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Environmental Demands and the Emergence of Social Structure: Technological Dynamism and Interorganizational Network Forms

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Abstract

This study investigates the origins of variation in the structures of interorganizational networks across industries. We combine empirical analyses of existing interorganizational networks with an agent-based simulation model of network emergence. Our insights are twofold. First, we find that differences in technological dynamism across industries and the concomitant demands for value creation engender variations in firms' collaborative behaviors. On average, firms in technologically dynamic industries pursue more open ego networks, which fosters access to new and diverse resources that help sustain continuous innovation. In contrast, firms in technologically stable industries on average pursue more closed ego networks, which fosters reliable collaboration and helps preserve existing resources. Second, we show that because of the observed cross-industry differences in firms' collaborative behaviors, the emergent industry-wide networks take on distinct structural forms. Technologically stable industries feature *clan networks*, characterized by low network connectedness and rather strong community structures. Technologically dynamic industries, in turn, feature *community networks*, characterized by high network connectedness and medium-to-strong community structures. *Convention networks*, which feature high network connectedness and weak community structures, were not evident among the empirical networks we examined. Taken together, our findings advance an environmental contingency theory of network formation.

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INTRODUCTION

Studies investigating how social structure shapes the behaviors and outcomes of actors constitute a vibrant area of organizational research. Prior work on the social structures of corporate actors has indicated that the structure of an interorganizational network helps explain a range of collective outcomes of organizations, such as diffusion of norms, knowledge, or other resources (Rogers, 2003; Uzzi and Spiro, 2005). Furthermore, recent studies suggest that networks in different interorganizational settings often show distinct structural properties. For example, studies of partnership networks among firms demonstrate that industry-wide structures of these networks differ across industries on a number of important dimensions (Rosenkopf and Schilling, 2007). Yet, despite mounting evidence that the variations in industry-wide networks may help explain firms' collective outcomes, there are limited insights regarding why interorganizational networks vary across different industrial contexts. Without a systematic understanding of the antecedents of variation in industry-wide network structures, it may be difficult to link the properties of these networks to the collective outcomes they engender for firms.

The present paper examines networks of technology partnerships among firms and explores why their structural properties differ across industries. Industry-wide networks represent the interlinked structure of firms' ego networks (i.e. ego and its direct contacts, as well as the connections among those contacts) and thus capture the overall system of firms and their ties in a given industry. Networks of technology partnerships are critical for the transfer of knowledge and resources among organizations, and they have been shown to affect a range of private and collective organizational outcomes (e.g., Owen-Smith and Powell, 2004). In developing our theory, we build on the basic property of complex social systems, whereby the emergence of distinct network forms can be traced to individual actors' collaborative behaviors (Coleman, 1990). Networks of technology partnerships constitute a highly dynamic setting in which firms constantly reshape their ties due to the economic imperatives of value creation. These dynamics are highly consequential for the structures of the emergent industry-wide networks (Powell, White, Koput, and Owen-Smith, 2005).

We seek to advance existing theory by exploring whether and to what extent variations in firms' collaborative behaviors across industries help explain the variation in industry-wide networks. We thus aim to understand why and how firms' collaborative behaviors differ across industries and whether these differences sufficiently explain the emergence of distinct industry-wide networks. We accomplish these interrelated goals by conducting two studies. In the first study, we examine whether the differences in demands for value creation lead to a significant variation in the collaborative behaviors of firms across industries. Although a range of behaviors can characterize the formation of interorganizational systems, we focus on those behaviors that have received particular attention in the past. Specifically, we study how firms pursue either closed or open ego networks. Pursuing a closed ego network entails forming ties to partners that are connected to one another; in turn, pursuing an open ego network involves forming ties to partners that are not connected (Burt, 2012).

Building on prior findings on the contribution of open and closed ego networks to firm advantage across different industrial contexts (Rowley, Behrens, and Krackhardt, 2000), our first study postulates that firms' collaborative behaviors are associated with the requirements of value creation imposed by the technological regime of an industry. In particular, we focus on an industry's technological dynamism, which reflects the extent to which resident firms emphasize investments in research and development (R&D) (Chan, Lakonishok, and Sougiannis, 2001). We posit that in technologically dynamic industries, firms are first and foremost driven to pursue more diverse resources and knowledge as critical inputs to innovation, and that doing so is best enabled by open ego network structures. In contrast, in technologically stable industries firms are driven to preserve their existing resources and ensure reliable cooperation, which are best enabled by closed ego network structures. We therefore anticipate that, on average, firms in technologically dynamic industries will display stronger tendencies toward open ego networks than those in technologically stable industries. We test these arguments using a longitudinal dataset on the formation of interfirm R&D partnerships in several industries from 1983 to 1999. Our dataset covers a wide range of industrial environments characterized by a varying emphasis on R&D, including the automotive industry, biotechnology and pharmaceuticals, chemicals, microelectronics, new materials, and telecommunications.

In the second study, we proceed to examine whether the variation in firm-level behaviors is sufficient to explain the structural differences in industry-wide networks. To do so, we construct an agent-based model of network emergence. The model operates under the conditions of varying technological dynamism across different industrial contexts. This feature helps us determine whether, in the presence of other forces driving interfirm ties, the variation in firms' collaborative behaviors along the continuum of closed to open ego networks explains the emergence of distinct global network properties. The agent-based model positions us to better address the aggregate complexity of firms' interactions, which may be complicated by varying collaborative preferences of firms as well as by possible exogenous perturbations. This approach is particularly fruitful because industry-wide networks represent highly dynamic systems; indeed, they are shaped by interactions among multiple firms and exhibit aggregate properties that cannot be predicted from the behaviors of individual firms. Moreover, the processes by which these networks form may be nonlinear, thus obscuring the link between micro-level behaviors and macro-level structures (Skvoretz, 2002; Davis, Eisenhardt, and Bingham, 2009). In addition, this approach allows us to capture the overall variation in network forms by offering a general typology of interorganizational systems in relation to their environment.

Jointly, our two studies represent a key step toward an environmental contingency theory of network formation. This theory proposes a close association between the characteristics of actors' external environment—including its technological regime and associated institutionalized practices and norms—and the processes of network formation. We expect that these features of actors' external environment and the collaborative behaviors they induce are among the main drivers of variation in network structures observed across different social and economic environments.

STUDY 1: TECHNOLOGICAL DYNAMISM AND THE FORMATION OF INTERORGANIZATIONAL TIES

A key insight from prior studies of complex social systems is that interactions among individual actors as they form new network ties are critical in shaping the properties of the emergent social system (Coleman, 1990). This general insight implies that depending on how individual firms form their collaborative ties with partners, different industry-wide network forms may emerge. Admittedly, in forming new partnership ties firms may exhibit a range of behaviors. Yet, recent research indicates that one of the central differentiators is the extent to which firms pursue either more closed or more open ego networks (Li and Rowley, 2002; Rosenkopf and Padula, 2008; Ahuja, Polidoro, and Mitchell, 2009; Sytch, Tatarynowicz, and Gulati, 2012). A closed ego network occurs when a firm forms ties to the partners of its current partners, while an open ego network occurs when a firm form ties to alters that are unconnected to its current partners.

A particularly intriguing insight into the formation of closed and open ego networks is that they may be driven by fundamentally different strategic motivations on the part of firms. Pursuing closed ego networks has been linked to ensuring reliable collaboration and preserving existing resources. Because information on other firms is distributed imperfectly and the costs of partner search and selection are high, firms often prefer to connect to alters on whom they can obtain private information through shared third-party ties (Gulati, 1995). Furthermore, having a third party in common begets a situation where the two partners do not necessarily bear the full costs of the partnership. In particular, a common third party may offer effective recourse in conflict situations and protection against opportunistic pursuits (Larson, 1992). Finally, by enabling quick diffusion of reputational insights, closed ego networks can make it costly for partners to engage in self-seeking behaviors to the detriment of the focal firm (Greif, 1989; Ahuja, 2000). These features of closed ego networks can make them particularly effective in ensuring reliable collaboration and minimizing the transaction costs of partnering.

In contrast, the central motivation for pursuing open ego networks is that such structures enable more entrepreneurial firms to acquire diverse information, knowledge, and resources (Burt, 1992). Alters that are not connected to one another are believed to represent distinct network regions with diverse technical knowledge and information endowments (Sytch and Tatarynowicz, 2014a). Firms' innovation activities often entail recombining existing knowledge elements (Schumpeter, 1934), and open networks can enable firms to leverage such diversity to pursue superior innovation outcomes. This benefit—access to diverse information—is largely unavailable to firms in closed ego networks. This is because ties between similar firms (Powell et al., 2005; Ahuja et al., 2009) and the loss of diversity due to increased knowledge and information sharing among densely interconnected firms (Lazer and Friedman, 2007; Gulati, Sytch, and Tatarynowicz, 2012) typically result in greater homogeneity of the available knowledge and information.

Given the fundamental tradeoff between the benefits and costs of closed and open ego networks, we expect that firms' collaborative behaviors may vary depending on the environmental requirements for value creation. Specifically, it is possible that slow-paced and technologically stable industrial settings in which firms focus on the preservation and incremental growth of the existing resource base will tend to engender more closed ego networks. In such industries, closed ego networks may help ensure collaborative continuity via high levels of trust and reputational lock-ins, both of which can help firms preserve their existing resources. In contrast, firms in technologically dynamic industries may lean toward more open ego networks where opportunities to leverage heterogeneous knowledge from diverse partners may outweigh the benefits of resource preservation.

This argument builds in part on the work of Rowley, Behrens, and Krackhardt (2000) who showed that closed ego networks provide greater performance benefits in the slow-paced steel industry than in the semiconductor industry, which is characterized by significantly greater technological dynamism and innovation demands.

Three points are worth noting with respect to this argument. First, to distinguish between closed and open ego networks, firms need not necessarily act as astute networkers. Instead of tracing their own network position or that of a potential partner, organizational agents may select partners based on the demands for value creation imposed by their industry. For example, in highly dynamic industries where innovation is at the core of competitive advantage, firms may be driven to select those partners who can provide unique and diverse skills, knowledge, and resources. Organizational agents may identify such partners by monitoring other firms' innovation activities, including new product announcements and patent grants. As firms reach out to partners with distinct technological profiles, particularly those that reside in more distant parts of the network relative to their existing contacts, such efforts may eventually result in the formation of more open ego networks.

Less technologically dynamic industries, in contrast, may drive firms to emphasize lower transaction costs and the preservation of existing resources while downplaying the potential rewards of continuous innovation. Under these conditions, a key criterion for partner selection may be the moral hazard that comes along with a new partnership. A potential partner's reliability, in turn, may be easily gauged based on information provided by a firm's existing or past contacts. Sharing a third-party connection with a potential collaborator can thus provide assurance of reliable collaboration through both thorough selection and a reputational lock-in; furthermore, parties can reasonably expect the common contact to act as a mediator in emerging disputes (Black, 1976), precluding the escalation of conflict and further reducing transaction costs. Taken together, these motivations drive firms in industries characterized by stable technological regimes into closed ego networks.

Second, our argument concentrates on firms' average tendencies to form open or closed ego networks across industries, and we naturally examine the entire spectrum of firms' collaborative behaviors and the resulting ego-network positions. We thus do not rule out the possibility of encountering hybrid network positions, whereby firms can pursue closed and open ego networks simultaneously (Sytch et al., 2012). Indeed, we expect that the differences in technological regimes across industries should result in a pull toward either end of the spectrum, rather than the formation of purely closed or purely open ego networks. Third, it is important to note that our argument about how firms' collaborative behaviors vary across industries focuses on (a) capturing firms' *average* tendencies toward open or closed ego networks in a given industry, and (b) comparing those average tendencies across different industries. Accordingly, we expect that the collaborative behaviors of individual firms may vary both within a given industry and over time, and we incorporate such firm-level heterogeneities in our analyses. That said, we anticipate that the differences in firms' *average behaviors across industries* should be associated with the cross-industry variations in technological regimes. In sum, the arguments advanced above lead us to formulate the following hypothesis:

> ***Hypothesis 1:*** *Firms' pursuit of open and closed ego networks is associated with the technological regime prevailing in their industry, such that firms in technologically stable industries will form more closed ego networks while firms in technologically dynamic industries will form more open ego networks.*

Data

To test Hypothesis 1, we used data on the technology partnerships between firms in the automotive industry, biotechnology and pharmaceuticals, chemicals, microelectronics, new materials, and telecommunications. The breadth of our sample allowed us to capture significant variation in technological dynamism across industries and thus positioned us to examine whether and to what extent this variation could explain differences in the collaborative behaviors of firms. To examine firms' collaborative behaviors, we traced interfirm partnerships formed between 1983 and 1999 in each industry in our sample. Because collaborative partnerships were rare before 1980 (Hagedoorn, 1996), focusing on this period enabled us to provide a detailed account of the collaborative history of each industry. We obtained partnership data from the MERIT-CATI database, which is among the most well-established and frequently used sources of empirical data on technology partnerships (e.g., Hagedoorn, 1993; Gulati, 1995; Gomes-Casseres, Hagedoorn, and Jaffe, 2006). This database tracks a broad range of partnerships that entail knowledge exchange and development of new products or technologies, including joint ventures, contractual agreements, R&D consortia, and licensing deals (Rosenkopf and Schilling, 2007). Overall, our data included 8,810 distinct technology partnerships formed by 4,400 firms.

From this data, we subsequently reconstructed the structures of interorganizational networks using standard empirical procedures. More than 95% of partnership agreements in our data were bilateral, and we treated them accordingly as dyadic relationships. We decomposed the remaining multilateral partnerships into sets of dyadic ties (Stuart, 1998). Because information on partnership terminations was limited, we built on prior work that suggested that interorganizational partnerships last an average of five years (e.g., Kogut, 1988a; Gulati and Gargiulo, 1999; Stuart, 2000; Lavie and Rosenkopf, 2006). To reproduce the evolution of each interorganizational system in our data from 1987 to 1999, we thus reconstructed 13 annual network structures for each of the six industries.[1]

Measures

Dependent Variable: Open vs. Closed Ego Networks

To differentiate between closed and open ego networks, we relied on Burt's (1992) measure of ego-network constraint, defined as $c_i = \sum_j (\varepsilon_{ij} + \sum_k \varepsilon_{ik}\varepsilon_{kj})^2$. Here, ε_{ij} indicates the fraction of i's

[1] Note that some prior studies of interorganizational networks considered a broader spectrum of interfirm ties and used other sampling strategies. For example, in their study of an interorganizational networks in biotechnology and pharmaceuticals, Powell, White, Koput, and Owen-Smith (2005) examined various financing, sales, and marketing agreements among dedicated biotechnology companies, while excluding ties between pharmaceutical firms. Nonetheless, their network showed some remarkable similarities to the interorganizational system mapped here, including high levels of network connectedness (Ibid: Footnote 17) and some discernible community structure (Ibid: Footnote 13). We thank Jason Owen-Smith for providing us with additional data that facilitated these comparisons.

ties with j, ε_{jk} indicates the fraction of i's ties with k, and ε_{kj} indicates the fraction of k's ties with j. This index increases with the extent to which ego's contacts become more connected to one another and decreases as they become more separated from one another. Because the pursuit of closed ego networks involves forming ties to partners that are connected to one another, firms that exhibit such a behavior should obtain higher levels of constraint. In contrast, firms that hold ties to partners that are not directly connected to one another should obtain lower levels of constraint.

Using this measure, we constructed two complementary sets of dependent variables. First, we estimated how likely an average firm is to pursue a more open (versus a more closed) ego network. It is important to note that in measuring these behaviors, we focused only on those firms that formed at least one new partnership in any given year. Doing so enabled us to get closer towards capturing the agency of the focal firm, in contrast to the changes in ego networks that could be a result of new partnerships not involving the ego (Sytch et al., 2012). For each of these firms, we first estimated the probability of forming a more open ego network in any year (p_i). Figure 1 demonstrates this procedure. Suppose that from t = 0 to t = 3, A increased its constraint twice (from t = 0 to t = 1, and from t = 1 to t = 2), and lowered it once (from t = 2 to t = 3). This means that A's propensity to form a more open ego network was $p_A = (0+0+1)/3 = 0.33$. Using the same approach, we estimated B's and C's propensities as $p_B = 0.66$ and $p_C = 0$, respectively. We then checked the distribution of p_i values for firms in each industry against a number of commonly known distribution functions. The results indicated that the best fit is provided by using two discrete parameters: (a) the fraction of firms with zero probability of forming open ego networks at any time ($frac_{p=0}$), and (b) the average probability that the remaining firms will form open ego networks (p).

Figure 1 about here

Second, we specified a time-variant firm-level dependent variable *Constraint Change*, defined as $c_{i,t} - ci_{,t+1}$, where $c_{i,t}$ and $c_{i,t+1}$ denote the focal firm's ego-network constraint in years t and t+1, respectively. A positive value indicated the pursuit of a more open ego network, whereas a negative value indicated the pursuit of a more closed ego network.

Independent Variable

The central independent variable of interest was *Industry-level RDI*, defined as the R&D intensity of a focal firm's industry in year t. In line with prior research, we estimated the technological dynamism of an industry by measuring its R&D intensity (RDI) (Chan et al., 2001). This index captures firms' aggregate R&D spending per year divided by firms' total assets. Extant research indicates that technologically dynamic industries should exhibit higher levels of RDI because their competitive dynamics are largely driven by innovation and technological change (Chan et al., 2001; Rosenkopf and Schilling, 2007). We obtained data on firms' R&D spending from COMPUSTAT and Orbis. Table 1 shows the average RDI measured for each of the six industries in our sample. The values indicate noticeable differences in technological dynamism across the six industries.[2]

Table 1 about here

Control Variables

We controlled for a range of other possible determinants of a firm's collaborative behavior, all lagged by one year with respect to the dependent variable. We first included a control for *Industry Maturity*, defined as the 5-year average yearly growth rate in the number of firms in an industry. We specified this variable as $1/5\sum_{y=t-2}^{t+2}(n_y - n_{y-1})/n_{y-1}$, where y = t is the focal year and n_t is the total

[2] In additional analyses, we explored the variation in RDI for a larger sample of industries including software and the Internet, aerospace and defense, and the consumer goods industry, in addition to our focal six sectors. To do so, we drew on more recent R&D data for 1,000 public companies over the period 2005–2011 provided by Booz & Company's *Global Innovation 1000* study. These additional results confirmed our original rank ordering of industries in terms of their RDI.

number of firms operating in the industry in year t (cf. Klepper and Graddy, 1990; McGahan and Silverman, 2001). Lower growth rates generally characterize mature industries facing diminishing market opportunities and growing consolidation. In contrast, higher rates are typically associated with younger industries. We obtained the yearly counts of firms per industry from the CRSP database. Second, we controlled for the competitive intensity of an industry using the Herfindahl-Hirschman index of *Industry Concentration* (Hirschman, 1964). For each industry and year, we defined this index as the sum of squares of the annual sales of the 50 largest firms in the industry. Third, we controlled for *Network Size*, which captured the total number of firms present in the network in year t, and for *Network Avg. Degree*, which captured the average number of network ties per firm in year t. These control variables accounted for the possibility that both larger and sparser interorganizational networks could make it structurally easier for firms to pursue more open ego networks.

In addition, we controlled for a number of behavioral determinants at the level of the focal firm. First, to capture the firm's market performance and financial condition, we included a control for its *Sales* and *Return on Assets* (ROA) in year t. Second, we controlled for *Firm-level R&D Intensity*, which was defined as the ratio between the firm's R&D spending in year t and its total assets in that year. This control helped us account for the possibility that the formation of an open ego network could reflect the firm's own technological dynamism, rather than the dynamism of its external environment. Third, to account for the characteristics of a firm's current ego network, we controlled for the firm-level *Network Constraint* in year t using the previously introduced measure of ego-network constraint. The *Sales* and *Firm-level R&D Intensity* controls were entered into the model as logged terms due to their skewed distributions over firms. Finally, in order to account for any unobserved time effects, we entered a set of eleven *Year Fixed* Effects, with 1987 specified as the default year.

Analysis

Hypothesis 1 predicted that firms in technologically dynamic industries are likely to form more open ego networks, while firms in technologically stable industries are likely to form more closed ego networks. To test this hypothesis, we used two types of analyses. First, we conducted a correlation analysis to test the relationship between *Industry-level RDI* and firms' average, time-invariant propensity to form more open ego networks as estimated by $frac_{p=0}$ and p. Second, we conducted a regression analysis to estimate the time-varying collaborative behavior of any active firm in the industry (as measured by the firm's *Constraint Change* from t to t+1) as a function of *Industry-level RDI*. In addition, the regression analysis also allowed us to control for a range of other determinants of the firm's collaborative behavior, including the potential effect of *Industry Maturity*.

Given the nested structure of the data, we estimated the model using the multilevel, mixed-effects regression technique, which mitigates the risk of biased parameter estimates and incorrect standard errors (Snijders and Bosker, 1999). Specifically, we applied a three-level model with the firm's *Constraint Change* in a given year specified at Level 1 and random intercepts specified at the firm level (Level 2) and the industry level (Level 3). Additional analyses indicated that adding random coefficients at any level does not improve model fit. Table 2 reports the descriptive statistics and correlations for the independent and control variables. The mean variance inflation factor (VIF) of 1.83 suggests that multicollinearity did not pose a serious concern (Belsey, Kuh, and Welsch, 1980).

Results

The correlation between $\mathrm{frac}_{p=0}$ and RDI is -0.99 ($p < 0.001$), and the correlation between p and RDI is 0.75 ($p < 0.1$). These results support our expectation that firms should generally pursue more open ego networks in those industries that are characterized higher levels of technological dynamism, as measured by *Industry-level RDI*. The results of the regression analysis in Table 3, in turn, demonstrate that the effect of *Industry-level RDI* on a firm's propensity to form more open ego networks is positive and statistically significant ($b = 1.769$, $p < 0.01$). This evidence thus further supports our hypothesis and the findings of the correlation analysis. Notably, this effect holds even after accounting for the effects of industry maturity (i.e. the corresponding coefficient is statistically insignificant), the focal firm's R&D intensity, firm size, financial condition, and the firm's current ego-network position.[3]

Tables 2 & 3 about here

Discussion

The results of Study 1 show that firms' collaborative behaviors differ significantly across industries, in line with the observed variations in the industries' technological regimes. As predicted by our theory, we found that higher levels of technological dynamism provide a greater drive for firms to pursue more open ego networks as compared with more stable industrial environments, in which firms were found to generally pursue more closed ego networks. Study 1, however, stops short of exploring whether the demonstrated firm-level variations lead to the emergence of distinct global network properties at the industry level. Building on the results of Study 1, we therefore address this question in Study 2. In particular, in the following study we explore to what extent the emergent industry-wide networks differ in terms of their global properties as firms respond to the variable innovation demands of their industries by pursuing either more open or more closed ego networks.

STUDY 2: ORIGINS OF DISTINCT INTERORGANIZATIONAL NETWORK FORMS

Network analysts have devised a comprehensive set of concepts to describe the structural properties of social systems (Wasserman and Faust, 1994). Within this vast array of concepts, *network connectedness* and the network's *community structure* stand out as fundamental for understanding how social systems shape actors' outcomes (see Figure 2). Scholars have observed that high network connectedness and strong community structure help explain a range of dynamic network processes,

[3] We also examined the possibility that more mature industries could be characterized by more densely interconnected partnership systems. Such dense networks could make it more difficult for firms to pursue more open ego networks. Our analyses revealed that the empirical networks analyzed in the present study are characterized by statistically similar density levels, which rules out the possibility that our results could be driven by network density.

such as the diffusion of innovations (Wejnert, 2002), exchange of information (Dodds, Muhamad, and Watts, 2003), social influence (Moody, 2001), or the spread of infectious diseases (Anderson and May, 1991). In interorganizational networks, both concepts have been linked to the adoption of innovations, diffusion of governance practices, and the dissemination of knowledge among firms (e.g., Davis and Greve, 1997; Reagans and McEvily, 2003; Rogers, 2003). Network connectedness reflects the extent to which network actors can reach one another via network ties (see Figures 1a and 1b). High network connectedness indicates that most firms can access one another via a network path of some length. This feature supports the flows of knowledge, information and influence among firms. In contrast, low connectedness indicates that most firms are structurally isolated from one another and are thus inhibited from accessing other firms' knowledge and resources.

Figure 1 about here

Unlike connectedness, community structure captures the distribution (rather than *existence*) of network ties throughout the network (Granovetter, 1973; Girvan and Newman, 2002; Sytch and Tatarynowicz, 2014a). Strong community structure signals that the distribution of ties is uneven and that the network is characterized by the presence of many relatively small groups (or communities) of densely interconnected firms. In contrast, weak community structure suggests a more homogenous distribution of ties, such that no particularly dense groups can be distinguished (see Figures 2c and 2d). Network community structure has been linked to a variety of collective outcomes of actors. For example, dense network communities have been shown to enable the development of unique pools of knowledge shared among firms (Sytch and Tatarynowicz, 2014a), and to act as vehicles of cohesion, social norms, and social influence (Moody and White, 2003; Rogers, 2003; Greve, 2009). Some studies have also suggested that network communities are among the key conditions necessary to withstand the homogeneity pressures and to sustain sufficient levels of knowledge diversity in creative environments (Uzzi and Spiro, 2005; Lazer and Friedman, 2007; Gulati et al., 2012).

Holding all other network properties constant, we can expect that in sparsely connected partnership systems (Rosenkopf and Schilling, 2007) the formation of more open ego networks should lead to higher levels of network connectedness but weaker community structures. As firms extend their partnerships into wider swaths of the system, the number of widely dispersed ties should go up while the number of local ties should go down, increasing the system's connectedness. Yet, in sparsely connected networks communities generally tend to be weaker by virtue of containing fewer local ties. As such, the process of redistributing the ties across wider swaths of the network may come at the expense of community structure. By the same token, sparse interorganizational networks may be subject to opposite pressures in those industries in which firms generally pursue more closed ego networks. Since in those industries firms tend to place their ties in more proximate parts of the overall network, the emergent industry-wide systems should be characterized by stronger community structures but lower network connectedness. Similar tradeoffs were anticipated in some formal representations of network dynamics in interpersonal settings (Rapoport, 1957; Skvoretz, Fararo, and Agneessens, 2004), and in empirical work on the dynamics of interfirm networks (Gulati et al., 2012).

It is worth noting that when applied to stylized low-density networks, the argument regarding the tradeoff between community structure and network connectedness could perhaps be derived analytically. However, our specific question, which is posed in the context of real-world partnership systems, is significantly more complex than that. First, although we know that the formation of open and closed ego networks varies across industries, it remains an empirical question to what extent this variation can lead to observable differences in the emergent industry-wide networks. Should the variation in firms' collaborative behaviors across industries not be strong enough, the relationship between firms' behaviors and the emergent industry-wide networks could ultimately be weak.

Second, even if we were to assume that the relationship between firms' varying behaviors and the emergent industry-wide networks is strong, we still need to examine the precise nature of that relationship to understand exactly when distinct networks can emerge and what are their properties. Specifically, we need to identify at which levels of firms' preferences for open versus closed ego networks the expected transitions from low to high network connectedness and from strong to weak community structures can occur. It is entirely possible that both properties may not follow a linear pattern of change but rather feature more complex, nonlinear transitions. For example, some formal studies of main component formation indicated that network connectedness is a rather malleable structural property while changes in community structure are more difficult to trigger (Newman and Watts, 1999). Such nonlinear transitions could effectively engender the emergence of intermediate network forms, which could combine high levels of connectedness and strong community structures.

Considering the complexities of our argument, we therefore abstain from hypothesizing the emergence of specific network forms linked to particular levels of the firms' propensity for either more open or more closed ego networks. Instead, we formulate a general prediction that the cross-industry variations in firms' collaborative behaviors should give rise to distinct industry-wide networks characterized by different levels of network connectedness and community structure:

> ***Hypothesis 2:*** *Firms' greater propensity to pursue open ego networks across industries will lead to the emergence of distinct types of industry-wide networks showing significantly higher levels of network connectedness and weaker community structures.*

Methods and Analyses

To test Hypothesis 2, we applied a mixed-methods approach that combined empirical analyses of existing interorganizational networks with agent-based modeling. The agent-based model allowed us to perform a series of controlled experiments in which actual firm behaviors are compared with numerous counterfactuals, many of which are unobserved in real data. By experimenting along the entire continuum of firms' collaborative behaviors from closed to open ego networks, we were thus able to observe the often complex and nonlinear effects that relate actors' micro-behaviors to the emergence of macro-level social and economic systems (Schelling, 1978). A particular advantage of the agent-based model in that respect was that it did not impose any strict assumptions regarding the nature of the hypothesized micro-macro relationships, whether linear or non-linear.

More fundamentally, the agent-based model enabled us to achieve an abstract and yet detailed representation of real-world network dynamics, in which the network's properties are assumed to co-evolve with actors' behaviors. This resulted in an interdependent social system in which the evolving network is not just shaped by firms' direct interactions with one another but also by their indirect interactions through the emergent industry-wide network itself. Importantly, our modeling approach reflected a growing emphasis on agent-based simulations in organizational research that occurs alongside a growing interest in the processes of network emergence and dynamics (Ahuja, Soda, and Zaheer, 2012). The empirical element in our approach, in turn, allowed us to use real-world data both to calibrate the simulation model analytically and to validate it against empirical evidence. While helping us to directly trace the complex dynamics of network emergence, the mixed-methods approach thus also positioned us well to explore how strongly the networks we observe empirically differ from one another, as well as how strongly they differ from other possible networks that are predicted by the model but are not directly observed in our data (Bonabeau, 2002).

Analysis of Global Network Properties

We assessed the variation in global network properties using the previous concepts of *network connectedness* and *community structure* (see Figure 2). We defined network connectedness formally as $C = \sum_k \left(n_k / N \right)^2$, where n_k is the size of the k-th network component and N is the size of the entire network. This index captures how many components are in the network and how they vary in terms of sizes. The possible values range from close to 0 for a highly disconnected network that contains many small components, to 1 for a fully connected network that contains one large component.

To measure community structure, we used the well-known method of Girvan and Newman (2002).[4] This method detects communities by computing the network's *modularity* index defined as $Q = 1/e\sum_{k}(e_{kk} - \{e_{kk}\})$. Here, e is the total number of ties in the network, e_{kk} is the number of ties in the k-th community, and $\{e_{kk}\}$ is the expected number of ties within communities estimated from a baseline network that connects firms at random while preserving the same distribution of ties as in the observed network. Effectively, this method evaluates to what extent the observed network differs from a fully random network in terms of its community structure. However, because the number of possible community splits grows exponentially with network size, finding the best split typically turns into an extensive search problem that requires various heuristics and optimization algorithms. In our analysis, we relied on the *simulated annealing* algorithm proposed by Guimera and Amaral (2005). Prior research has evaluated this algorithm as particularly fast and efficient in finding maximum modularity associated with the best network community split (Danon, Diaz-Guilera, Duch, and Arenas, 2005).

Table 4 reports the values of network connectedness and community structure along with the size, average degree, and density of each network, averaged over the study period. As expected, we found the six networks in our sample to exhibit rather different structural forms, ranging from highly connected (biotechnology and pharmaceuticals, microelectronics, and telecommunications) to rather disconnected systems (automotive, chemicals, and new materials); and from strong community structures (biotechnology and pharmaceuticals, chemicals, and new materials) to medium community structures (automotive, microelectronics, and telecommunications). Somewhat unexpectedly, we also found that the anticipated tradeoffs between network connectedness and community structure do

[4] Our conceptualization of network communities builds on the structural accounts of communities as dense and cohesive social groups, whose members are closer to each other than to other actors in the system (e.g., Laumann, Galaskiewicz, and Marsden, 1978; Laumann and Marsden, 1979). This view is consistent with prior studies that built on the behavioral account of communities as interactional fields (Kaufman, 1959; Turk, 1970; Kasarda and Janowitz, 1974), where network communities were considered as being shaped by local interactions and the resulting social proximities among actors.

not apply equally to all industries; indeed, the system in biotechnology and pharmaceuticals indicated both a high level of network connectedness and a strong community structure.[5]

Table 4 about here

Agent-based Model of Interorganizational Network Emergence

We simulated the process of network emergence starting from a random Erdös-Rényi network with a fixed number of firms (denoted N) and a fixed average number of ties per firm (denoted k). In such a network, any two firms are connected with an equal probability k/(N-1) (Erdos and Renyi, 1959). This approach offered us several advantages (for alternative starting conditions see Appendix 2). First, starting from a purely random network that is unlikely to be the result of any systematic processes of tie formation provided an uncontaminated testing ground to explore how the simulated firm behaviors could transform and shape the emergent network systems. Second, an Erdös-Rényi network also helped us approximate the empirically observed variation in partnership counts among firms in any given industry (Cowan and Jonard, 2004; Rosenkopf and Schilling, 2007).[6] Finally, we used constant network size and network density to maintain consistent analytic conditions across different simulation runs (cf. Reagans and Zuckerman, 2001; Buskens and van de Rijt, 2008).

The network system emerges as firms form new ties to one another, thereby realizing their preferences for more open versus more closed ego networks.[7] The model distinguishes between open and closed ego networks using Burt's (1992) measure of network constraint. Figure 3 illustrates how the process works. Suppose that A is the ego; B, D, and E are A's current alters; and C, F, G,

[5] Additional analyses confirmed that the observed structural differences among industry-wide networks persist over time.
[6] The distribution of tie counts in the Erdös-Rényi network is roughly Poisson (Newman, 2010).
[7] Rather than having firms choose between open and closed ego networks, an alternative model would be to allow firms to connect either locally (within their own network community) or globally (outside their community). Such a model could perhaps explain the observed changes in community structure and network connectedness more directly. One key limitation that makes this model less plausible, however, is that not all interorganizational networks contain strong community structures that may affect firms' behaviors equally (Rosenkopf and Schilling, 2007). According to our results, for example, the degree of community structure varies from medium to strong between different industrial contexts. Our model, which limits firms' focus to their proximate ego networks (rather than to broader communities), allowed us to extend the analysis to a wider spectrum of interorganizational networks with variable degrees of community structure.

and H are A's potential alters. A first ranks its potential alters according to the *expected* change in network constraint. For illustrative purposes, Figure 3 provides A's constraint at time t ($c_{A,t}$ = 0.59) and its expected constraint at t+1 following the formation of a new tie ($c_{A,t+1}$ = [0.46, 0.48, 0.66]). In our example, the greatest negative change in A's network constraint is associated with alter G ($c_{A,t+1}$ = 0.46), and the greatest positive change is associated with alter C ($c_{A,t+1}$= 0.66). Depending on A's preference for a more open or more closed ego network, A should thus partner with either G or C.

Figure 3 about here

We defined an ego's decision to pursue a more open versus more closed ego network using a probabilistic parameter p. In technical terms, this parameter reflected the ego's probability to pursue an alter associated with the greatest *decrease* in ego's network constraint. The ego's probability to pursue an alter associated the greatest *increase* in constraint was thus 1 – p. To ensure some degree of matching between the preferences of the ego and the alter, the model considered both actors' constraint preferences and allowed only for those ties that reflected the alter's expectations, as well. Otherwise, the ego would pursue the next best option.[8]

Furthermore, we set the same level of p for all firms in the industry and used this modeling approach to distinguish between firms' varying collaborative behaviors across industries. Although this modeling approach implied that all firms in an industry would be subject to the same *average propensity* to pursue more open ego networks, in practice our model featured substantial behavioral heterogeneity across firms. This was primarily guaranteed by the stochastic nature of the network formation process, which allowed individual firms to act entirely differently than an *average firm*. In addition, each firm would also be exposed to different local network structures determining the

[8] We modeled this process by allowing the alter to reject a tie if forming it would not change its constraint level in the desired direction. The ego would then simply move down the list to the next available alter, with the possibility of not forming a new tie at all. This process was thus akin to a *satisficing* behavioral model (Simon, 1947). An alternative approach would be to consider a *maximizing* behavioral model, in which both actors must draw maximum benefits from the new tie. We discuss this possibility in Appendix 2.

access to and the availability of potential partners (cf. Ibarra, Kilduff, and Tsai, 2005). Taken together, our specifications ensured close representation of a real-world interorganizational setting.

Building on prior work, we also included a range of other behavioral mechanisms to ensure realistic modeling. First, because organizational agents are unlikely to observe the entire social space around them, we assumed that an ego's probability to observe any potential alter declines as a function of network distance (Friedkin, 1983). Formally, we specified the probability that i can observe j as $1/(d_{ij}-1)$, where d_{ij} is the number of links along the shortest network path between i and j. Should j be entirely unobservable to i by virtue of the two actors residing in disconnected network components, we assumed that a tie between i and j is still possible, albeit with a very low probability equal to $1/(N-1)$. This rule allowed us to consider the dynamics of real interorganizational networks, in which both isolates and disconnected network components can occasionally become connected.[9]

Second, we assumed that two partners can terminate their existing relationship and that the likelihood of relationship termination varies by tie duration. In modeling this process, we built on prior research indicating that partnership terminations are often time-consuming and costly, and that alliance partners typically avoid premature contract terminations (Malhotra and Lumineau, 2011). Consistent with the observation that interorganizational partnerships have a clear average lifespan (Kogut, 1988b; Gulati, 1995; Stuart, 2000), we specified a normally distributed duration of ties with a mean of 10 time steps and a standard deviation of 2 time steps. With the total simulation length of 100 time steps, our analyses thus extended over ten full partnership formation rounds by firms.[10]

Third, in order to compare the results among different simulation runs and across different time steps, the agent-based model required us to control for changes in network density. To ensure

[9] Information on potential partners may also travel outside the network and come from other sources, such as media, the Internet, or various industry events and conferences (Rosenkopf, Metiu, and George, 2001). As a result, even those firms that dissolve all their ties may still find a way to form new partnerships and reenter the network (Powell et al., 2005).
[10] It may be helpful to consider these modeling choices in the context of the dynamics of real interorganizational systems, in which two simulation steps could correspond to one year in the data. This means that 10 time steps could correspond to 5 years, which constitutes the typical lifespan of an interorganizational tie in our sample. Our entire analysis could thus be regarded as equivalent to tracing the evolution of a real interorganizational system over the period of some 50 years.

constant density, we controlled that the number of ties terminated in each time step is exactly the same as the number of newly created ties. We modeled this process by first selecting two random subsets of firms that were chosen independently of each other but could overlap. Both subsets were given the same sizes equal to 15% of the entire network, which closely reflected the dynamics of real interorganizational networks in our data. Then, each firm in the first subset was allowed to create one new tie per time step, while each firm in the second subset was allowed to delete one of its existing ties. Finally, firms could connect both to entirely new partners and to partners who were either their current or past ties. This condition helped us introduce further realism into the model.

Model Validation Against Empirical Data

To validate the model empirically, we explored how closely it represents real collaborative behaviors of firms observed across different industrial settings. A useful validation test entails examining whether the model—when supplied with the actual collaborative behaviors of firms—reproduces roughly the same levels of network connectedness and community structure as those found in the real setting (Davis, Eisenhardt, and Bingham, 2007). We specified firms' collaborative behaviors using the empirical values of the fraction of firms with zero probability to form an open ego network ($frac_{p=0}$) and the propensity of the remaining firms to form a more open ego network (p). To guarantee some baseline concordance with the conditions of each industry, we also matched the size and density of each network with the corresponding empirical values (see Table 1). For each industry, we conducted 100 simulations to mitigate stochastic variation in the results and recorded average levels of connectedness and community structure along with their standard deviations.

We then compared these results statistically with the corresponding properties obtained from real interorganizational networks using z-scores. Specifically, for network connectedness we specified $z_C = [C - E(C)] / \sigma_C$, where C is the connectedness of the empirical network, and E(C) and σ_C are the mean and standard deviation levels of connectedness measured for the simulated network (Szell, Lambiotte, and Thurner, 2010). For community structure, we specified $z_Q = [Q - E(Q)] / \sigma_Q$ where Q is the modularity of the empirical network, and E(Q) and σ_Q are the mean and standard deviation levels of modularity produced by the simulation model. Table 5 illustrates close correspondence between the real and simulated networks, thus indicating that our model is empirically valid and can produce generalizeable results (Davis et al., 2007).[11]

Table 5 about here

Analytic Procedure

To understand the precise link between firms' local behaviors and the emergent global network properties, we conducted the simulation over the entire range of conceivable values of $frac_{p=0}$ and p. We obtained these values by varying both parameters over the maximum range from 0 to 1 in 0.01 increments. This procedure resulted in a comprehensive set of 101 × 101 = 10,201 analytic cases. To achieve a realistic interorganizational setting, we again followed our descriptive results and those of prior research in specifying the key model parameters (Rosenkopf and Schilling, 2007). This involved modeling a medium-sized network with 200 firms with an average of four ties per firm (see Appendix 2 for alternative specifications). For each set of $frac_{p=0}$ and p values, we simulated the network for 100 time steps to ensure sufficient stability in the emergent network properties (see Appendix 1 for a formal analysis of model stability). To mitigate stochastic variance, we repeated the simulation 100 times for each analytic case and recorded average levels of network connectedness and community structure. Overall, our complete analysis involved conducting 1,020,100 simulation runs to generate the final results.

Results

[11] The results of this test support our model but cannot explicitly rule out other behavioral mechanisms that could be present in our empirical context and could possibly lead to other types of networks. We therefore additionally tested a range of alternative models of network formation among firms. We report these results in Appendix 2.

We summarize our final results in Figure 4 using two-dimensional heat maps. The results are consistent with the basic intuition of Hypothesis 2, which suggested that as firms' propensity for open ego networks increases the emergent industry-wide networks should be more connected and should exhibit weaker community structures. Two results are particularly striking, though. First, Figure 4a indicates that a sharp initial increase in network connectedness occurs over a relatively narrow range of p values.[12] Second, Figure 4b documents that community structure follows a more stable pattern over p. Particularly noteworthy, however, is the fact that the initial increase in p is accompanied by a growing (rather than a declining) community structure. This appears somewhat at odds with Hypothesis 2, which predicted that in sufficiently sparse systems the formation of open ego networks should weaken (rather than strengthen) the system's community structure.[13]

Figure 5 below provides a more precise illustration of the above transition effects. In this figure, we plotted a representative set of scenarios with low $frac_{p=0}$, medium $frac_{p=0}$, and high $frac_{p=0}$, tracing the changes in network connectedness and community structure over the entire range of p values. The individual plots were produced by fitting a series of Bézier curves that help smooth out the results of different simulations (Farin, 1997). Using their first-order derivatives, we also estimated when each of the fitted Bézier curves indicates a transition in slope from positive to negative.[14] Our analytic results suggest a rather complex, nonlinear pattern of co-variance that occurs along exactly the same set of inflection points ($p = 0.15$, $frac_{p=0} = 0$; $p = 0.22$, $frac_{p=0} = 0.35$; and $p = 0.34$, $frac_{p=0}$

[12] This process is akin to the rise of a giant component as the network's density goes up, a dynamic that was noted in some prior studies (de Sola Pool and Kochem, 1978; Skvoretz, 1991; Holme and Newman, 2006). In our case, however, connectedness increases not because actors are adding new ties to the network at random, but because they are spreading their ties more widely across the entire system. We thank an anonymous reviewer for pointing us towards this parallel.

[13] One way to understand these results is to explore where the observed changes in community structure come from: inside or outside the main network component. As firms create more open ego networks, the initial boost in community structure may come from outside the main component and be the result of integrating other, smaller components into the main component. Given only weak firm propensities toward open ego networks, however, this process is unlikely to fully absorb the other components and thus eliminate any emergent community structure. Rather, the integrated components may continue to exist inside the main component as distinct network communities. But after the transition toward a highly connected network is finalized, firms' opportunities to pursue more open ego networks by connecting outside their component may diminish. Instead, firms may be increasingly required to pursue open ego networks across the distinct network communities that exist inside the main component. Taken together, these processes may form the basis of an initial rise and a subsequent decline in community structure, as observed in our results.

[14] These analyses are not reported but are available from the authors upon request.

= 0.70 for both network connectedness and community structure). Within this pattern of co-variance, there are certain intervals that are characterized by rather intuitive effects, such as the quick rise of connectedness over low p and the subsequent decline of community structure over medium to high p. However, these results also indicate that a simple linear trade-off between both properties does not exist at all levels of p. Instead, the plots show a concurrent rise in *both network properties* over low p values and a subsequently more stable trend in connectedness than in community structure.[15]

Figure 4 about here

Figure 5 about here

Taken together, these results allow us to develop a general typology of the emergent network archetypes that are engendered by varying firm preferences towards either more open or more closed ego networks. These network archetypes are characterized by significant differences in the emergent global properties of network connectedness and community structure (see Figure 6). The first network archetype is characterized by low connectedness and a rather strong community structure. Because this configuration is reminiscent of a set of clans with strong in-group ties and almost no existing ties to other groups, we call it a *clan network* (Figure 6a). In our results, clans appeared to be associated with the lowest firm propensities to form more open ego networks. For example, in the set of scenarios with $frac_{p=0} = 0$, clan networks were found for $p < 0.15$.

The second network archetype is characterized by high connectedness and a medium-to-strong community structure. It is noteworthy that this structure corresponds to an intermediate network form that is linked to the complex nonlinearities that were uncovered by our agent-based model. In view of the sparsely interconnected and dense network communities that populate this

[15] We also found that network connectedness plateaus at around C = 0.8 instead of reaching the maximum value of 1.0. One explanation could be that by dissolving their ties, firms automatically introduce some fractures into the system, which then serve to prevent the emergence of a single-component network (see Online Supplement 1 for videos that illustrate this process).

system, we call it a *community network* (Figure 6b). Our analysis indicated that community networks are associated with firms' moderate propensities for more open ego networks. For example, in the set of scenarios with $frac_{p=0} = 0$, community networks were found from p = 0.15, where community structure peaks at Q = 0.7, to p = 0.65, where community structure drops below Q = 0.5.

Finally, the third network archetype we identify in our results is described by high network connectedness and a rather weak community structure.[16] This structural form features more disorder than the previous two, bearing some resemblance to a large public gathering; we therefore call it a *convention network* (Figure 6c). In our results, convention networks seemed to be associated with strong firm propensities toward open ego networks. For example, in the set of scenarios with $frac_{p=0} = 0$, convention networks were found for p > 0.65. Using a series of one-way ANOVA tests (Table 6), we found that this typology indeed represents a set of statistically significant differences in the networks' connectedness and community structure (connectedness: F = 278,270.49, $p < 0.001$; community structure: F = 10,960.46, $p < 0.001$). The complete typology is plotted in Figure 6d.[17]

Figure 6 about here

Table 6 about here

In a representative application of our typology, we explored which network archetype best characterizes our sample of industries. Given that the networks in automotive, chemicals, and new materials were found to combine rather low connectedness with strong community structures, and

[16] Our description of a *convention network* as a system with a rather weak community structure is consistent with other work on network cohesion, including the work of Moody and White (2003) who defined cohesion as the presence of *multiconnectivity* among actors. According to their view, cohesive social groups are those that manage to withstand separation even in the face of losing multiple in-group ties. Although it is possible that an entire network could display such a property by virtue of offering sufficient tie redundancy to withstand separation, the convention networks produced by our model were not sufficiently dense to provide such system-level cohesion.
[17] We also validated these differences post hoc using the Tukey-Kramer test of deviance, which allowed us to compare a given network archetype directly against the other two types using a standard t-score. The results of this additional test consistently indicated significant pairwise differences in network connectedness and community structure ($p < 0.001$).

that this configuration seemed to be the result of relatively weak firm propensities toward open ego networks, we classified these systems as *clan networks*. In turn, the networks in biotechnology and pharmaceuticals, microelectronics, and telecommunications were all found to combine high network connectedness with medium-to-strong community structures driven by moderate firm propensities toward open ego networks. Hence, we classified them as *community networks*. To illustrate our classification, Figure 7 provides two real-world images of (a) a clan network in the new materials industry in 1994, and (b) a community network in the telecommunications industry in 1994. Broadly speaking, these results suggest that *clan networks* may be associated with technologically more stable environments, while *community networks* may arise in environments that are characterized by greater technological dynamism. Notably, our data showed no evidence of an existing convention network.

Figure 7 about here

Discussion

The findings of Study 2 demonstrate that the variation in firms' collaborative behaviors leads to the emergence of three distinct network archetypes. Clan networks, which combine rather low network connectedness with strong community structures, are associated with the lowest firm propensities to form more open ego networks. As a result, we find that such networks tend to describe industries with low levels of technological dynamism, such as chemicals, automotive, and new materials. Community networks, in contrast, combine high network connectedness with medium-to-strong community structures, and we find that such networks are engendered by moderate firm propensities toward open ego networks. As a result, these networks are associated with technologically dynamic industries, such as biotechnology and pharmaceuticals, microelectronics, and telecommunications. Finally, convention networks are distinguished by high network connectedness and rather weak community structures that result from firms' strongest tendencies towards open ego networks. Such networks are not found in our empirical data and we address this finding in the General Discussion.

Extensions to the Analysis of Collective Outcomes

So far, we have deliberately limited our focus to the study of variations in industry-wide network structures. However, underlying this focus is an assumption that the macro-level structures of industry-wide networks can be highly consequential for various collective outcomes of firms. We briefly explored this assumption in supplementary analyses, where we modeled a simple process of knowledge diffusion across the industry network. In line with prior research, we considered a basic process of knowledge diffusion where the probability of knowledge transfer between two firms is a function of (a) the existence of a network tie between the two firms, and (b) the firms' level of familiarity and trust in each other (Rogers, 2003). We modeled firms' familiarity and trust using the sum of their current and past ties and the fraction of ties held to the same third parties, respectively (Gulati, 1995). We considered a dynamic model of network diffusion in which new knowledge diffuses in parallel with the processes of network emergence (Cowan, 2005).[18] We subsequently evaluated how quickly and broadly new knowledge can diffuse over the emergent network.

Results suggest that among the three archetypes of networks analyzed in the present study, community networks have the greatest capacity to sustain the diffusion process. Such networks facilitate the spread of new knowledge for two reasons. First, they help attain higher levels of network connectedness, which allows knowledge to spread more widely across the emergent industry system. Second, they also help firms attain higher levels of familiarity and trust in one another, which are enabled by the emergent structure of dense and cohesive network communities. Clan networks

[18] Modeling the dynamics of network formation independently from the dynamics of diffusion is consistent with the majority of empirical work on network diffusion, which typically assumes independence between the two processes (e.g., Haunschild, 1994; Davis and Greve, 1997). Furthermore, a model in which diffusion interferes with network formation might preclude us from capturing the precise impact of the emergent network on diffusion outcomes. In some diffusion scenarios, for example, the dynamics of network formation could be shaped by actors' desire to access knowledge via new ties. Future work could examine such interdependent dynamics of network structure and diffusion in more detail.

provide a rather strong community structure as well, but they fail to offer enough global range to facilitate knowledge flows. Thus, compared to community networks, clan networks inhibit diffusion.

Interestingly, we found that clan networks perform better at spreading new among firms knowledge than convention networks. Given that firms are significantly more isolated from one another in clan networks than in convention networks, we expected to see the opposite effect (cf. Davis and Greve, 1997; Westphal, Gulati, and Shortell, 1997). In additional analyses, we found that clan networks tend to provide a rather dynamic network setting that enables sufficient knowledge access via temporary network ties that span different network components (see Online Supplements 2-3). Over time, such *transient bridges* may effectively substitute for permanent connections through the wider network, thus mitigating the negative effects of low overall connectedness.

One example of a transient bridging tie in our data was the 1989 joint venture between the Japanese automaker Daihatsu and Balkancar, a state-owned Bulgarian manufacturer of large utility vehicles. The two companies got together to exchange knowledge and pool resources to eventually come up with the first Japanese–Bulgarian truck. Although the partnership got off to a good start and in the beginning managed to facilitate substantial knowledge transfer between both firms, it dissolved as the political turmoil swept across Eastern Europe in early 1990's. The two companies have not collaborated ever since, and ties between members of their respective network communities have been just as rare. Another example of a *transient bridge* was the 1992 alliance between BP and the Japanese new materials specialist Ube Industries. Here, the objective was to transfer knowledge and technology with the shared goal of developing a new line of low-density plastics. The partnership ended in 1997 with both companies as well as their respective network communities remaining disconnected ever since. Thus, this transient bridge also stands out for its key role in supporting knowledge flows across wider areas of the industry-wide network (see also Online Supplement 3).

Existing studies treat network connectedness as one of the key determinants of diffusion (Coleman, Katz, and Menzel, 1957; Watts and Strogatz, 1998; Cowan, 2005). Our study and the examples we just shared, however, suggest that successful diffusion does not necessarily require high overall levels of connectedness. Even if the overall network appears as rather disconnected, this *static* image could mask the system's dynamic capacity to compensate through transient bridging ties that can offer sufficient range for a system-wide diffusion, albeit over relatively short periods of time. An important implication of this finding is that understanding actors' collective outcomes may require reframing network connectedness as a *dynamic* system property. As our additional analyses suggest, for example, repositioning network connectedness as a dynamic system property could significantly enhance our conclusions with respect to the link between social structure and knowledge diffusion.

GENERAL DISCUSSION

This work was motivated by the recognition that the networks we observe in different social and economic settings vary significantly in terms of their structural properties, and that this variation can be consequential for a range of collective outcomes of actors. With this insight in mind, we set out to explore the differences in the structures of interorganizational networks among firms. We presented two complementary studies that combined empirical analyses of several interorganizational networks with agent-based modeling of interorganizational network emergence. Our first study showed that firms' collaborative behaviors vary significantly with the technological dynamism of the industry. Complementing these results, the second study showed that this behavioral variation can lead to the emergence of distinct structural forms of the industry-wide network.

Our combined results represent an important step toward an environmental contingency theory of network formation. This theory proposes a close association between the characteristics of the environment in which actors reside and the processes of network formation among actors. In relation to this theory, we demonstrated that organizations may be responding to the environmental demands not only in terms of their internal organizational design (Lawrence and Lorsch, 1967; Davis et al., 2009), but also in terms of the patterns of collaboration with other organizations. The main findings of the paper are thus twofold. In our first study, we found that in technologically dynamic industries firms on average pursue more open ego networks. In contrast, in technologically stable industries firms on average pursue more closed ego networks. This effect likely indicates that firms in technologically dynamic industries may favor access to novel and non-redundant knowledge and resources, which is best enabled by open ego networks. In technologically stable industries, in turn, firms may favor the benefits of resource preservation and safe collaboration, which are best enabled by closed ego networks.

In our second study, we explored whether the variations in firms' collaborative behaviors across industries are sufficiently strong to lead to the emergence of distinct industry-wide networks. In our extensive analyses, we found that although the differences in firms' behaviors seem rather subtle, they result in entirely different industrial network archetypes characterized by significant differences in network connectedness and community structure. These effects seem to result from the complex interactions between firms' local behaviors and the emergent global network properties. With respect to this finding, our results indicated that technologically stable industries are associated with the emergence of *clan networks* which exhibit low connectedness and a rather strong community structure. More dynamic industries, in contrast, are associated with the emergence of *community networks* which exhibit high network connectedness and medium-to-strong community structures.

The results of Study 2 also revealed another network archetype, a *convention network*, which showed high connectedness and a weak community structure. In our model, the convention network was produced by firms' strong tendencies to pursue open ego networks. Interestingly, the convention network was not found among the six empirical networks analyzed in this paper. One explanation is that firms could be driven to form more closed ego networks by several potent forces. For example, the formation of closed ego networks could correlate with geographic proximity, which could enable co-located firms to draw on the economic efficiencies and the institutional support mechanisms of an industry cluster (Krugman, 1991; Marquis, 2003). As another possibility, firms could be driven into dense communities by structural similarities or homophily (Powell et al., 2005). Finally, closed ego networks could also result from inertia and the comfort of familiarity, which could overshadow the economic imperatives of interorganizational collaboration (Li and Rowley, 2002).

Intriguingly, the very same forces might also serve to align firms' private goals with the shared goal of creating an overall network structure that best serves the entire collective. This conjecture is consistent with research in complexity science showing that many complex systems self-organize in distinct ways, and that this self-organization can help reduce the high costs of tie formation or make the system more robust to failure (Simon, 1962; Boisot and McKelvey, 2010). It is also relevant that self-organization may be adaptive and may occur in response to pressures stemming from the environment. Based on this logic, firms might be increasingly adapting their collaborative behaviors to respond to the requirements of value creation that are present in their industry. For example, we see community networks in technologically dynamic industries where these networks are particularly valuable and are needed to facilitate knowledge transfer among firms. Although our theory and analyses focused on the particular requirement of knowledge transfer, future research could extend this logic to a wider range of systems and other possible outcomes. In some systems, for example, environmental adaptation could reflect the need to minimize the costs of tie formation or to avoid network failure (Jackson and Wolinski, 1996; Schrank and Whitford, 2011).

Our paper offers several contributions to studies of social systems. First, we advance studies in the social embeddedness domain (Baker, 1984; Granovetter, 1985; Uzzi, 1996) by exploring the relationship between the micro-processes of tie formation by individual actors and the emergent macro-structures of social systems. Our primary insight is that the variation in actors' collaborative behaviors across different social and economic contexts helps explain the emergent differences in macro-level networks, and we find that these differences are stable over time. Our work thus extends research on network variation that focused on a *single* social context (Rosenkopf and Padula, 2008; Zaheer and Soda, 2009; Gulati et al., 2012). In relation to this work, we show that networks may show different global features not just over time but also across different socio-economic contexts. Importantly, we relate these differences to the varying behavioral tendencies of actors, such as the pursuit of open or closed ego networks, and demonstrate their link to different industrial settings, their varying levels of technological dynamism, and the associated demands of value creation.

Second, the typology of network structures developed in this paper offers fruitful opportunities for a comprehensive analysis of a wider range of systems. Our typology provides conceptual and analytical guidance with respect to the link between the differences in actors' collaborative behaviors and the salient transitions between different industry-wide networks. These transitions characterize the emergence of distinct archetypes of *clan*, *community*, and *convention networks*, which feature pronounced differences in network connectedness and community structure and seem to exert profound effects on actors' collective outcomes. It is important to note that the scope of our argument is conditioned by generally low network density that characterizes many interorganizational settings. Yet, because sparse networks occur in other settings as well (Podolny and Baron, 1997), we believe that our typology has the potential for applicability to a wider range of empirical contexts.

In particular, the typology of *clan, community,* and *convention networks* allows for a more precise classification of network forms in comparison with alternative typologies that use other network-analytic concepts, such as betweenness centralization, closeness centralization, degree centralization, or the small-world quotient (e.g., Uzzi and Spiro, 2005). First, our typology is applicable to a broader range of network structures, including highly fragmented structures as well, for which many of these alternative typologies are undefined. Because the emergent *clan*, *community*, and *convention networks* are differentiated in part by their degree of network connectedness, using our typology allows scholars to assess precisely how network systems differ structurally, as well as how they shape actors' outcomes. The additional analyses we conducted showed that none of the alternative typologies could capture the emergent differences in interorganizational networks as precisely as the combination of network connectedness and community structure. As applied to our present analyses, the centralization-based metrics produced only two crude network forms while the small-world quotient turned out to be higher for *conventions* than for *clans*. Unsurprisingly, we also found that the typology of *clan, community,* and *convention networks* significantly outperforms alternative typologies in terms of explaining global diffusion outcomes (by a factor of 1.8 to 8.8 depending on which alternative typology was used).

Third, the results of this paper also contribute to the ongoing debate about the varying implications of social structures in different environments (Rowley et al., 2000; Xiao and Tsui, 2007). More specifically, our results establish a connection between the collaborative behaviors of firms and the technological dynamism of their industry, which is essential for understanding the antecedents of network variation. This connection helps reconcile some of the conflicting findings regarding how social networks emerge and how they affect actors' outcomes (Kilduff and Brass, 2010). For example, the present study sheds more light on why closed ego networks prevail in technologically stable contexts, such as the automotive industry or new materials (Gulati, 1995), but not in dynamic contexts such as biotechnology and pharmaceuticals (Sytch and Tatarynowicz, 2014b). The present paper also helps clarify why chemical companies have been found to benefit more from closed ego networks (Ahuja, 2000), and why companies in the media sector (Zaheer and Soda, 2009) and the semiconductor industry (Rowley et al., 2000) have been found to gain greater advantages from open ego networks. Although our goal has not been to examine how a firm's network position affects its performance, the present findings suggest that one way for research to explore this link would be to account for the baseline differences in value creation regimes across different industrial settings.

Appendices

Appendix 1: Stability of the Emergent Industry-wide Networks

We examine the stability condition at t = 100 time steps for a large network with N firms and a small number of K components (K << N). Network connectedness is inversely proportional to K, such that C = 1/K. We also assume that every component has the same size n, such that n = N/K, and that every firm has the same network constraint, such that average constraint across all firms is equal to the constraint of any given firm. For this condition to hold, we assume that the components are characterized by the maximum density of network ties.

Given these simplifying assumptions, it is straightforward to show that any changes in network connectedness will be related to the changes in firms' ego network constraint, provided that network size is fixed (which is true in our model). First, we derive firms' average constraint (c_i) as:

$$\begin{aligned} c_i &= (n-1)\left[\frac{1}{n-1}+\left(\frac{1}{n-1}\right)^2\right]^2 \\ &= \frac{1}{n-1}\left(1+\frac{1}{n-1}\right)^2 \end{aligned} \tag{1}$$

By substituting n = N/K and rearranging the terms, we obtain:

$$c_i = \frac{K}{N-K}\left(1+\frac{K}{N-K}\right)^2 \tag{2}$$

Because K << N, 1 + K/(N-K) → 1. By substituting, we can simplify Equation (2) to:

$$c_i = \frac{K}{N-K} \tag{3}$$

By solving the above for K, we get:

$$K = N\frac{c_i}{1+c_i} \tag{4}$$

Equation (4) captures the relationship between the total number of network components (K) and the constraint of any given firm (c_i). To derive the association between network connectedness (C) and constraint, we substitute K = 1/C and solve for C:

$$C = \frac{1}{N}\left(1+\frac{1}{c_i}\right) \tag{5}$$

This suggests that network connectedness decreases proportionally to firms' constraint ($0 \leq c_i \leq 1$). The precise rate at which connectedness decreases is given by the derivative of C with respect to c_i:

$$\frac{dC}{dc_i} = -\frac{1}{Nc_i^2} \tag{6}$$

Expression (6) captures the relationship between the stability of network connectedness (dC/dc_i) and the stability of firms' ego networks. It suggests that once firms obtain their optimal constraint levels such that no further improvements are possible, then (*ceteris paribus*) the connectedness of the entire network should stabilize as well.[19] To understand when this happens, we explored how long it takes for a typical firm to obtain an optimal constraint level. To this end, we assumed that each firm must replace all of its initial ties assigned to it at t = 0. Because the likelihood of forming a new tie is 0.15 at any time and a typical firm is initially assigned 4 unique ties, replacing these ties with new ones will roughly take $4/0.15 \approx 27$ time steps. The most critical changes in the firm's ego network should thus occur approximately over the first 20-30 time steps of the simulation.

We validated these analytic conclusions with our model (see Figure 8). Figure 8a plots firms' average constraint levels in a typical *clan* ($frac_{p=0} = 0.9$, p = 0.1), a typical *community* ($frac_{p=0} = 0.7$, p = 0.3), and a typical *convention network* ($frac_{p=0} = 0.2$, p = 0.8) over time. Figures 8b and Figure 8c, in turn, plot the related changes in network connectedness and community structure at the system level. Results confirm the analytically derived relationship between stable constraint levels and stable global network properties, both of which emerge just over the first 20 to 30 time steps of the simulation.

Figure 8 about here

Appendix 2: Robustness Analyses

We conducted additional tests to determine if our results are robust to alternative parameters or model specifications. First, we tested some alternative values of network size and density. In the main analysis, we used values that were supplied by our own data and were also consistent with prior research on interorganizational networks (Rosenkopf and Schilling, 2007). In additional tests, we extended our modeling to a broader range of network sizes (N = 2,000; N = 20,000) and densities ($2 \leq k \leq 6$). The results were similar to those reported in the paper. The only difference was when we applied extremely low density (k = 2). Under these conditions, the emergent network was too sparse to obtain high connectedness at any level of p. This suggests that our findings could be less applicable to extremely sparse systems that preclude the formation of a large main component (Callaway, Newman, Strogatz, and Watts, 2000). Although such extremely sparse networks are rare in the interorganizational setting, some studies have identified the occurrence of sparse networks in certain industries, such as the footwear industry or paper mills (Rosenkopf and Schilling, 2007).

Second, we varied the starting conditions of the simulation. We specifically extended the set of initial networks to two other stylized networks: (a) the regular network in which every firm is connected to four other firms, and (b) the small-world network in which most firms are connected to four other firms but 10% of the firms are connected at random (Watts and Strogatz, 1998). Furthermore, in addition to the Erdös-Rényi random network used in the paper, we also tested four alternative random networks with variable degree distributions. These included: (a) a normal degree distribution with a mean of 4 and a standard deviation of 4, (b) a log-normal distribution with a mean of 4 and a standard deviation of 4, (c) an exponential distribution with $\lambda = 2.5$, and (d) a power-law distribution with $\gamma = 2.5$. All these models produced similar results to those reported in the paper.[20]

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[19] Equation (3) leads to similar conclusions with respect to the relationship between firms' average network constraint and the network's community structure. Consider a simple network with K interconnected network communities (rather than K components), where community structure Q increases proportionally to K. Following the same reasoning as in the appendix, we can express the stability of community structure as a function of c_i, namely $Q'(c_i) = N/(1+c_i)^2$.

[20] In addition to reaffirming the robustness of our main model, changing the initial degree distribution also allowed us to validate our assumptions with respect to the costs of interorganizational ties. Our theory postulated that one reason firms might choose between open and closed ego networks relates to the benefits and costs of these distinct positions, which might vary across industries. Yet, interorganizational partnerships could also involve other types of costs, such as the costs of managing and coordinating across different collaborations. By considering other degree distributions, one can account for these various types of costs indirectly. For example, a normal degree distribution implies that firms could realize certain benefits and synergies from multiple ties; however, only provided that their number does not exceed the

Third, we considered a model with greater behavioral heterogeneity of firms in the industry. Our main model assumed that firms in a given industry would choose between open and closed ego networks with a certain probability p, equal for all firms. This specification offered the best fit to the data. In alternative specifications, we assumed that p is not fixed but varies randomly across firms. We considered five different specifications of this model using a normal distribution of p with a fixed mean between 0 and 1 and a standard deviation varied from 0.1 to 0.5 (in 0.1 increments). Introducing this additional behavioral heterogeneity to the model did not affect our results.

Fourth, we revisited our assumptions regarding firms' visibility across the wider network. The assumption we made in the main analysis was that the extent to which an ego can observe potential alters is inversely proportional to network distance. One possibility to extend this model is to restrict ego's visibility to a certain maximum range, beyond which no alter can be "seen." To implement a limited range of visibility, we specified an alternative model in which the ego can observe only those alters who are up to d_{max} links away from the ego. We tested values from $d_{max} = 2$, which corresponds to the shortest distance between any two unconnected firms, to $d_{max} = 10$, which corresponds to the longest distance measured for any two firms in our dataset. The results remained unchanged.

Fifth, we considered two alternative models of tie formation between firms that deviate from the *satisficing* model implemented in the paper. These included: (a) a model in which both firms do not maximize their benefits but merely strive for a change that reflects their individual preferences in terms of obtaining higher or lower constraint, and (b) a model in which both firms strive to obtain the maximum change in constraint. The results of the first model were similar to our main results. The second model, in turn, showed the same pattern of covariance between network connectedness and community structure, but with absolute values of both properties substantially lower than those observed in the data. Such a poor fit was evident particularly in the case of the automotive industry, chemicals, and new materials, where firms were found to pursue more closed ego networks. For this set of industries, we found that the maximizing model on average underestimates the observed levels of network connectedness by about 75%, and of community structure by about 60%.

Sixth, we considered an alternative mechanism by which firms can dissolve their existing ties. To reflect the contractual nature of interorganizational partnerships, in the main analysis we assumed that partnership duration is a function of time. In the alternative model we tested whether in addition to the passage of time, tie dissolution can also be driven by firms' desire to create a more open or a more closed ego network. We found that such a model yields substantially poorer fit to the data over low to medium p values, producing networks with substantially lower levels of connectedness (on average 50% below the main results), and weaker community structures (on average 80% below the main results). As a result, we were unable to validate this model against our six empirical networks.

Seventh, rather than measuring network connectedness through the variation in component sizes, we specified connectedness as the fraction of dyads that are accessible to one another via an existing network path of some length. This alternative measure strongly correlated with the original measure of connectedness used in the paper (at over 0.8), and the main results remained unchanged.

Finally, we verified our model against two other models of network formation established by prior research: (a) a model in which firms select between entirely new alters and the alters they know through previous ties (e.g., Beckman, Haunschild, and Phillips, 2004; Baum, Rowley, Shipilov, and Chuang, 2005), and (b) a model in which firms follow the strategy of preferential attachment by favoring highly central actors (e.g., Barabási and Albert, 1999; Powell et al., 2005). We first checked whether these models are supported empirically. We found that our data provide some support for the first model but not the second one, offering no evidence of preferential attachment among firms.

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mean value of four. Beyond this threshold level, the partnership costs would start to rise and would eventually exceed the benefits. The power-law distribution, in turn, implies an exponential increase in partnership costs. Such an increase could eventually outweigh any benefits and synergies that firms could realize from having multiple ongoing ties.

This insight is consistent with recent work on the dynamics of interorganizational networks, which showed that firms are unlikely to be unconditionally attracted to central partners (Powell et al., 2005; Gulati et al., 2012). We then checked the validity of the first model, which distinguishes between new and familiar partners and found that it underestimates the empirical levels of network connectedness by about 60%, and community structure by about 65%. This suggests that when compared to other agent-based models of network emergence, the model proposed in this paper provides a realistic account of firms' collaborative behaviors with broad relevance across different empirical contexts.

Tables & Figures

Table 1. The fraction of firms with zero propensity for open ego networks ($frac_{p=0}$), average propensity of the remaining firms to create open networks (p), and the average industry-level R&D intensity (RDI) over 1987–1999.

Industry	$frac_{p=0}$	p	*RDI*	Industry	$frac_{p=0}$	p	*RDI*
Automotive	0.808	0.343	0.039	Microelectronics	0.760	0.433	0.050
Biotech & pharma	0.630	0.406	0.075	New materials	0.832	0.247	0.031
Chemicals	0.787	0.314	0.038	Telecom	0.764	0.352	0.048

Table 2. Descriptive statistics and bivariate correlations.

	Variable	Mean	SD	1	2	3	4	5	6	7	8	9
DV	*Constraint Change*	0.169	0.235									
1	*Sales (log)*	7.779	3.079	1.000								
2	*ROA*	-0.014	0.274	0.473	1.000							
3	*Firm-level RDI (log)*	0.257	0.509	-0.699	-0.566	1.000						
4	*Network Constraint*	0.480	0.348	-0.275	-0.082	0.128	1.000					
5	*Network Size*	328.658	148.865	-0.371	-0.204	0.359	-0.022	1.000				
6	*Network Avg. Degree*	3.973	0.646	0.153	0.089	-0.183	-0.210	-0.368	1.000			
7	*Industry Concentration*	0.201	0.155	-0.031	0.014	0.008	-0.039	0.195	-0.098	1.000		
8	*Industry-level RDI*	0.054	0.020	-0.443	-0.216	0.462	-0.033	0.642	-0.166	0.038	1.000	
9	*Industry Maturity*	0.030	0.019	-0.052	-0.024	0.066	0.093	-0.063	-0.251	0.473	0.058	1.000

Table 3. Three-level mixed-effects regression with random intercepts (DV: Firm-level *Constraint Change* from year *t* to *t+1*; SE's in parentheses; ***$p<.01$, **$p<.05$, *$p<.10$).

	Model
Constant	-0.136** (0.061)
Sales (log)	0.001 (0.002)
ROA	0.017 (0.017)
Firm-level RDI (log)	0.009 (0.012)
Network Constraint	0.550*** (0.012)
Network Size	-0.000 (0.000)
Network Avg. Degree	0.002 (0.011)
Industry Concentration	0.030 (0.039)
Year Fixed Effects	Included
Industry-level RDI	1.769*** (0.585)
Industry Maturity	0.733 (2.113)
Observations	1,253
Log-likelihood	654.6

Table 4. Network size (N), average degree (k), network density (D), network connectedness (C), and community structure (Q), averaged over 1987-1999.

Industry	*N*	*k*	*D*	*C*	*Q*	Industry	*N*	*k*	*D*	*C*	*Q*
Automotive	179	3.24	0.02	0.21	0.64	Microelectronics	212	4.39	0.02	0.51	0.59
Biotech & pharma	386	4.13	0.01	0.44	0.76	New materials	336	4.00	0.01	0.09	0.73
Chemicals	311	4.07	0.01	0.20	0.73	Telecom	291	4.03	0.01	0.48	0.67

Table 5. Analysis of the results on network connectedness [$E(C)$] and community structure [$E(Q)$] produced by the model with respect to the empirical values (Table 4). Model fit is evaluated using two z-scores: one for network connectedness (z_C) and the other for community structure (z_Q). Insignificant z-scores indicate good fit.

Industry	*E(C)*	*E(Q)*	z_C	z_Q	Industry	*E(C)*	*E(Q)*	z_C	z_Q
Automotive	0.20	0.63	-0.19†	0.09†	Microelectronics	0.51	0.60	-0.05†	-0.24†
Biotech & pharma	0.46	0.75	-0.24†	0.42†	New materials	0.11	0.71	0.07†	-0.65†
Chemicals	0.22	0.69	0.21†	-0.38†	Telecom	0.47	0.69	-0.01†	0.48†

†*Difference insignificant at any standard level (two-tailed test).*

Table 6. Tukey-Kramer tests of pairwise deviance between network connectedness and community structure.

Network property	Test	*t*-score
Network connectedness	Clans vs. communities	-355.62***
	Clans vs. conventions	-904.60***
	Communities vs. conventions	-432.03***
Community structure	Clans vs. communities	-135.07***
	Clans vs. conventions	-70.09***
	Communities vs. conventions	70.94***

**** Difference significant at p < 0.001.*

Fig. 1. Estimation of a firm's propensity to pursue a more open ego network.

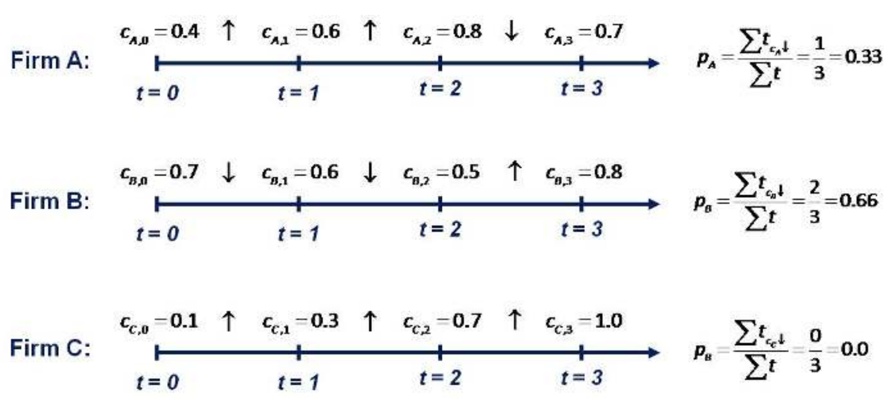


Fig. 2. Network connectedness and community structure.

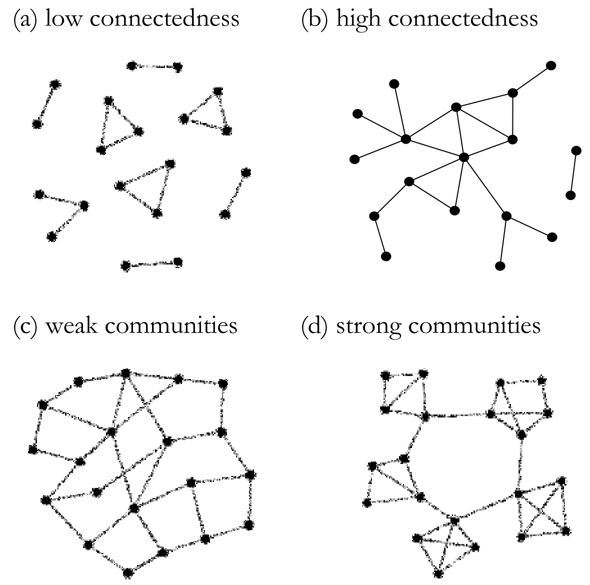


Fig. 3. Simple stylized model of network emergence.

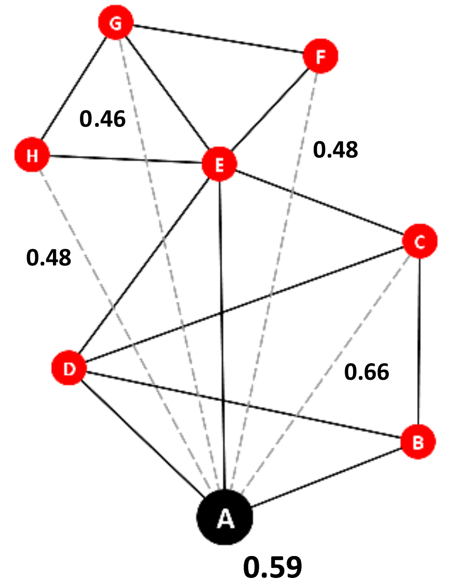


Fig. 4. Network connectedness and community structure produced by the simulation model at *t* = *100* time steps.

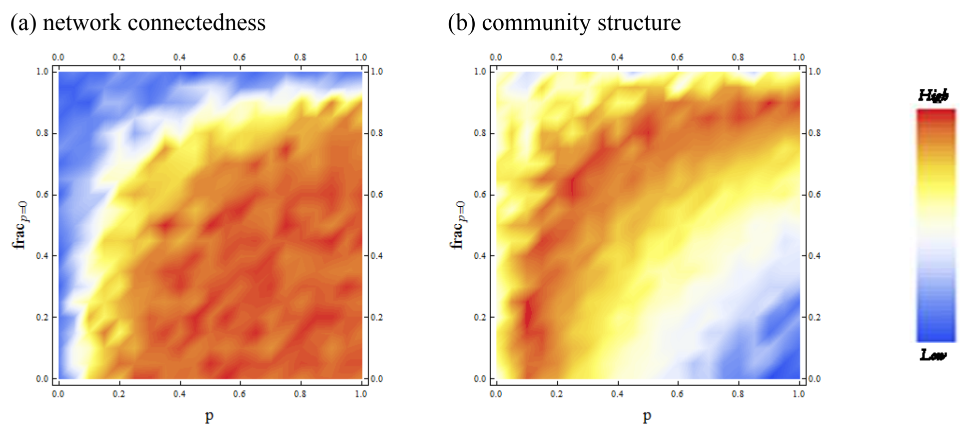


Fig. 5. Smooth Bézier curves capturing the critical transitions in network connectedness and community structure. The curves represent three distinct scenarios with low $frac_{p=0} = 0$, medium $frac_{p=0} = 0.35$, and high $frac_{p=0} = 0.70$, respectively.

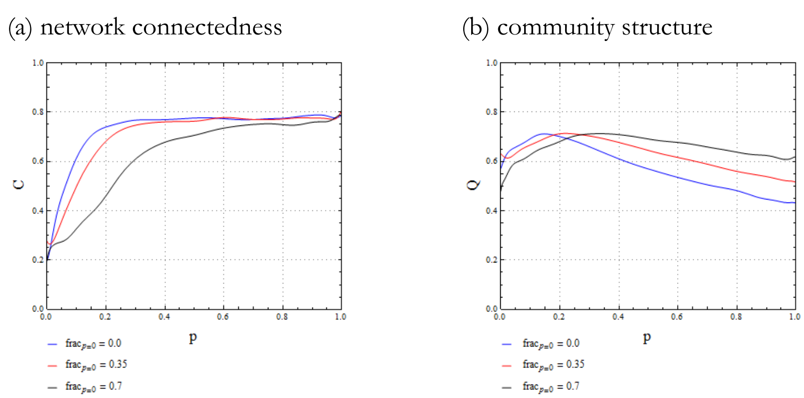


Fig. 6. Typical structure of a (a) clan network, (b) community network, and (c) convention network. Figure 6d summarizes the overall typology with respect to $frac_{p=0}$ and p.

(a) *clan network* (b) *community network* (c) *convention network* (d) overall network typology

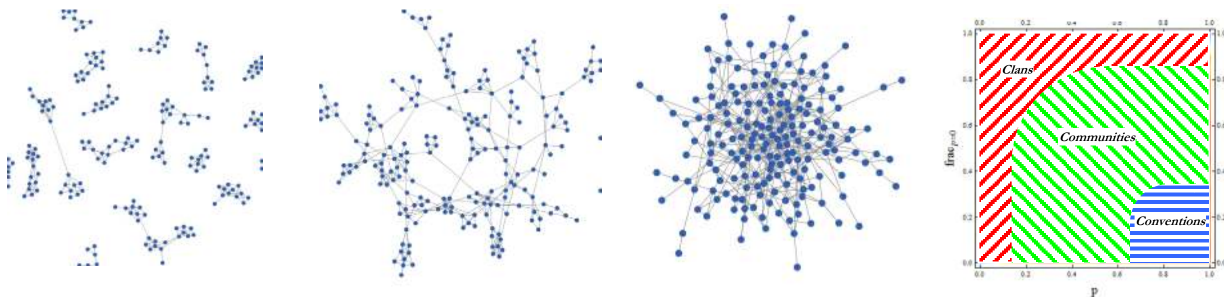


Fig. 7. Two representative images of a clan network and a community network obtained from the dataset.

(a) new materials network in 1994 (*clan network*) (b) telecommunications network in 1994 (*community network*)

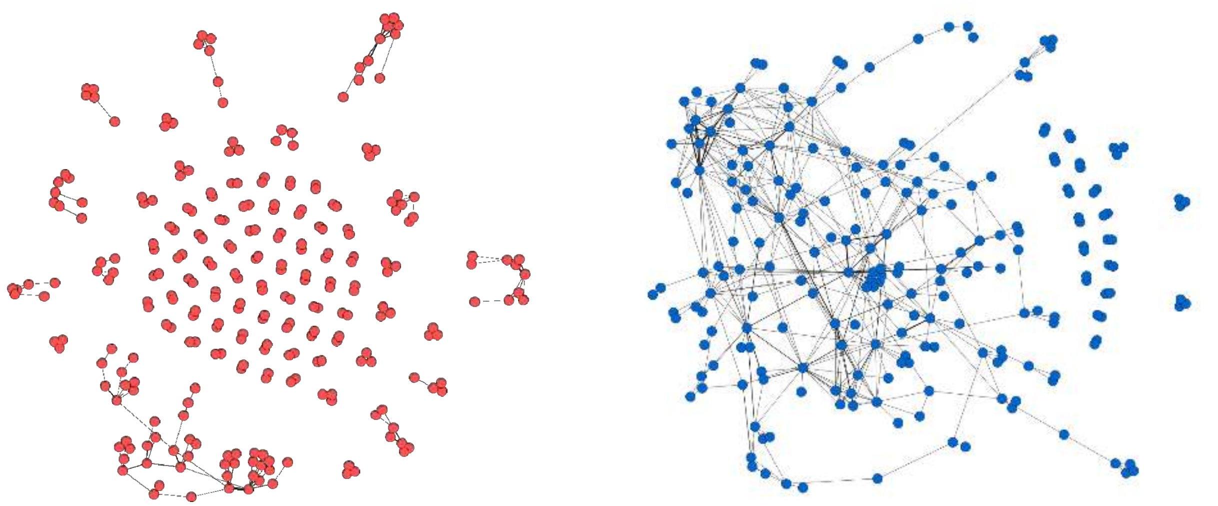
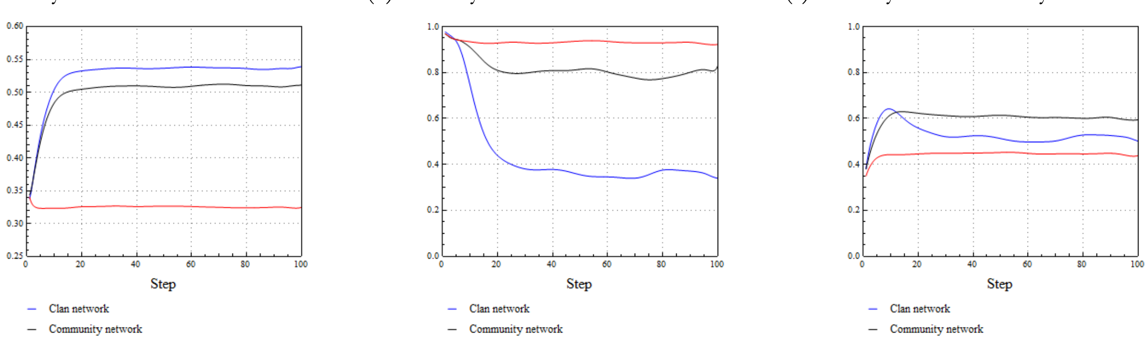


Fig. 8. Relationship between the stability of firms' ego networks (a) and the emergent global network properties (b-c).

(a) stability of network constraint (b) stability of connectedness (c) stability of community structure



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