How Employees' Prior Affiliations Constrain Organizational Network Change: A Study of U.S. Venture Capital and Private Equity

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What is This?
How Employees’ Prior Affiliations Constrain Organizational Network Change: A Study of U.S. Venture Capital and Private Equity

Christopher I. Rider

Abstract
This paper investigates how organizations’ reliance on employees’ prior educational and employment affiliations for both employment relationships and interorganizational relationships contributes to inertia in organizational networks. Analyses of data from U.S. venture capital and private equity firms support the theory I develop. First, increasing differences in educational prestige decrease both interpersonal co-employment rates and interorganizational co-investment rates. Second, two individuals who share a prior educational or a prior employment affiliation are more likely to be employed by the same organization than are two individuals who do not share such an affiliation. Third, the likelihood of two organizations forming a co-investment relationship increases with the number of prior educational or employment affiliations shared by their employees. I propose that these tendencies stabilize advantaged organizations’ positions and limit disadvantaged organizations’ positional mobility, thereby constraining change in interorganizational networks. Implications for studies of network evolution and socioeconomic inequality are discussed.

Keywords: networks, education, employment, affiliation, venture capital, private equity

To secure resources, organizations typically become interdependent with other organizations (Aldrich and Pfeffer, 1976; Hannan and Freeman, 1977; Pfeffer and Salancik, 1978). By forming these relational dependencies, organizations structure and occupy positions in interorganizational networks. Because opportunity and constraint are functions of structural position, some positions are superior to others. For example, prior research has found that organizations in

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central network positions face lower marketing costs (Podolny, 1993), generate
greater revenues (Podolny, Stuart, and Hannan, 1996; Powell, Koput, and
Smith-Doerr, 1996), and produce more innovations (Ahuja, 2000) than do organi-
izations in peripheral positions. Despite extensive research, our knowledge of
positional advantage exceeds our knowledge of how advantageous network
positions are occupied and how disadvantageous positions may be strategically
improved (Brass et al., 2004; Stuart and Sorenson, 2007).

Credible inferences about network advantage necessitate a clearer under-
standing of why organizations that occupy advantageous or disadvantageous
network positions tend to continue doing so (Kogut and Walker, 2001; Kim, Oh,
and Swaminathan, 2006; Stuart, 2007). Perhaps the most obvious way to
improve network position is to strategically form relationships with other orga-
nizations by leveraging employees’ interpersonal networks (Stuart, Hoang,
and Hybels, 1999; Rosenkopf, Metiu, and George, 2001). To obtain reliable informa-
ton on other organizations’ capabilities and behavioral tendencies, organiza-
tions often embed such relationships in social structures, like relationships
between two organizations’ employees, that generate trust, discourage malfae-
sance, and facilitate the exchange of fine-grained, private information
(Granovetter, 1985; Gulati, 1995; Uzzi, 1996; Ingram and Roberts, 2000). If an
organization does not employ individuals who can facilitate the formation of
such relationships, then hiring individuals who can is also a viable strategy for
improving the organization’s position (Dokko and Rosenkopf, 2010). Given such
straightforward strategies, why are organizations in disadvantageous network
positions not more aggressive in trying to improve their positions?

Motivated by this question and intending to contribute to our understanding
of network evolution, I propose that advantaged organizations’ positions are
reinforced and also that disadvantaged organizations’ efforts to improve their
positions are constrained by organizational reliance on employees’ interpersonal
networks to alleviate information asymmetry in both employment relationships
and interorganizational relationships. Two large but disconnected literatures
document how organizational employees’ interpersonal networks alleviate
information asymmetries: (1) the network literature on organizational hiring and
(2) the network literature on interorganizational relationships.

First, organizations often hire candidates referred by employees (e.g.,
Fernandez, Castilla, and Moore, 2000; Petersen, Saporta, and Seidel, 2000;
Castilla, 2005; Yakubovich, 2006) because networks regulate flows of informa-
tion on job opportunities to potential candidates (Rees, 1966; Granovetter,
1973) and on candidates to potential employers (Fernandez and Weinberg,
1997; Marsden and Gorman, 2001). Second, interorganizational relationships—
voluntary organizational commitments of resources to the pursuit of common
objectives (Lincoln, Gerlach, and Takahashi, 1992)—tend to form between organi-
izations whose employees know each other because networks facilitate informa-
tion exchange across organizational boundaries (Ingram and Roberts, 2000;
Rosenkopf, Metiu, and George, 2001). These insights imply that interorganiza-
tional network positions will be stabilized if organizations embed both employ-
ment relationships and interorganizational relationships in the same employee
affiliations. Together, these organizational tendencies can restrict the set of
organizations likely to form a relationship with a focal organization as well as
the organization’s set of potential employees.
Building on the idea that individuals not only define organizations but are also
defined by their organizational affiliations (Simmel, 1955; Breiger, 1974;
Schneider, 1987) and departing from research that takes network contacts as
given, I theorize about the effects of employees’ prior education and employ-
ment affiliations, because such affiliations convey information (Spence, 1973;
Zuckerman et al., 2003) and also structure contact-formation opportunities
(Feld, 1981; Burt, 2001). By shaping the set of individuals that organizations
typically employ as well as the set of organizations that typically form relation-
ships with each other, these affiliations can contribute to cliquish tendencies
that constrain network change. I test these claims by analyzing data on prior
affiliations for 8,101 employees of 1,082 U.S. venture capital and private equity
firms and 6,981 co-investment relationships formed by those firms.

EFFECTS OF PRIOR AFFILIATIONS ON ORGANIZATIONAL NETWORKS

One of organizational theory’s central tenets is that behaviors and outcomes
vary by position in interorganizational networks. Network positions are differen-
tiated by structural properties like centrality (Bonacich, 1987) or autonomy
(Burt, 1992) and may evolve passively or actively. For example, a focal organiza-
tion’s position may passively become more central if the organizations with
which it is connected form relationships with more central organizations or,
conversely, more peripheral if those organizations withdraw from relationships
with central organizations. Organizations may also proactively enhance their
network positions by forming relationships to gain access to valuable resources
(e.g., Stuart, Hoang, and Hybels, 1999).

Positional change is most likely when new interorganizational relationships
are formed, as repeated relations typically reinforce the organization’s current
position. Relationships generally tend to form between organizations whose
employees know each other (Rosenkopf, Metiu, and George, 2001) and also
tend to dissolve when those individuals leave organizations (Broschak, 2004). If
employees shape the set of potential collaborating organizations, then organiza-
tions seeking to improve their network positions might hire well-connected indi-
viduals capable of forming new, beneficial relationships (Dokko and Rosenkopf,
2010).

Employing better-connected individuals may not be a realistic positional
improvement strategy for many organizations because many organizations also
rely on employees’ networks for information on potential employees. Individuals often learn of jobs, gain employment, get promoted, and remain
employed due to network contacts (Granovetter, 1973; Podolny and Baron,
1997; Fernandez, Castilla, and Moore, 2000; Petersen, Saporta, and Seidel,
2000; Marsden and Gorman, 2001). Employees typically refer candidates from
a small homogenous portion of the available labor pool, as initial job-holders are
replaced by others with increasingly similar attributes (McPherson, 1983;
Fernandez and Weinberg, 1997; Fernandez, Castilla, and Moore, 2000; Boone
et al., 2004; Mouw, 2006; Yakubovich and Lup, 2006; Burton and Beckman,
2007). Such similarity probably does not diminish with organizational age; both
new (Ruef, Aldrich, and Carter, 2003) and established organizations (Phillips,
2005; Castilla, 2005) embed employment relationships in employees’ networks
by hiring people who are connected to current employees.
Generally, embedding employment relationships in employees’ networks may limit a disadvantaged organization’s attempts to improve its network position by forming new interorganizational relationships. If referred individuals are similar to the organization’s employees and employees hired by referral exhibit higher retention rates than non-referrals (Castilla, 2005), then employees’ networks restrict the set of individuals most likely to be employed by a focal organization. Changing an organization’s employee demography by strategically altering its recruiting niche is difficult (Baty, Evan, and Rothermel, 1971; McPherson, 1983; Schneider, 1987; Sørensen, 1999). Consequently, organizations’ remedies for alleviating information asymmetry in hiring probably stabilize networks in ways that reinforce the positions of advantaged organizations and thwart the attempts of disadvantaged organizations to improve their positions. For this possibility to be more than merely plausible, two conditions must be met. First, relative to employees of two different organizations, employees of the same organization must be more likely to share a prior affiliation. Second, two organizations must be more likely to form a relationship the more prior affiliations their employees share.

Which Prior Affiliations?

Some specific affiliations are likely to influence both employment relationships and interorganizational relationships. Because individual identities are largely defined by group affiliations, and group identities are similarly defined by their affiliated individuals (Simmel, 1955; Breiger, 1974), numerous affiliations might be examined, but several reasons justify focusing on employees’ prior educational and employment affiliations. First, school and work are two important foci for developing social relationships that provide access to professional information (Feld, 1981; Burt, 2001; Stuart and Ding, 2006; Ding, 2011). Second, individuals typically join modern organizations after obtaining education and employment experience that regulates access to jobs and social positions (Weber, 1958; Blau and Duncan, 1967; Jencks and Riesman, 1968; Phillips and Zuckerman, 2001). Third, many organizations restrict the consideration set of potential employees based on individuals’ prior education and employment affiliations (Collins, 1971; Spence, 1973; Zuckerman et al., 2003). Equal opportunity employment laws explicitly prohibit organizations from excluding candidates based on other common affiliations, such as ethnicity or religion. Last, one can draw credible inferences about how these affiliations influence both organizational employment and interorganizational relationships because educational affiliations typically precede employment affiliations, which precede organizational employment and interorganizational relationships (Barton, 1985).

Prior educational affiliations. Sociologists have been examining for a long time how education influences individual employment and organizational behaviors. Weber (1958) theorized how the allocation of societal rewards was based on educational credentials. Collins (1971) theorized how high-status groups use education as a key criterion for imposing their cultural standards on organizational hiring and employment. Others suggest that organizational decision makers might cope with uncertainty by hiring and promoting employees with educational backgrounds similar to theirs (Barton, 1985; Useem and Karabel,
In these ways, higher education institutions act as “social sieves” that structure opportunities for individuals to interact, to form relationships, and to obtain employment (Jencks and Riesman, 1968).

Educational prestige, or the esteem accorded an individual on the basis of his or her educational institution’s perceived academic quality, probably influences both employment and interorganizational relationships for several reasons. First, two individuals are more likely to form a tie and to confide in each other if their educational backgrounds are more similar (Marsden, 1988). Second, educational prestige signals familiarity with the attitudes, beliefs, and norms of the social elite (Jencks and Riesman, 1968; Collins, 1971; Barton, 1985). Many organizations, therefore, apply educational prestige as a criterion for employment (Rivera, 2011). Consequently, individuals often sort into organizations and further into organizational positions on the basis of educational prestige (Useem and Karabel, 1986; Ishida, Spilerman, and Su, 1997; Phillips and Zuckerman, 2001). Third, and perhaps consequently, educational differences become smaller and smaller as individuals enter into organizations and then into interpersonal relationships within those organizations (McPherson and Smith-Lovin, 1987). Consequently, individuals tend to work with others of similar educational prestige (Burris, 2004).

If individuals tend to form relationships with others of similar educational prestige and many of these relationships govern both organizational employment and interorganizational relationships, then one should expect two empirical consequences. First, within an industry, differences in educational prestige should be smaller for coworkers than for two employees of different organizations. Second, two organizations will form a relationship less often the more their employees differ in educational prestige.

Hypothesis 1a: The greater the difference in educational prestige between two individuals, the less likely they are to be employed by the same organization.

Hypothesis 1b: The greater the difference in educational prestige between two organizations’ employees, the lesser the likelihood that the organizations will form a relationship.

Specific prior educational affiliations are also likely to influence both employment and interorganizational relationships for at least three reasons. First, shared educational backgrounds facilitate trusting interpersonal relationships that encourage both information exchange and interorganizational relationships (Marsden, 1988; Zaheer, McEvily, and Perrone, 1998). For example, 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). Another longitudinal study found that individuals relied on school contacts for support up to ten years after completing their education (Suitor and Keeton, 1997).

Second, individuals who attended the same institution but at different times may also share valuable information because their educational experiences imprint them with similar beliefs. For example, a study of over 25,000 individual investors found that similarity in their investment styles (e.g., growth, value) was positively related to having attended the same school (Massa and Simonov, 2011). Third, institution-based sentiment encourages individuals to
share resources with those who share their educational affiliations (Mael and Ashforth, 1992). For example, South Korean private sector employees regularly exchange business and political information with individuals who attended the same high school—even at different times (Siegel, 2007).

Several studies have documented the informational advantages of shared prior educational affiliations. First, mutual fund managers have been found to invest heavily in companies whose executives attended the same educational institution as the fund manager, and such “connected” investments realize abnormal returns around major corporate announcements (Cohen, Frazzini, and Malloy, 2008). Although direct ties (i.e., same cohort) exerted stronger influences than did indirect ties (i.e., same institution, different times), both influenced 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, 2010). Third, executive compensation is more similar among graduates of the same MBA section than among same-year graduates of different sections, and the effects are strongest in years following class reunions (Shue, 2011).

If shared prior education helps alleviate information asymmetry, then one should expect two empirical consequences. First, two employees of the same organization should be more likely to share a prior educational affiliation than two individuals employed by two different organizations. Second, the likelihood that two organizations will form a relationship should increase with the number of prior educational affiliations shared by their employees.

**Hypothesis 2a:** Two individuals who share a prior educational affiliation are more likely to be employed by the same organization than are two individuals who do not share a prior educational affiliation.

**Hypothesis 2b:** The more prior educational affiliations shared by two organizations’ employees, the greater the likelihood that the organizations will form a relationship.

**Prior employment affiliations.** The arguments about prior employment affiliations are similar to those about prior educational affiliations. The prior employment affiliations of their employees signal the quality of organizations (Burton, Sørensen, and Beckman, 2002; Higgins and Gulati, 2003) and their offerings (Roberts, Khaire, and Rider, 2011) and probably also provide access to information. The General Social Survey documents that nearly 50 percent of individuals report a coworker as being among their closest friends (Marks, 1994), and coworkers constitute large portions of managers’ core discussion networks (Carroll and Teo, 1996). Moreover, Kuhnen (2009) found that mutual fund directors and advisory firms continue working with each other even after changing employers. Furthermore, entrepreneurs obtain valuable information from prior employment contacts (Freeman, 1986; Aldrich and Zimmer, 1986; Audia and Rider, 2005), often founding new organizations near existing ones to remain in close proximity to customers, employees, and suppliers (Sorenson and Audia, 2000; Phillips, 2005).

Prior employment networks may also lead organizations to embed current employment relationships in their employees’ prior employment affiliations.
because shared prior employment affiliations promote greater organizational growth (Eisenhardt and Schoonhoven, 1990) and accelerate product introductions (Beckman, 2006). If so, then coworkers should be more likely to share a prior employment affiliation than two employees of different but similar organizations.

**Hypothesis 3a:** Two individuals who share a prior employment affiliation are more likely to be employed by the same organization than are two individuals who do not share a prior employment affiliation.

Shared prior employment affiliations may similarly lead two organizations to become interdependent or to increase their interdependence. For example, repeated interorganizational relationships result from growing familiarity between two organizations (Podolny, 1994; Gulati, 1995). If shared prior employment affiliations facilitate collaboration, then interorganizational relationships should be more likely to develop the more prior employment affiliations are shared by two organizations’ employees.

**Hypothesis 3b:** The more prior employment affiliations are shared by two organizations’ employees, the greater the likelihood that the organizations will form a relationship.

**Moderating Effect of Prior Relationships**

Mechanisms other than information exchange might produce effects similar to those hypothesized thus far. Theories of homophily (McPherson, Smith-Lovin, and Cook, 2001) or focus (Feld, 1981) do not necessitate information exchange but, rather, emphasize how similarity or participation in the same activities, respectively, might lead individuals to work together or organizations to form a relationship. According to these theories, individuals with shared prior affiliations may simply encounter similar opportunities for employment or interorganizational collaboration and evaluate those opportunities similarly, independent of information exchange.

One key moderating effect might differentiate these possibilities. People generally prefer firsthand experience to secondhand information on an actor’s capabilities and reliability, while they prefer secondhand information to an actor’s generalized reputation (Granovetter, 1985: 490). As two organizations form more and more relationships, then, the predominant source of information on each other will be that gathered from those relationships and not from employees’ prior affiliations. Consequently, shared prior affiliations should be most influential when two actors otherwise lack familiarity with each other. Homophily and focus theories do not necessarily imply that the main effects of shared affiliations will vary with familiarity.

Consistent with this logic, Rosenkopf, Metiu, and George (2001) found that employees’ joint participation in industry committees increased the rate of alliance formation between companies, but this effect was weaker for companies that had previously formed more alliances. Although consistent with the notion of diminishing marginal returns to shared prior affiliations, similarity in two companies’ interests and/or relational intentions (e.g., homophily) may have led to joint committee assignments (e.g., same foci). Because educational and
employment affiliations are acquired prior to organizational employment, these mechanisms can be clearly disentangled. If information is the dominant mechanism, then prior relationships will attenuate the effect of shared prior affiliations on interorganizational relationship formation.

**Hypothesis 4a:** The more relationships two organizations previously formed, the weaker the main effect of shared prior educational affiliations on relationship formation.

**Hypothesis 4b:** The more relationships two organizations previously formed, the weaker the main effect of shared prior employment affiliations on relationship formation.

**METHOD**

The empirical setting is the U.S. venture capital and private equity industry, defined as all “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 by hedge funds and angel investors were excluded. Total investments in 2006 were approximately $107 billion (PricewaterhouseCoopers, 2008). These firms are typically organized as general partnerships. In the data analyzed here, the median firm employed six investors (mean = 8.1; s.d. = 7.5).

To make investment decisions quickly, firms typically operate according to routines and principles acquired from prior experiences (Gupta, 2000; Gompers and Lerner, 2001). Some observers suggest that industry cliques are maintained by investors’ reliance on school contacts to get hired, source deals, and raise funds (Gamba and Kleiner, 2001). Shared employment affiliations are also thought to be important, as the tendency of coworkers to start spinoff firms is well documented (Freeman, 1986). In this way, employment is often embedded in investors’ prior educational and employment affiliations.¹ Because these experiences accumulated before individuals began investing, prior affiliations are unlikely to be compromised by the reverse causality concerns that cloud inferences about the causal effects of social relations on economic behaviors and outcomes (Manski, 2000; Mouw, 2006).

Investors value access to private information because investments do not involve publicly traded securities. For each target company, firms typically form syndicates of “co-investors” in order to pool information, diversify investment risk across a portfolio of investments, perform due diligence, and advise portfolio companies (Lerner, 1994; Fenn, Liang, and Prowse, 1997; Gompers and Lerner, 2001). As such, co-investment relationships constitute voluntary resource commitments of organizations pursuing common objectives (i.e., investment returns). Capable and reliable co-investors must be identified and their participation negotiated; trust is critical, and shared prior affiliations

¹ Although school placement offices strongly influence recruiting in other industries (e.g., legal services), it is uncommon for venture capital and private equity investors to join partnerships immediately upon graduation.
probably encourage such trust. Importantly, co-investment relationships form a stable network structure (Sorenson and Stuart, 2008).

To gauge this setting’s appropriateness for testing the hypotheses, I examined co-investment network inertia using data described in Rider and Swaminathan (2011). For 430 firms that were part of the co-investment network in both 1996 and 2006, I found that the correlation between their Bonacich centrality scores in 1996 and in 2006 was 0.60. Furthermore, 68 percent of the top quartile firms (by centrality) in 1996 were also in the top quartile in 2006, and only 28 percent of the sample firms changed position by more than one quartile of the centrality distribution. So the co-investment network is fairly stable. More central, advantaged organizations tend to maintain their positions and more peripheral, disadvantaged organizations find it difficult to improve their positions.²

**Research design.** There are at least two analytical approaches to testing the theory developed herein. One approach is to examine longitudinally both organizational hiring and relationship formation as a function of change in employees’ prior affiliations. Another approach is to examine both employees’ affiliations and interorganizational relationships in the cross-section for a large, representative sample of organizations. Ideally, one would combine these approaches, but because systematically collecting such data is extremely resource-intensive and time-consuming, I analyzed organizational employees and interorganizational relationships cross-sectionally.

**Sample.** I sampled all U.S. venture capital and private equity deals reported in the SDC Thomson VentureXpert database in 2006. To isolate firms that principally make equity investments in private companies, I limited the sample to U.S.-based firms listed in 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). I collected prior education and employment data for each firm employee who was listed in either directory. I excluded 40 firms and 779 individuals due to unavailable education or employment data, reducing the analyzed sample to 96 percent of firms and 91 percent of all employees listed in VentureXpert and the directories. This sample consists of 1,082 firms that employed 8,101 individuals, forming 53,191 co-employment relationships between individuals, and participated in nearly 4,000 rounds of investment in over 3,000 companies in 2006, forming 6,981 co-investment relationships. This sample covers approximately 95 percent of all investment rounds in over 95 percent of the companies reported as receiving financing by VentureXpert in 2006.

**Co-employment analysis.** I tested hypotheses 1a, 2a, and 3a by analyzing all possible individual-individual dyads formed from the employee sample. This approach is preferable to alternative methods, such as estimating the conditional probability that two individuals employed by the same firm share an affiliation given the prevalence of their affiliations in the industry (Oyer and

² Results of this analysis are available from the author.
Schaefer, 2010); this approach simultaneously conditions the co-employment probability on multiple variables (e.g., geographic location, investment focus).

I excluded all dyads in which one or more of the individuals lacked either prior educational or prior employment data to produce 32,809,050 unique, undirected individual \( ij \) dyads; 53,191 dyads were employed by the same firm in 2006—a co-employment rate of 0.16 percent. For each dyad, I estimated a cross-sectional, rare events logit model in which the dependent variable takes a value of 1 if individuals \( i \) and \( j \) were employed by the same firm and 0 otherwise. Hypothesis 1a predicted that the likelihood of the dependent variable equaling 1 will decrease as the educational prestige differential between two individuals grows larger. Hypotheses 2a and 3a predicted that this likelihood will be higher for two individuals who share a prior affiliation than for two who do not.

**Co-investment analysis.** To test hypotheses 1b, 2b, 3b, 4a, and 4b, I constructed a firm-by-firm co-investment matrix consisting of all 584,821 unique, undirected firm \( ij \) dyads with complete data; 6,981 of these dyads co-invested at least once in 2006, and 577,840 dyads did not co-invest at all—a co-investment rate of 1.19 percent. For each dyad, I estimated a cross-sectional, rare events logit model in which the dependent variable takes a value of 1 if firms \( i \) and \( j \) co-invested (i.e., participated in the same company-round of investment) and 0 otherwise. Hypothesis 1b predicted that the likelihood of the dependent variable equaling 1 will decrease as the educational prestige differential between two organizations’ employees grows larger. Hypotheses 2b and 3b predicted that this likelihood will increase with the prior affiliations shared by two firms’ employees. Hypotheses 4a and 4b predicted that the dyad’s prior co-investments (a control variable detailed below) will attenuate the main affiliation effects.

**Empirical adjustments for rare events in dyadic data.** The co-employment and co-investment analyses present two statistical issues: (1) non-independence of observations attributable to multiple occurrences of individuals (or firms) in the dyads and (2) a rare events bias attributable to the 0.16 percent co-employment rate (1.19 percent co-investment rate). First, to correct for systematically underestimated standard errors attributable to the non-independence of observations, I estimated models with and without a control variable that gauges the extent to which autocorrelation across dyads biases results. Second, a rare events bias can produce inflated standard errors for coefficients on the variables that are most responsible for the infrequently occurring positive outcomes. To correct for this, in both sets of analyses I generated robust standard errors and adjusted for rare events bias by implementing King and Zeng’s (2001) `relogit` procedure in Stata SE 12.

**Independent variables: Prior educational and employment affiliations.** I created a proprietary, hand-collected database to identify the prior educational

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3 I coded the dependent variable dichotomously because only 331 of the 6,981 co-investing dyads (0.02 percent) formed more than two co-investment relationships in 2006. The continuous dependent variable produces results that are very similar to those reported here.
and employment affiliations of firm employees. First, I recorded the full names and titles of all firm employees listed in either the Greyhouse Directory or the Galante Directory. Identifying duplicates, reconciling name variations, and excluding firms that did not report investment activity in VentureXpert produced a sample of 1,082 firms.\(^4\)

The Greyhouse Directory includes prior educational and employment data for most of the individuals listed; either I or a trained research assistant manually coded this information for approximately 5,700 individuals. The Galante Directory does not list such information, so Internet searches located prior education and/or employment affiliations for almost 10,000 individuals. Either I or a trained research assistant recorded each individual’s degree-granting institution for all degrees and the names of all prior employers listed in individual biographies on firm websites. Additional data were collected from ZoomInfo, a web-based business information company that has used Internet search technology to aggregate professional information for over 50 million business people since 1999, and LinkedIn, an online network on which over 160 million people list their professional experiences and professional contacts.\(^5\) News articles and other online content (e.g., press releases, speakers’ biographies) provided additional data. This full sample was reduced to 8,101 individuals based on data availability and firms’ investments.

It would have been ideal to identify the specific schools each individual attended at each higher education institution, but the data sources did not uniformly list information this specific (e.g., “He holds a degree from Harvard.”). Therefore, I aggregated all schools (e.g., Harvard Business School, Harvard College, Harvard Graduate School of Education) to the institution level (e.g., Harvard University). I manually reconciled all firm, school, and institution names (e.g., Univ. of North Carolina, UNC, University of North Carolina), as well as employers’ names (e.g., HP, Hewlett-Packard). 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) to reduce the likelihood of capitalizing on spurious correlations produced by subsequent mergers and acquisitions. The 8,101 sample investors had 13,674 unique prior educational affiliations to 1,081 educational institutions and 25,562 unique prior employment affiliations to 12,143 prior employers. On average, each individual contributed 1.7 prior educational affiliations (s.d. = 0.61) and 3.2 prior employment affiliations (s.d. = 2.2) and each firm contributed 13.0 prior educational affiliations (s.d. = 12.1) and 24.7 prior employment affiliations (s.d. = 23.7) to the database.

Table 1 lists the 20 most common education institutions and employers of investors in the sample. A total of 1,487 investors are affiliated with Harvard University by at least one degree, which represents 18.4 percent of all investors in the sample. There are 244 ex-McKinsey employees represented in the data, or 3 percent of all investors in the sample. The prior educational network is highly concentrated in a few institutions, while the prior employment

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\(^4\) As detailed in Rider and Swaminathan (2011), the directories list many firms that did not actively invest in 2006.
\(^5\) Economists use biographical data from firms’ websites to study within-firm and within-office concentration of lawyers based on law school attended (Oyer and Schaefer, 2010). Several studies have used managers’ prior educational data from ZoomInfo (Graffin et al., 2008; Cohen, Frazzini, and Malloy, 2010).
network is much sparser. For example, over 38 percent of investors hold a degree from Harvard, Stanford, or the University of Pennsylvania; in contrast, the top 22 employers in the sample sum up to a similar figure. Notably, over 86 percent of all prior educational affiliations are to the top twenty-five most-represented schools in the data. Such a concentration is consistent with cliquishness in organizational employment and interorganizational relationships.

To measure educational prestige, I used *U.S. News & World Report*’s 2011 worldwide rankings of the top 400 global universities. Each educational affiliation was assigned that institution’s overall score, which is based on surveys that gauge academic reputation, citations per faculty member, faculty-student ratio, reputation with employers, and international student and faculty representation. The maximum score is 100 and the 400th ranked school received a score of 29.2. I assigned all unranked schools (24 percent of all affiliated schools) a score of 28.0.\footnote{Results similar to those reported here were also obtained when assigning unranked schools a score of 0.}

Based on the overall institution scores, I computed an individual-level measure of educational prestige as the median score among all prior educational affiliations held by each individual. For each individual-individual dyad, I then computed the *educational prestige differential* as the absolute value of the difference between the educational prestige scores assigned to individuals \(i\) and \(j\).\footnote{Computing these differentials based on the mean or maximum prestige score of each individual’s prior educational affiliations, instead of the median, produced results similar to those reported here.} Hypothesis 1a predicted a negative coefficient on this prestige differential variable. For firm dyads, I computed the *educational prestige differential* using the same data as were used in the co-employment

### Table 1. Top 20 Schools and Employers Based on Prior Affiliations of 8,101 Private Equity Investors at 1,082 U.S. Firms in 2006

<table>
<thead>
<tr>
<th>School</th>
<th>Affiliated individuals</th>
<th>% of all</th>
<th>Employer</th>
<th>Affiliated individuals</th>
<th>% of all</th>
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analysis. This differential is the absolute value of the difference between the median educational prestige score of all firm $i$ employees and the median educational prestige score of all firm $j$ employees. Hypothesis 1b predicted a negative coefficient on this prestige differential variable.

To identify shared prior affiliations, I first constructed an individual-by-school matrix and an individual-by-employer matrix in which the rows represent the 8,101 individuals and the columns represent all 1,081 prior educational institutions or all 12,143 prior employers, respectively. Then I transformed these matrices into two separate individual-by-individual matrices to construct two independent variables for each dyad. The first equals 1 if individuals $i$ and $j$ share a prior educational affiliation and 0 otherwise; 7 percent of all dyads do. The second equals 1 if $i$ and $j$ share a prior employment affiliation and 0 otherwise; 1 percent do. For the co-employment analysis, hypothesis 2a predicted a positive coefficient on the shared prior educational affiliation variable, and hypothesis 3a predicted a positive coefficient on the shared prior employment affiliation variable.

Descriptively, two individuals who share neither a prior educational nor a prior employment affiliation are employed by the same firm in 0.14 percent of such dyads ($N = 30.2$ million). Sharing a prior educational affiliation increases that rate to 0.26 percent ($N = 2.3$ million dyads), and the rate of co-employment for dyads that share a prior employment affiliation is 1.3 percent ($N = 280,430$ dyads). The co-employment rate for dyads that share both a prior education and a prior employment affiliation ($N = 51,347$) is 1.7 percent. Although these statistics are consistent with hypotheses 2a and 3a, the dyadic co-employment analyses account more rigorously for alternative explanations related to geography, investment focus, or firm size.

Individual affiliation data were aggregated at the firm level to construct a firm-by-school matrix and a firm-by-employer matrix in which the rows represent the 1,082 firms and the columns represent all 1,081 prior educational institutions or all 12,143 prior employers, respectively. I then transformed both matrices into firm-by-firm matrices in which the cells represent counts of prior educational or employment affiliations, respectively, shared by firms $i$ and $j$. UCINET’s cross-products method for valued data (Borgatti, Everett, and Freeman, 2002) counted the schools or prior employers jointly affiliated with two firms’ employees. For example, if firm $i$ has three employees who hold degrees from Emory University (or previously worked at Merrill Lynch) and firm $j$ has two employees who hold degrees from Emory (or were previously employed by Merrill Lynch) then the two firms share six prior educational (or employment) affiliations to Emory (or Merrill Lynch). In other words, the three firm $i$ employees each share a prior educational (or employment) affiliation with both firm $j$ employees.

For each of the 584,821 firm-firm dyads in these matrices, I constructed two independent variables: the number of shared prior educational affiliations and the number of shared prior employment affiliations. Hypothesis 2b predicted a positive coefficient on the shared prior educational affiliations variable, and hypothesis 3b predicted a positive coefficient on the shared prior employment affiliations variable. In descriptive statistics, the co-investment rate does

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8 Computing these differentials based on the mean or maximum prestige score of each firm’s prior educational affiliations, instead of the median, produces results similar to those reported here.
increase with the number of prior affiliations shared by the firm-firm dyads. Again, the dyadic co-investment analysis addresses the possibility that these descriptive figures are skewed by sorting into firms based on geography, investment focus, or firm size.

I measured the number of prior co-investments as the number of times over the previous five years that two firms invested in the same portfolio company. This variable was interacted with the number of shared prior educational and employment affiliations to test hypotheses 4a and 4b, which predicted negative coefficients on the interaction terms with prior co-investments. As a control variable, the number of prior co-investments accounts for cohesion produced by previous relationships (Gulati and Gargiulo, 1999) and for unobserved dyad-level heterogeneity because the lagged measure is correlated with prior disturbances but not with present or future disturbances (Johnston and DiNardo, 1997; Stuart, 1998).

Control variables: Co-employment analysis. Several dyad-level covariates were included in the co-employment models to account for alternative explanations. Most individual variables are common to all employees of the same firm (e.g., location, investment focus). To account for variance in affiliation prevalence across space, I included three separate indicator variables that equal 1 if both individuals are employed by firms located in California, Massachusetts, or New York, respectively, and 0 otherwise. The baseline dyad is one in which the individuals work in two different states or one in which the individuals both work in a state other than California, Massachusetts, or New York. To account for variance in affiliation prevalence across investment areas, I included an indicator variable that takes a value of 1 if both individuals in the dyad are employed by firms that are primarily engaged in venture capital investing. The baseline comparison is either a dyad that includes one venture capital investor and one investor or a dyad that includes two investors.

Two more control variables accounted for the fact that two individuals with many prior affiliations are more likely to share an affiliation than are two individuals with few prior affiliations. Total prior educational affiliations is the product of the total number of prior educational affiliations held by individuals i and j. Similarly, total employment affiliations is the product of the total number of prior employment affiliations held by individuals i and j. Last, individuals enter the sample multiple times, so the observations violate modeling assumptions of non-independence. Therefore, in select models, I included a control variable for the ij dyad that is the mean value of the dependent variable for all dyads in which either i or j appears, excluding the ij dyad (Lincoln, 1984). Table 2

9 Counting the number of prior co-investments over the previous ten years to construct this variable yielded results similar to those reported here. I used the five-year window because only 11 percent of firms in the sample are less than 5 years old but 52 percent are less than 10 years old.

10 Differentiating “true state dependence” associated with cohesion from “spurious state dependence” associated with the autocorrelation of omitted variables is difficult (Heckman, 1978), but including this variable should assuage specification concerns pertaining to omitted variable bias.

11 It is not possible to separate dyads consisting of one venture and one private equity investor from dyads consisting of two private equity investors because all mixed dyads are, by definition, composed of two different firms’ employees. Alternative baseline specifications do not substantially alter the reported results.
presents summary statistics and correlations among co-employment analysis variables.

**Control variables: Co-investment analysis.** In the co-investment analyses, two control variables account for a co-investment rate that declines with the geographic and industry differences between two firms (Sorenson and Stuart, 2008). *Geographic distance* between the two firms in the dyad is the natural log-transformed distance in miles, computed using spherical geometry (Sorenson and Audia, 2000), between the main offices of firms $i$ and $j$. *Industry focus dissimilarity* accounts for two firms’ overlapping investments by summing the squared differences between the proportion of firm $i$’s or firm $j$’s total number of investments between 2001 and 2005 that were made in the following nine industry VentureXpert categories: 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* accounts for dyad-level age differences and was calculated as the age ratio of the younger of firms $i$ and $j$ to the older of the two firms (Gulati and Gargiulo, 1999). Firm age is the difference between 2006 and a firm’s founding year, as listed in the *Greyhouse* or *Galante* directory. If founding year was unavailable, then the year of the firm’s first recorded equity investment was used to calculate age. *Network centrality similarity* accounts for status homophily in relationship formation (Podolny, 1994; Gulati and Gargiulo, 1999). Using deals completed between 2001 and 2005, I followed prior work (Podolny, 2001; Sorenson and Stuart, 2001; Rider, 2009) in computing Bonacich’s (1987) eigenvector centrality in the co-investment network so that each firm’s centrality is a weighted measure of its co-investors’ centralities.\(^{12}\)

---

\(^{12}\) As in prior work, a weighting factor of $\frac{3}{4}$ of the maximum eigenvalue was used to account for a focal firm’s access to network-based resources.
The control variable is the Bonacich centrality ratio of the less central of firm \( i \) and firm \( j \) to the more central of the two firms.

The control variable *interpersonal interaction opportunities* is the product of the total number of individuals employed by firms \( i \) and \( j \).\(^{13}\) This variable ensures that any observed effects of two firms’ shared prior affiliations are not simply attributable to firm scale. To account for investment focus heterogeneity, I included two binary indicator variables. The first takes a value of 1 if *both firms in the dyad are primarily engaged in venture capital investing* and 0 otherwise; the second takes a value of 1 if *neither of the firms in the dyad is primarily engaged in venture capital investing* and 0 otherwise. The baseline dyad, then, is one in which one firm is primarily engaged in venture capital investing and the other is not.

Approximately 76 percent of the firms in the sample are primarily engaged in venture capital investing; the remaining firms are primarily engaged in leveraged buyout transactions, mezzanine investments, real estate, or other private equity investments. Although 5,700 of the observations in the full sample involve two co-investing venture capital firms, 1,281 dyadic co-investments involve at least one firm that is not primarily engaged in venture capital investing. So nearly 18 percent of all 2006 co-investment relationships are between venture capital and private equity firms, justifying the inclusion of such dyads in the analysis.

The *autocorrelation control* variable for the \( ij \) dyad is the mean value of the dependent variable for all dyads in which either \( i \) or \( j \) appears, excluding the \( ij \) dyad (Lincoln, 1984). Models with and without this variable enable comparisons with prior dyadic research (e.g., Stuart, 1998; Jensen, 2003; Hallen, 2008), gauge the extent to which autocorrelation may cloud inferences, and account for unobserved heterogeneity in firm-level propensities to co-invest with many versus few firms. Table 3 presents summary statistics and correlations among co-investment analysis variables.

**RESULTS**

**Co-employment results.** Table 4 presents the results of the co-employment analyses. Model 1 includes only control variables. Two individuals located in the same state or investing in similar niches (e.g., venture) are more likely to be employed by the same organization than two individuals located in different states or investing in different niches. The more educational institutions or prior employers two individuals are affiliated with, the less likely they are to be employed by the same organization. Model 2 supports hypothesis 1a: the greater the educational prestige differential between two individuals, the less likely they are to be employed by the same organization. Model 3 supports hypothesis 2a: sharing a prior educational affiliation increases the likelihood that two individuals are to be employed by the same organization. Model 4 supports hypothesis 3a: sharing a prior employment affiliation increases the likelihood that two individuals are employed by the

\(^{13}\) In unreported analyses, 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 educational and employment variables. Both approaches produced similar coefficient magnitudes and statistical significance. Because the product of the two firms’ employee counts is the most parsimonious of these various measures, I report models with this variable.
same organization. Model 5 demonstrates that support for these hypotheses is robust to simultaneous tests.

Model 6 explores the relationship between shared prior educational affiliations and shared prior employment affiliations by inserting an indicator variable that equals 1 if the individuals share both a prior educational and a prior employment affiliation and 0 otherwise. The negative coefficient on this variable indicates that the two variables similarly influence co-employment (i.e., substitution). Importantly, this result is also inconsistent with alternative explanations that emphasize factors other than information exchange that might draw two affiliated individuals into the same firm (e.g., focus, homophily). Model 7 accounts for the non-independence of observations and also gauges the possibility that individuals with common prior affiliations simply work at larger firms with more coworkers. The theorized effects are insensitive to the inclusion of the autocorrelation control.

Using the coefficients in model 7 of table 4 and the formula detailed in Petersen (1985), I computed changes in the likelihood of co-employment associated with increasing the educational prestige differential by one standard deviation for two venture investors located in California, holding all other control variables at their means. A one standard deviation increase above the mean prestige differential decreases the likelihood of co-employment by approximately 0.4 percent. For two individuals who do not share a prior employment affiliation, the marginal effect of sharing a prior educational affiliation is to increase the likelihood of co-employment by approximately 2.3 percent. For two individuals who do not share a prior educational affiliation, the marginal effect of sharing a prior employment affiliation on the likelihood of co-employment is approximately 6.1 percent.

Co-investment results. Table 5 displays the results of cross-sectional logit models of the likelihood that firms $i$ and $j$ co-invest in 2006. Model 1 includes only control variables. The more co-investments two firms made in the previous five years, the more likely they are to co-invest again. Firms are less likely

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<td>-.04</td>
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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 are more likely to co-invest, suggesting that sheer firm scale increases the likelihood of two organizations co-investing. Two venture firms are more likely to co-invest than a mixed dyad (one venture and one non-venture), and two private equity firms are the dyad least likely to co-invest. These effects are fairly consistent with prior dyadic research (Gulati and Gargiulo, 1999; Rosenkopf, Metiu, and George, 2001; Sorenson and Stuart, 2008) and also consistent across models. Model 2 supports hypothesis 1b: the greater the educational prestige differential between two firms’ employees, the lower the likelihood that they co-invest.

Model 3 offers preliminary support for hypothesis 2b. The likelihood of two organizations forming a relationship increases with the number of prior educational affiliations shared by the organizations’ employees. Model 4 includes the interaction term associated with hypothesis 4a. The main effect of shared prior educational affiliations on the likelihood of co-investment is attenuated by previous co-investments. Therefore, the effect of shared prior educational affiliations

<table>
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<th>(4)</th>
<th>(5)</th>
<th>(6)</th>
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<td>1.82**</td>
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<td>2.98**</td>
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<td>-0.002**</td>
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<td>-0.003**</td>
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<td></td>
<td>(0.581)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Chi-square (d.f.)</td>
<td>105,988 (6)</td>
<td>106,526 (7)</td>
<td>108,975 (8)</td>
<td>128,963 (8)</td>
<td>131,040 (9)</td>
<td>130,712 (10)</td>
<td>131,248 (11)</td>
</tr>
</tbody>
</table>

*p < .05; **p < .01.

* Robust standard errors are in parentheses. Coefficients and standard errors are adjusted for rare events bias.
is weaker for firms that made more co-investments in the past than for those that made few, and the coefficient on the main effect—the main effect for dyads that did not co-invest in the previous five years—is strongly positive and greater in magnitude than the coefficient in model 3. These results are consistent with hypotheses 2b and 4a.

Model 5 examines the effects of shared prior employment affiliations. Supporting hypothesis 3b, the likelihood of relationship formation between two firms is positively correlated with the prior employment affiliations shared by the firms’ employees. Model 6 includes the interaction term associated with hypothesis 4b. The effect of shared prior employment affiliations is significantly

<table>
<thead>
<tr>
<th>Variable</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>0.957**</td>
<td>0.954**</td>
<td>0.952**</td>
<td>1.06**</td>
<td>0.954**</td>
<td>1.02**</td>
<td>0.925**</td>
<td>0.927**</td>
</tr>
<tr>
<td>Geographic distance</td>
<td>−0.125**</td>
<td>−0.124**</td>
<td>−0.120**</td>
<td>−0.117**</td>
<td>−0.123**</td>
<td>−0.121**</td>
<td>−0.113**</td>
<td>−0.112**</td>
</tr>
<tr>
<td>Industry focus</td>
<td>−2.27**</td>
<td>−2.27**</td>
<td>−2.26**</td>
<td>−2.22**</td>
<td>−2.27**</td>
<td>−2.26**</td>
<td>−1.81**</td>
<td>−1.80**</td>
</tr>
<tr>
<td>Industry dissimilarity</td>
<td>(0.007)</td>
<td>(0.007)</td>
<td>(0.007)</td>
<td>(0.007)</td>
<td>(0.007)</td>
<td>(0.007)</td>
<td>(0.006)</td>
<td>(0.006)</td>
</tr>
<tr>
<td>Age similarity</td>
<td>−0.478</td>
<td>−0.477**</td>
<td>−0.483</td>
<td>−0.465**</td>
<td>−0.470**</td>
<td>−0.476**</td>
<td>−0.478</td>
<td>−0.476**</td>
</tr>
<tr>
<td>Network centrality similarity</td>
<td>0.051**</td>
<td>0.050**</td>
<td>0.050**</td>
<td>0.050**</td>
<td>0.050**</td>
<td>0.050**</td>
<td>0.053**</td>
<td>0.035**</td>
</tr>
<tr>
<td>Interpersonal interaction opportunities</td>
<td>(0.004)</td>
<td>(0.004)</td>
<td>(0.004)</td>
<td>(0.004)</td>
<td>(0.004)</td>
<td>(0.004)</td>
<td>(0.006)</td>
<td>(0.006)</td>
</tr>
<tr>
<td>Both firms are venture firms (0/1)</td>
<td>0.862**</td>
<td>0.864**</td>
<td>0.867**</td>
<td>0.886**</td>
<td>0.867**</td>
<td>0.873**</td>
<td>0.565**</td>
<td>0.570**</td>
</tr>
<tr>
<td>Neither firm is a venture firm (0/1)</td>
<td>−0.416**</td>
<td>−0.418**</td>
<td>−0.421**</td>
<td>−0.428**</td>
<td>−0.428**</td>
<td>−0.466**</td>
<td>0.044</td>
<td>0.036</td>
</tr>
<tr>
<td>Educational prestige differential/</td>
<td>−0.004</td>
<td>−0.004**</td>
<td>−0.004**</td>
<td>−0.004**</td>
<td>−0.004**</td>
<td>−0.005**</td>
<td>−0.002**</td>
<td>−0.002**</td>
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<tr>
<td>Shared prior educational affiliations</td>
<td>0.005**</td>
<td>0.011**</td>
<td>0.005**</td>
<td>0.011**</td>
<td>0.005**</td>
<td>0.006**</td>
<td>(0.001)</td>
<td>(0.001)</td>
</tr>
<tr>
<td>Shared prior co-investments</td>
<td>−0.007**</td>
<td>−0.007**</td>
<td>−0.007**</td>
<td>−0.007**</td>
<td>−0.007**</td>
<td>−0.007**</td>
<td>(0.001)</td>
<td>(0.001)</td>
</tr>
<tr>
<td>Shared employment affiliations</td>
<td>0.013**</td>
<td>0.030**</td>
<td>0.016**</td>
<td>0.027**</td>
<td>0.005</td>
<td>0.005**</td>
<td>0.005</td>
<td>0.006</td>
</tr>
<tr>
<td>Autocorrelation control</td>
<td>46.9**</td>
<td>46.5**</td>
<td>(0.767)</td>
<td>(0.774)</td>
<td>(0.767)</td>
<td>(0.774)</td>
<td>(0.003)</td>
<td>(0.003)</td>
</tr>
<tr>
<td>(0.065)</td>
<td>(0.067)</td>
<td>(0.068)</td>
<td>(0.068)</td>
<td>(0.067)</td>
<td>(0.067)</td>
<td>(0.071)</td>
<td>(0.072)</td>
<td></td>
</tr>
<tr>
<td>Log pseudolikelihood</td>
<td>−27,499</td>
<td>−27,482</td>
<td>−27,469</td>
<td>−27,281</td>
<td>−27,478</td>
<td>−27,374</td>
<td>−25,696</td>
<td>−25,692</td>
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<tr>
<td>Chi-square (d.f.)</td>
<td>8,727 (8)</td>
<td>8,767 (9)</td>
<td>8,788 (10)</td>
<td>9,836 (11)</td>
<td>8,776 (10)</td>
<td>9,394 (11)</td>
<td>15,405 (14)</td>
<td>15,518 (15)</td>
</tr>
</tbody>
</table>

* p < .05; ** p < .01.

*Robust standard errors are in parentheses. Coefficients and standard errors are adjusted for rare events bias.
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, supporting both hypotheses 3b and 4b.

Model 7 includes both affiliation count variables and their interactions with the number of prior co-investments. The effects of shared prior educational and employment affiliations are positive and statistically significant and so are the coefficients on the interaction terms. Although unobserved heterogeneity is largely accounted for by the prior co-investments variable, firm-type dummy variables, and other controls, inclusion of the autocorrelation control variable should assuage any remaining concerns about unobserved heterogeneity as well as non-independence of observations. 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 7 remain consistent with the hypotheses. The main effects of shared prior educational and employment affiliations on co-investment likelihoods are positive and significant but strongest for firms that made few or no co-investments over the previous five years.

Model 8 includes an exploratory interaction term of shared prior educational affiliations and shared prior employment affiliations. The coefficient on this interaction term is negative, implying that prior educational and employment affiliations are substitutable in terms of facilitating interorganizational relationships. This possibility is in contrast to the alternative complementary relationship in which one shared affiliation accentuates the other’s influence. This result is also consistent with the relationship observed in the co-employment analysis. Perhaps most importantly, this result is more consistent with an information exchange explanation than with plausible alternatives that emphasize other factors that might lead highly affiliated firms to co-invest (e.g., foci, homophily).

Using the coefficients in model 8 of table 5 and Petersen’s (1985) formula, I computed changes in the likelihood of co-investment associated with increasing the educational prestige differential by one standard deviation for two venture firms located in California, holding all other control variables at their means. A one standard deviation increase above the mean prestige differential decreases the likelihood of co-investment by approximately 2.2 percent.

The effects of shared prior affiliations on the likelihood of co-investment for two venture capital firms that did not previously co-invest are depicted graphically in figure 1. The figure is based on the reported coefficients in model 7 of table 5 and generated using the `relogitq` command in Stata SE 12. To generate predicted changes in the relative risk of co-investment for two California-based venture capital firms that did not previously co-invest, I set all other control variables at mean levels so that only the number of shared prior educational and employment affiliations vary. The Y-axis represents the change in

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14 I followed precedent (Stuart, 1998; Jensen, 2003) in utilizing Lincoln’s (1984) method instead of Mizruchi’s (1989) firm-level fixed effects specification because of the computational challenge of performing dyadic analyses with dummy variables for 1,082 firms. In two separate models, I also clustered observations on firm i or on firm j to account for non-independence (e.g., Hallen, 2008) and found results similar to those reported here.
co-investment risk relative to a baseline likelihood that equals 1.0 when both shared affiliation counts equal zero. The shaded area bounds a 95-percent confidence interval around the mean shared prior employment affiliation effect size estimate. The vertical lines with circular endpoints bound a 95-percent confidence interval around the mean shared prior educational affiliation effect size estimate.

Figure 1 demonstrates that two firms’ relative risk of co-investment increases by approximately 5.9 percent as the number of prior employment affiliations shared by firms $i$ and $j$ increases from the mean (0.6 affiliations) to one standard deviation above the mean (2.7 affiliations). Similarly, the likelihood of co-investment increases by approximately 6.7 percent as the number of shared prior educational affiliations increases from the mean (4.1 affiliations) to one standard deviation above the mean (14.1 affiliations). As evidenced by the overlapping confidence intervals at each point along the X-axis, the effects of shared prior educational and prior employment affiliations are statistically indistinguishable from each other.

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 just one previous co-investment. For two dyads that share the mean number of shared prior educational affiliations for all dyads (4.1 shared affiliations), the relative risk of co-investment is approximately 2.8 percent lower for the dyad that previously co-invested once than for the dyad that did not. For two dyads that share the mean number of shared prior employment affiliations for all dyads (0.6 shared affiliations), the relative risk of co-investment is approximately 0.5 percent lower for the dyad that previously co-invested once than for the dyad that did.

Figure 1. Effects of shared prior affiliations on relative risk of co-investment for venture dyads that did not co-invest in previous five years.
not. The results presented in table 5 thus demonstrate that firms are less likely to co-invest the greater is the educational prestige differential for their employees. Moreover, two firms that share more prior educational and/or employment affiliations are more likely to co-invest, and this is most true for two firms that made no co-investments in the previous five years.

DISCUSSION

This study considered how organizational reliance on organizational employees’ interpersonal networks stabilizes interorganizational networks and limits positional change. The analyses reveal that organizations embed both their current employment relationships and interorganizational relationships in their employees’ prior educational and employment affiliations. Although alternative explanations like status homophily or unobserved focus remain plausible, the attenuation results implicate information exchange as the dominant mechanism.

Network inertia could result if advantaged organizations occupy stable positions and disadvantaged organizations’ attempts to improve their positions by forming new interorganizational relationship are constrained by employees’ prior affiliations. But this constraint alone is an insufficient explanation for network inertia. Disadvantaged organizations could hire individuals to form new, position-improving relationships. But organizations typically embed employment relationships in the same employee affiliations in which interorganizational relationships are embedded. Together, these two tendencies contribute to the cliquish tendencies that constrain network change and limit the occupancy of advantageous network positions.

Despite prior research on how career experiences govern organizational behaviors (e.g., Fligstein, 1987; Thornton and Ocasio, 1999), the link between individual careers and interorganizational networks has remained implicit. By explicitly linking interorganizational network evolution to higher educational institutions and labor markets, this study offers a sociological account of how organizations reproduce both market and non-market social structures (e.g., Bourdieu and Passeron, 1977).

Because educational and employment experiences are so intertwined, caution is warranted in evaluating the relative influences of prior education and employment. Most individuals’ educational experiences precede their employment experiences (Barton, 1985), but many employers hire from a restricted set of schools (e.g., Phillips and Zuckerman, 2001; Oyer and Schaefer, 2010). Future studies might disentangle the relative strength of educational versus employment affiliations in settings in which the time decay of each can be accounted for or held constant. At this point, though, inferences should be limited to the general relevance of organizational employees’ prior affiliations to interorganizational network evolution.

This study also contributes to our understanding of stratification. In many markets, “actors try to produce a ‘local’ stable world where the dominant actors produce meanings that allow them to reproduce their advantage” (Fligstein, 2002: 29). Embedding interorganizational relationships in employees’ prior affiliations is one way to reproduce advantage. For example, a one standard deviation increase in the number of shared affiliations increases the likelihood that two firms form a new relationship by approximately 6 percent. To
put these figures in context, the firms analyzed in this study made, on average, 7.6 investments in 2006 (s.d. = 10.6). Over several years, small preferences for embedding deals in prior affiliation networks could contribute substantially to producing and maintaining cliques. Simulation models might formalize assumptions about such preferences across organizations and over time to illuminate just how advantageous it is—in terms of occupying an advantageous co-investment network position—for a firm to employ investors who attended Harvard and worked for Goldman Sachs instead of, say, Georgetown and J. P. Morgan. Such inquiries would further inform our understanding of how organizational closure around prior affiliations hinders entry into an industry for some individuals and enables entry for others (e.g., Rivera, 2011). Future research might also examine how shared prior affiliations influence relationship formation among coworkers and influence the evolution of intraorganizational networks.

Similarly, research on labor markets (e.g., Fernandez and Su, 2004; Fernandez and Sosa, 2005; Fernandez and Fernandez-Mateo, 2006; Sørensen and Sorensen, 2007) documents how space, social networks, and organizational demography contribute to stratification. Exploiting the composition of prior employment affiliations across industries or space and/or over time would likely reveal how network evolution reproduces inequality. This study implies that the advantages and disadvantages attributable to stratification in higher education and labor markets are likely to be most pronounced in settings in which access to network-based resources like private information is particularly valuable (e.g., investment management, politics).

Studying prior affiliation networks addresses the “endogeneity critique” of organizational network research (Manski, 2000; Mouw, 2006) because individuals clearly became affiliated prior to the observed behavior and arguably independent of behavioral intentions. This study can stimulate more specific critiques of how endogeneity compromises inferences about networks and can also motivate research designs that produce increasingly credible inferences about network evolution. One such avenue of inquiry would be to investigate the relationship between performance and the evolution of new organizations’ network positions, clearly identifying how that relationship differs based on whether or not one conditions on founders’ prior affiliations and other time-of-founding covariates. Barring such efforts, “the ground underneath the findings of network effects will always be at least a little shaky” (Stuart, 2007: 81).

This study’s limitations expose opportunities for future research. Researchers should investigate to what extent the organizational concentration of employees’ prior affiliations is attributable to selection at founding versus post-founding retention and/or hiring on the basis of prior affiliations. Although the data are cross-sectional, several testable predictions about the evolution of network positions flow naturally from the theory developed here. Organizations that hire individuals who are more central in prior affiliation networks than the organization’s employees should, on average, become more central in the interorganizational network. Conversely, organizations that lose employees who are central in the prior affiliation network should become more peripheral in the interorganizational network. Longitudinal analyses would permit such investigations.

This study did not isolate the effects of overlapping experiences from the effects of non-overlapping experiences because specific years of attendance and employment were unavailable for most individuals in the data. If
overlapping experiences are more influential than non-overlapping experiences in facilitating the sharing of information (Cohen, Frazzini, and Malloy, 2008; Kacperczyk, 2012), then the effect sizes reported here are conservative estimates. Of course, future studies that isolate the two effects would be insightful. Additionally, I aggregated both venture capital and private equity firms in the sample because these two organizational types exhibit similar co-employment patterns and also co-invest regularly. But unreported analyses reveal that the theorized effects are most characteristic of co-investments involving at least one venture capital firm. Future research might investigate variance in reliance on prior affiliations for different types of investments and/or investors.

Last, venture capital and private equity firms are fairly small, flat organizations that employ individuals of high socioeconomic status. On the one hand, these investors probably exercise greater influence over their firms than do employees of large, hierarchical organizations. On the other hand, prior research attributes numerous organizational behaviors and outcomes to just a few key employees of large, hierarchical organizations. For example, boards of directors (Davis, 1991), executives (Hambrick and Mason, 1984), top management teams (Higgins and Gulati, 2003), and managers (Boeker, 1997) are considered highly influential. Future research should probe external validity in settings with large, hierarchical organizations and employees of lower socioeconomic status.

Conclusion

Theories of endogenous network evolution neglect an important aspect of organizational life. Many individuals join organizations already embedded in networks that influenced their current employment relationships (Granovetter, 1973; Fernandez, Castilla, and Moore, 2000). Continued study of how interorganizational network positions evolve out of employees’ prior affiliations will further inform us of how networks evolve, how social structures are reproduced, and how stratification persists in modern societies.

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John Freeman provided wisdom and encouragement and generously supported data collection. Jerry Engel shared industry knowledge and contacts. I appreciate constructive comments from Associate Editor Phil Anderson, Pino Audia, Waverly Ding, Heather Haveman, Linda Johanson, Peter Roberts, Anand Swaminathan, and Jim Wade; from seminar participants at the Atlanta Competitive Advantage Conference, Georgia Tech, Harvard Business School, INSEAD, the Institutions and Innovation Conference, and the National University of Singapore; and from three dedicated anonymous reviewers. Many research assistants helped me collect the data. All errors are mine. Research support from the Ewing M. Kauffman Foundation and the UC Berkeley Lester Center for Entrepreneurship & Innovation is acknowledged.

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Oyer, P., and S. Schaefer

Petersen, T.

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Phillips, D. J.

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Podolny, J. M., T. E. Stuart, and M. T. Hannan

Powell, W. W., K. W. Koput, and L. Smith-Doerr

PricewaterhouseCoopers
Stuart, T. E.

Stuart, T. E., and W. W. Ding

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Stuart, T. E., and O. Sorenson

Suitor, J., and S. Keeton

Thornton, P. H., and W. J. Ocasio

Useem, M., and J. Karabel

Uzzi, B.

Weber, M.

Yakubovich, Y.

Yakubovich, Y., and D. Lup

Zaheer, A., B. McEvily, and V. Perrone

Zuckerman, E., W. T. Kim, K. Ukanwa, and J. von Rittmann

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