examining how variance in diversity across educational institutions and over time relates to variance in the importance of prior education ties in markets would extend Coleman’s (1988) classic observations on how education relates to social capital.
Similarly, recent empirical research on labor markets (e.g., Fernandez and Su, 2004; Fernandez and Sosa, 2005; Fernandez and Fernandez-Mateo, 2006; Sørensen and Sorenson, 2007) documents how geographic space, social networks and organizational demography contribute to stratification. Reviews of this literature might reveal promising opportunities to exploit the composition of prior employment networks across industries or regions and/or over time to understand how network evolution reproduces inequality. More generally, focusing on both the origins and effects of individuals’ prior education and employment networks on organizational behaviors and outcomes is likely to be fruitful for organizational researchers. This study’s findings imply that the advantages and disadvantages attributable to stratification in higher education and labor markets are likely to be most pronounced in settings where access to network-based resources like private information is particularly valuable (e.g., private equity, investment banking, politics). Future studies could investigate this claim in additional settings.

Future research might also examine how graduates of particular higher education institutions or the former employees of specific companies vary in terms of their tendencies to embed business relationships in prior affiliation networks. For example, one might expect that the greater the identification with a group, the greater the tendency of group members to exhibit prosocial behaviors like sharing private information (O’Reilly and Chatman, 1986; Mael and Ashforth, 1992). March and Simon (1958: 85) propose that identification increases with the frequency of group interaction and with group prestige and the alumni of prestigious schools are represented disproportionately in the ranks of corporate executives (Useem and Karabel, 1986. Investigations related to prestige and prevalence of specific prior education affiliations would likely be insightful. Similarly, former employees of certain companies (e.g., Goldman Sachs)
have reputations for being particularly embedded in their prior employment networks. Research that investigates such sources of heterogeneity across higher education institutions and employers would be quite informative, especially if a study design can isolate the effects of prestige from those of network scale. As Table 1 documents, the most prestigious schools and companies produce most private equity investors.

CONCLUSION

Previous work demonstrates how networks are reproduced by inter-organizational relations but this emphasis on endogenous network evolution neglects an important aspect of organizational life. Individuals join organizations already embedded in networks and these network contacts are largely responsible for many joining and remaining with organizations (Granovetter, 1973; Fernandez, Castilla and Moore, 2000). This study demonstrated that the prior education and employment networks of organizational members influenced the formation of inter-organizational relationships and especially the formation of relationships that challenge endogenous accounts of network dynamics. These findings offer valuable insights into how inter-organizational networks evolve out of the personal networks of organizational members. Longitudinal examinations of such processes will further inform our understanding of how networks evolve, how social structures are reproduced and how stratification persists in modern societies.
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Trapido, D.  

Useem, M. and J. Karabel  

Uzzi, B.  
Walker, G. Kogut, B. and W. Shan  

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Zarutskie, R.  
Sources: SDC Thomson Financial VentureXpert (2006) and hand-collected prior affiliation data on 8,800 individual members of 1,110 U. S. venture capital and private equity firms that attended 1,098 educational institutions and worked for 12,745 prior employers.
Note: These curves depict changes in the relative risk of co-investment for two firms that did not co-invest in the previous five years. The number of prior co-investments and their interaction terms were set to zero and all other control variables were set at mean levels; only the number of shared prior affiliations varies. For example, the relative risk of co-investment increases by approximately 11% as the number of prior employment affiliations shared by firms $i$ and $j$ changes from the mean (1.01) to two standard deviations above the mean (1.12). Coefficients from Model 8 of Table 3 were used to create the graph.
Table 1

Top 20 schools and employers based on prior education and employment affiliations of 8,880 private equity investors at 1,110 U.S. firms, 2006.

<table>
<thead>
<tr>
<th>Rank</th>
<th>School</th>
<th>Affiliated Individuals</th>
<th>% of All</th>
<th>Rank</th>
<th>Employer</th>
<th>Affiliated Individuals</th>
<th>% of All</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Harvard University</td>
<td>1,678</td>
<td>18.9%</td>
<td>1</td>
<td>McKinsey &amp; Co.</td>
<td>251</td>
<td>2.8%</td>
</tr>
<tr>
<td>2</td>
<td>Stanford University</td>
<td>997</td>
<td>11.2%</td>
<td>2</td>
<td>Goldman Sachs</td>
<td>234</td>
<td>2.6%</td>
</tr>
<tr>
<td>3</td>
<td>University of Pennsylvania</td>
<td>817</td>
<td>9.2%</td>
<td>3</td>
<td>Morgan Stanley</td>
<td>225</td>
<td>2.5%</td>
</tr>
<tr>
<td>4</td>
<td>Northwestern University</td>
<td>361</td>
<td>4.1%</td>
<td>4</td>
<td>Merrill Lynch</td>
<td>203</td>
<td>2.3%</td>
</tr>
<tr>
<td>5</td>
<td>Columbia University</td>
<td>357</td>
<td>4.0%</td>
<td>5</td>
<td>Bain &amp; Co.</td>
<td>195</td>
<td>2.2%</td>
</tr>
<tr>
<td>6</td>
<td>University of California, Berkeley</td>
<td>357</td>
<td>4.0%</td>
<td>6</td>
<td>Lehman Brothers</td>
<td>176</td>
<td>2.0%</td>
</tr>
<tr>
<td>7</td>
<td>Dartmouth College</td>
<td>304</td>
<td>3.4%</td>
<td>7</td>
<td>General Electric</td>
<td>162</td>
<td>1.8%</td>
</tr>
<tr>
<td>8</td>
<td>University of Chicago</td>
<td>293</td>
<td>3.3%</td>
<td>8</td>
<td>Arthur Andersen</td>
<td>161</td>
<td>1.8%</td>
</tr>
<tr>
<td>9</td>
<td>Yale University</td>
<td>282</td>
<td>3.2%</td>
<td>9</td>
<td>Donaldson, Lufkin &amp; Jenrette</td>
<td>149</td>
<td>1.7%</td>
</tr>
<tr>
<td>10</td>
<td>Massachusetts Institute of Technology</td>
<td>274</td>
<td>3.1%</td>
<td>10</td>
<td>IBM</td>
<td>148</td>
<td>1.7%</td>
</tr>
<tr>
<td>11</td>
<td>University of Virginia</td>
<td>260</td>
<td>2.9%</td>
<td>11</td>
<td>Credit Suisse First Boston</td>
<td>146</td>
<td>1.6%</td>
</tr>
<tr>
<td>12</td>
<td>Princeton University</td>
<td>259</td>
<td>2.9%</td>
<td>12</td>
<td>Ernst &amp; Young</td>
<td>146</td>
<td>1.6%</td>
</tr>
<tr>
<td>13</td>
<td>New York University</td>
<td>222</td>
<td>2.5%</td>
<td>13</td>
<td>J. P. Morgan</td>
<td>122</td>
<td>1.4%</td>
</tr>
<tr>
<td>14</td>
<td>Cornell University</td>
<td>221</td>
<td>2.5%</td>
<td>14</td>
<td>Citigroup</td>
<td>120</td>
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<tr>
<td>15</td>
<td>University of Michigan</td>
<td>216</td>
<td>2.4%</td>
<td>15</td>
<td>PricewaterhouseCoopers</td>
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<tr>
<td>16</td>
<td>University of California, Los Angeles</td>
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<td>2.2%</td>
<td>16</td>
<td>Hewlett-Packard</td>
<td>102</td>
<td>1.1%</td>
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<tr>
<td>17</td>
<td>Duke University</td>
<td>186</td>
<td>2.1%</td>
<td>17</td>
<td>Boston Consulting Group</td>
<td>101</td>
<td>1.1%</td>
</tr>
<tr>
<td>18</td>
<td>University of Texas</td>
<td>135</td>
<td>1.5%</td>
<td>18</td>
<td>Deloitte Consulting</td>
<td>97</td>
<td>1.1%</td>
</tr>
<tr>
<td>19</td>
<td>University of Illinois</td>
<td>131</td>
<td>1.5%</td>
<td>19</td>
<td>Robertson Stephens</td>
<td>95</td>
<td>1.1%</td>
</tr>
<tr>
<td>20</td>
<td>Georgetown University</td>
<td>125</td>
<td>1.4%</td>
<td>20</td>
<td>Coopers &amp; Lybrand</td>
<td>89</td>
<td>1.0%</td>
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Table 2
Summary statistics for variables in co-investment analyses of 78,232 dyads.

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<tr>
<th></th>
<th>Mean</th>
<th>St. Dev.</th>
<th>1</th>
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<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
<th>8</th>
<th>9</th>
<th>10</th>
</tr>
</thead>
<tbody>
<tr>
<td>Dyad co-invests in 2006 \textit{(ij)}, 1 if &quot;Yes&quot;</td>
<td>0.09</td>
<td>0.29</td>
<td>1.00</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Number of prior co-investments \textit{(ij)}</td>
<td>0.21</td>
<td>1.07</td>
<td>0.51</td>
<td>1.00</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Geographic distance \textit{(ij)}</td>
<td>6.19</td>
<td>1.86</td>
<td>-0.13</td>
<td>-0.10</td>
<td>1.00</td>
<td></td>
<td></td>
<td></td>
<td></td>
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</tr>
<tr>
<td>Industry focus dissimilarity \textit{(ij)}</td>
<td>0.51</td>
<td>0.42</td>
<td>-0.22</td>
<td>-0.17</td>
<td>0.05</td>
<td>1.00</td>
<td></td>
<td></td>
<td></td>
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<tr>
<td>Age similarity \textit{(ij)}</td>
<td>0.55</td>
<td>0.25</td>
<td>0.00</td>
<td>0.02</td>
<td>0.01</td>
<td>-0.09</td>
<td>1.00</td>
<td></td>
<td></td>
<td></td>
<td></td>
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</tr>
<tr>
<td>Network centrality similarity \textit{(ij)}</td>
<td>2.97</td>
<td>2.89</td>
<td>0.05</td>
<td>-0.04</td>
<td>0.12</td>
<td>-0.02</td>
<td>1.00</td>
<td></td>
<td></td>
<td></td>
<td></td>
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</tr>
<tr>
<td>Inter-personal interaction opportunities \textit{(ij)}</td>
<td>68.8</td>
<td>112.7</td>
<td>0.19</td>
<td>-0.06</td>
<td>-0.14</td>
<td>0.01</td>
<td>0.03</td>
<td>1.00</td>
<td></td>
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<tr>
<td>Shared prior education affiliations \textit{(ij)}</td>
<td>4.59</td>
<td>11.6</td>
<td>0.21</td>
<td>0.21</td>
<td>-0.12</td>
<td>-0.14</td>
<td>0.01</td>
<td>0.03</td>
<td>0.77</td>
<td>1.00</td>
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<tr>
<td>Shared prior employment affiliations \textit{(ij)}</td>
<td>0.67</td>
<td>2.32</td>
<td>0.14</td>
<td>0.14</td>
<td>-0.11</td>
<td>-0.10</td>
<td>0.01</td>
<td>0.04</td>
<td>0.61</td>
<td>0.61</td>
<td>1.00</td>
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</tr>
<tr>
<td>Autocorrelation control \textit{(ij)}</td>
<td>0.10</td>
<td>0.09</td>
<td>0.43</td>
<td>-0.06</td>
<td>-0.28</td>
<td>-0.02</td>
<td>-0.09</td>
<td>0.33</td>
<td>0.31</td>
<td>0.17</td>
<td>1.00</td>
<td></td>
</tr>
</tbody>
</table>
### Table 3

Cross-sectional logit models of the likelihood that firms $i$ and $j$ co-invest in 2006 ($Y_{ij} = 1$ if "Yes"; 0 if "No").

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
<th>(6)</th>
<th>(7)</th>
<th>(8)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of prior co-investments</td>
<td>1.00 **</td>
<td>1.00 **</td>
<td>1.00 **</td>
<td>1.12 **</td>
<td>1.02 **</td>
<td>1.00 **</td>
<td>1.09 **</td>
<td>1.50 **</td>
</tr>
<tr>
<td></td>
<td>(0.048)</td>
<td>(0.048)</td>
<td>(0.048)</td>
<td>(0.049)</td>
<td>(0.048)</td>
<td>(0.048)</td>
<td>(0.046)</td>
<td>(0.026)</td>
</tr>
<tr>
<td>Geographic distance</td>
<td>-0.109 **</td>
<td>-0.104 **</td>
<td>-0.106 **</td>
<td>-0.104 **</td>
<td>-0.107 **</td>
<td>-0.108 **</td>
<td>-0.108 **</td>
<td>-0.117 **</td>
</tr>
<tr>
<td></td>
<td>(0.010)</td>
<td>(0.010)</td>
<td>(0.010)</td>
<td>(0.010)</td>
<td>(0.010)</td>
<td>(0.010)</td>
<td>(0.010)</td>
<td>(0.008)</td>
</tr>
<tr>
<td></td>
<td>(0.079)</td>
<td>(0.078)</td>
<td>(0.078)</td>
<td>(0.078)</td>
<td>(0.079)</td>
<td>(0.079)</td>
<td>(0.079)</td>
<td>(0.068)</td>
</tr>
<tr>
<td>Age similarity</td>
<td>-0.321 **</td>
<td>-0.328 **</td>
<td>-0.326 **</td>
<td>-0.289 **</td>
<td>-0.315 **</td>
<td>-0.321 **</td>
<td>-0.324 **</td>
<td>-0.089</td>
</tr>
<tr>
<td></td>
<td>(0.082)</td>
<td>(0.082)</td>
<td>(0.082)</td>
<td>(0.081)</td>
<td>(0.081)</td>
<td>(0.082)</td>
<td>(0.082)</td>
<td>(0.067)</td>
</tr>
<tr>
<td>Network centrality similarity</td>
<td>0.029 **</td>
<td>0.029 **</td>
<td>0.028 **</td>
<td>0.036 **</td>
<td>0.030 **</td>
<td>0.029 **</td>
<td>0.032 **</td>
<td>0.041 **</td>
</tr>
<tr>
<td></td>
<td>(0.005)</td>
<td>(0.005)</td>
<td>(0.005)</td>
<td>(0.005)</td>
<td>(0.005)</td>
<td>(0.005)</td>
<td>(0.005)</td>
<td>(0.008)</td>
</tr>
<tr>
<td>Inter-personal interaction opportunities</td>
<td>0.001 **</td>
<td>0.001 **</td>
<td>0.001 **</td>
<td>0.001 **</td>
<td>0.001 **</td>
<td>0.001 **</td>
<td>0.001 **</td>
<td>0.000 *</td>
</tr>
<tr>
<td></td>
<td>(0.000)</td>
<td>(0.000)</td>
<td>(0.000)</td>
<td>(0.000)</td>
<td>(0.000)</td>
<td>(0.000)</td>
<td>(0.000)</td>
<td>(0.000)</td>
</tr>
<tr>
<td>Shared prior education affiliations</td>
<td>0.010 **</td>
<td>0.005 **</td>
<td>0.008 **</td>
<td>0.006 **</td>
<td>0.006 **</td>
<td>0.006 **</td>
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<td></td>
<td>(0.001)</td>
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<td>(0.002)</td>
<td>(0.002)</td>
<td>(0.002)</td>
<td>(0.002)</td>
<td>(0.002)</td>
</tr>
<tr>
<td>Shared educ. affil’s * Prior co-investments</td>
<td>-0.008 **</td>
<td>-0.008 **</td>
<td>-0.008 **</td>
<td>-0.008 **</td>
<td>-0.008 **</td>
<td>-0.008 **</td>
<td>-0.008 **</td>
<td>-0.008 **</td>
</tr>
<tr>
<td></td>
<td>(0.001)</td>
<td>(0.001)</td>
<td>(0.001)</td>
<td>(0.001)</td>
<td>(0.001)</td>
<td>(0.001)</td>
<td>(0.001)</td>
<td>(0.001)</td>
</tr>
<tr>
<td>Shared prior employment affiliations</td>
<td>0.033 **</td>
<td>0.003</td>
<td>0.022 *</td>
<td>0.023 **</td>
<td>0.023 **</td>
<td>0.023 **</td>
<td>0.023 **</td>
<td>0.023 **</td>
</tr>
<tr>
<td></td>
<td>(0.006)</td>
<td>(0.009)</td>
<td>(0.010)</td>
<td>(0.010)</td>
<td>(0.010)</td>
<td>(0.010)</td>
<td>(0.010)</td>
<td>(0.010)</td>
</tr>
<tr>
<td>Shared emp. affil’s * Prior co-investments</td>
<td>-0.040 **</td>
<td>-0.017 **</td>
<td>-0.017 **</td>
<td>-0.017 **</td>
<td>-0.017 **</td>
<td>-0.017 **</td>
<td>-0.017 **</td>
<td>-0.017 **</td>
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<td></td>
<td>(0.008)</td>
<td>(0.005)</td>
<td>(0.005)</td>
<td>(0.005)</td>
<td>(0.005)</td>
<td>(0.005)</td>
<td>(0.005)</td>
<td>(0.005)</td>
</tr>
<tr>
<td>Autocorrelation control</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.088)</td>
<td>(0.088)</td>
<td>(0.088)</td>
<td>(0.083)</td>
<td>(0.083)</td>
<td>(0.085)</td>
<td>(0.088)</td>
<td>(0.086)</td>
</tr>
<tr>
<td>Log likelihood</td>
<td>-14,884</td>
<td>-14,888</td>
<td>-14,875</td>
<td>-14,809</td>
<td>-14,835</td>
<td>-14,884</td>
<td>-14,849</td>
<td>-13,357</td>
</tr>
<tr>
<td>Chi-square (d.f.)</td>
<td>17,897 (6)</td>
<td>17,898 (6)</td>
<td>17,915 (7)</td>
<td>18,046 (8)</td>
<td>17,795 (6)</td>
<td>17,897 (7)</td>
<td>17,967 (8)</td>
<td>20,950 (11)</td>
</tr>
<tr>
<td>Pseudo $R^2$</td>
<td>0.376</td>
<td>0.375</td>
<td>0.376</td>
<td>0.379</td>
<td>0.373</td>
<td>0.376</td>
<td>0.377</td>
<td>0.440</td>
</tr>
</tbody>
</table>

Robust standard errors in parentheses. Coefficients and standard errors adjusted for rare events and case-control sampling. ** $p < 0.01$; * $p < 0.05$; † $p < 0.10$