Environmental Demands and the Emergence of Social Structure

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 global 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 variation in firms' collaborative behaviors. Specifically, firms in technologically dynamic industries on average pursue more open networks, which foster access to new and diverse resources that help sustain continuous innovation. By contrast, firms in technologically stable industries on average pursue more closed networks, which foster reliable collaboration and help 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 global forms. Technologically stable industries feature *clan networks*, characterized by low global connectedness and medium-to-strong community structures. Technologically dynamic industries, by contrast, feature *community networks*, characterized by high connectedness and medium community structures. *Convention networks*, which feature high global connectedness and weak community structures, were not evident among the empirical networks we examined. The findings of this study advance an environmental-contingency theory of network formation.

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INTRODUCTION

Studies of how social structures shape 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). Recent studies, in turn, have demonstrated that networks in different interorganizational settings often have distinct global features. For example, studies of partnership networks among firms demonstrate that the global structures of these networks differ across industries on a number of structural dimensions (Rosenkopf and Schilling, 2007). However, while there is mounting evidence that variations in global networks may help explain collective outcomes, there are limited insights regarding why global networks differ across different industrial contexts. Yet, without a systematic understanding of the antecedents of variation in global, industry-wide network structures, it may be difficult to draw a link between the properties of global networks and the collective outcomes they engender for firms.

This paper examines the networks of technology partnerships among firms and explores why their global, industry-wide structures differ across industries. Global networks represent the interlinked structure of 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. Global networks of technology partnerships are critical for the transfer of knowledge and resources among organizations. They have thus been shown to affect a wide range of private and collective outcomes of firms (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 global networks can be traced to individual actors' collaborative behaviors (e.g., Coleman, 1990; Buskens and van de Rijt, 2008). Partnership networks 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 structure 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 the variation in firms' collaborative behaviors across industries helps explain the variation in industry-wide network structures. We thus aim to understand why and how firms' collaborative behaviors differ across industries and whether these differences are sufficient to explain the emergence of distinct global networks across industries. Accomplishing these goals requires two analytical steps. First, we examine whether the differences in value-creation demands across industries lead to a significant variation in the collaborative behaviors of firms. Though a range of behaviors can characterize the formation of interorganizational networks, we focus on those behaviors that have received particular attention in prior research. Specifically, we study how firms pursue either more closed or more open ego networks. Pursuing a closed ego network entails forming ties to those partners that are directly connected to one another; pursuing an open ego network, in turn, involves forming ties to those partners that are not directly connected (Burt, 2012).

Building on prior findings about the contribution of open and closed networks to firm advantage across different industrial contexts (Rowley, Behrens, and Krackhardt, 2000), our theory postulates that firms' collaborative behaviors are closely associated with the requirements of value creation imposed by an industry's technological regime. In particular, we focus on the technological dynamism of an industry, which reflects the extent to which firms in that industry 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 technologically stable industries, by contrast, firms may be driven to preserve their existing resources and ensure reliable cooperation, which are best enabled by closed ego-network structures. We therefore anticipate that firms in technologically dynamic industries will on average display stronger tendencies toward open ego networks than those in technologically stable industries.

In the second step, we examine whether the variation in firm-level behaviors is sufficient to explain the differences in global, industry-level networks. To do so, we construct an agent-based simulation model of network emergence. The model operates under the conditions of varying technological dynamism across industries. This feature of the model helps us determine whether, in the presence of many other forces driving interfirm ties, the variation in firms' collaborative behaviors along the continuum of closed to open networks can explain the emergence of different global networks. To capture the possible variation in global networks, we develop a general typology of interorganizational network structures in relation to their technological environment.

To provide a comprehensive test of our arguments, we use a combination of statistical analyses and agent-based computer simulations. In order to explore whether firms' collaborative behaviors differ systematically across industries with different technological regimes, we analyze the formation of interfirm R&D partnerships from 1983 to 1999 statistically. The analyzed data cover a wide range of industries with varying emphasis on R&D, including the automotive sector, biotechnology and pharmaceuticals, chemicals, microelectronics, new materials, and telecommunications. In order to examine whether the variation in firms' collaborative behaviors shapes different industry-wide networks, we then use an agent-based model. The agent-based model positions us well to 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 global networks represent highly dynamic systems: they take shape as a result of the interactions among multiple actors and exhibit aggregate properties that cannot be predicted from the properties of individual actors. Moreover, the processes by which global networks form may be highly non-linear and non-deterministic, obscuring the link between local behaviors and the global outcome (Skvoretz, 2002; Davis, Eisenhardt, and Bingham, 2007).

Jointly, our analyses represent a key 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—which include its technological regime and the associated institutionalized practices and norms—and the processes of network formation among actors. We expect that these features of actors' external context and the collaborative behaviors they induce are among the main reasons for the variation in global network structures across different types of social and economic environments.

THEORY: TECHNOLOGICAL DYNAMISM AND NETWORK FORMATION

A key insight from the studies of complex social systems is that the interactions of individual actors as they form new network ties critically shape the structural properties of the emergent global system (Coleman, 1986). In our context, this implies that depending on exactly how individual firms collaborate with partners, different global network structures may emerge. Admittedly, in forming new partnerships firms can exhibit a range of behaviors. Yet, recent research indicates that one central differentiator is the extent to which firms pursue either closed or 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; an open ego network occurs when a firm forges relationships with 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 motivations on the part of firms. The pursuit of closed networks has been linked primarily to ensuring reliable collaboration and preserving existing resources. Since information on other firms is imperfectly distributed and the costs of partner search are high, firms often prefer to form connections to alters about whom they can obtain private information through shared third-party ties (Gulati, 1995). Furthermore, having a third party in common begets a situation in which two partners do not necessarily have to bear the full costs of the partnership. The common third party can provide protection against opportunistic pursuits and offer effective recourse in conflict situations (Larson, 1992). Finally, by enabling quick diffusion of reputational insights, closed ego networks can make it prohibitively costly for partners to engage in self-seeking behaviors to the detriment of the firm (Greif, 1989; Ahuja, 2000). These features of closed networks make them particularly effective in ensuring reliable collaboration and minimizing the transaction costs of partnering.

In contrast, a central motivation for the pursuit of open ego networks is that such structures enable more entrepreneurial firms to acquire diverse information, knowledge, and resources (Burt, 1992). Partners that are not directly connected to one another are believed to represent distinct network clusters with diverse technological knowledge and information endowments. Much innovative activity entails recombining existing knowledge elements (Schumpeter, 1934), and open networks can enable firms to leverage such diversity in pursuit of superior innovation outcomes. This benefit—access to diverse information—is largely unavailable to firms with closed networks. This is because ties among similar firms (Powell et al., 2005; Ahuja et al., 2009) and the loss of diversity due to increased knowledge and information sharing among densely connected firms (Lazer and Friedman, 2007) typically result in greater homogeneity of knowledge in closed networks.

In view of 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 help firms to preserve their existing resources. In contrast, technologically dynamic industries will tend 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 were more beneficial in the slow-paced steel industry than in the semiconductor industry, which was characterized by significantly greater technological dynamism and innovation demands.

Three points are worth noting with respect to this argument. First, in order 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 their potential partner, organizational agents may select partners on the basis of 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 a unique and diverse combination of skills, knowledge, and resources. Organizational agents may identify such partners by monitoring other firms' innovation activities, including their new product announcements and patent grants. As firms are reaching out to partners with different technological profiles, who are likely to reside in more distant parts of the network and far beyond firms' existing contacts, these efforts may eventually result in the formation of more open ego networks.

Less technologically dynamic industries, by contrast, may drive firms to emphasize lower transaction costs and preservation of existing resources while downplaying continuous innovation. Under these conditions, a key criterion for partner selection is likely to be the moral hazard associated with a new partnership. A potential partner's reliability, in turn, may be most easily gauged on the basis of the information provided by the firm's existing or past contacts. Sharing a third-party connection with a potential collaborator can provide further assurance of reliable collaboration in the form of a reputational lock-in, and the parties can also reasonably expect the common contact to act as a mediator in emerging disputes (e.g., Black, 1976), precluding the escalation of conflict and further reducing the anticipated transaction costs. Taken together, these motivations may lead firms in industries characterized by stable technological regimes to favor the formation of closed networks.

The second point is that 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 network positions. We therefore do not rule out the possibility of encountering hybrid network positions, whereby firms can pursue closed and open ego networks simultaneously (Burt, 2005). Indeed, we expect that the differences in technological regimes across industries should result in a pull toward either end of the hypothesized spectrum of behaviors, rather than the formation of purely closed or purely open ego networks.

Finally, 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 industries. In other words, 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 heterogeneity in our analyses. We simply anticipate that the differences in firms' average behaviors *across industries* can be associated with 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 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.*

COROLLARY: EMERGENCE OF DISTINCT GLOBAL NETWORK STRUCTURES

Network analysts have devised a comprehensive set of concepts to describe the global 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 global networks shape actors' outcomes (see Figure 1 below). Scholars have observed that high network connectedness and strong community structure help explain a range of global network processes, such as diffusion of innovations (Wejnert, 2002), exchange of information (Dodds, Muhamad, and Watts, 2003), social influence (Moody, 2001), and the spread of infectious diseases (Anderson and May, 1991). In interorganizational networks in particular, both concepts have been linked to the adoption of innovations, diffusion of governance practices, and dissemination of knowledge among organizations (e.g., Davis and Greve, 1997; Rogers, 2003; Uzzi and Spiro, 2005). Network connectedness reflects the extent to which actors in the network can reach one another via a network path (see Figures 1a and 1b). High network connectedness thus indicates that most firms can access one another via an existing network path of some length. This property allows for uninterrupted flows of new information, knowledge, and influence. By contrast, low connectedness indicates that most firms may be isolated from one another.

Unlike connectedness, community structure captures the distribution (rather than existence) of network ties throughout the network (Reagans and McEvily, 2003; Moody, 2004; Centola and Macy, 2007; Sytch and Tatarynowicz, 2014a). Strong community structure indicates that the distribution of ties is uneven and the network is characterized by the presence of many smaller subgroups (or communities) of densely interconnected firms. By contrast, weak community structure suggests a more even distribution of ties, such that no dense subgroups can be distinguished (see Figures 1c and 1d). Network community structure has been linked to a variety of collective outcomes. For example, dense network communities have been shown to enable the development of unique pools of knowledge among firms (Sytch and Tatarynowicz, 2014a) and to act as vehicles of cohesion, social norms, and influence (e.g., Rogers, 2003; Greve, 2009). Some studies have also suggested that network communities are among the key conditions necessary to withstand homogeneity pressures and sustain sufficient levels of knowledge diversity in creative environments (Uzzi and Spiro, 2005; Lazer and Friedman, 2007; Gulati, Sytch, and Tatarynowicz, 2012).

Figure 1 about here

As a corollary to our first hypothesis, it is reasonable to expect that as firms respond to the value-creation demands of their industry by pursuing either more open or more closed ego networks, the emergent global networks should vary in terms of their connectedness and community structure. 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 connectedness but weaker community structures. As firms extend their partnerships into wider swaths of the partnership system, the number of widely dispersed ties should go up while the number of local ties should go down, thus increasing the system's connectedness. Yet, since in sparse networks communities generally tend to be weaker by virtue of containing fewer internal ties, the process of redistributing ties to distant parts of the network may come at the expense of the strength of local community structure. By the same token, sparse interorganizational networks are likely to be subject to opposite pressures in those industries where firms generally pursue more closed (rather than more open) ego networks. Since in those industries firms tend to place their ties in more local parts of the network, the emergent systems should be characterized by stronger community structures but lower levels of connectedness. Such 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 interorganizational networks (Gulati et al., 2012). Considering the arguments advanced above, we thus formulate the following hypothesis:

> ***Hypothesis 2.*** *Variations in firms' average propensity to pursue open versus closed ego networks observed across different industries will lead to the emergence of distinct types of global, industry-wide networks showing significantly different levels of network connectedness and community structure.*

When applied to low-density networks, the hypothesis above builds on a rather straightforward association between the formation of open or closed ego networks by firms and the emergent global properties of network connectedness and community structure. In application to real-world systems, however, this hypothesis leaves several questions open. First, although we anticipate that the pursuit of open and closed ego networks will vary across different industrial settings, it is unclear how significant this variation will be. Thus, we cannot plausibly predict to what extent our conceptualization will provide sufficient explanation for the differences in global networks that are observed empirically. Clearly, low variation in firm behaviors may weaken the relationship between firm-level behaviors and the emergent industry-level networks. Second, even if we find that the variation in firms' collaborative behaviors is substantial and may potentially explain the observed differences in global networks, the precise nature of this relationship remains unclear. For instance, we cannot hypothesize exactly at what 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 structure will occur. It is unclear whether both properties will follow a linear pattern of change as implied by our argument, or will feature more complex, non-linear paths. For instance, some studies of main component formation have indicated that connectedness is rather malleable, while changes in community structure are generally more difficult to trigger (Newman and Watts, 1999). Such non-linear paths could engender the emergence of intermediate network forms, which could for example combine high levels of network connectedness with strong community structure.

To address these complexities, we test the above arguments using an agent-based simulation model. Doing so offers two benefits. First, an agent-based model does not impose strict assumptions of linearity on the hypothesized relationships. Second, the model enables 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 the behaviors of actors. This results in an interdependent system in which the evolving network is influenced not just by firms' direct interactions within dyads but also by their indirect contact to other firms, as well as by the emergent global network itself. Importantly, our approach reflects a growing emphasis on agent-based models in organizational research that occurs alongside the growing interest in network dynamics and emergence (Ahuja, Soda, and Zaheer, 2012).

ANALYSIS

Variation in Firms' Collaborative Behaviors

Our first hypothesis predicted that firms' propensities to form more open versus more closed ego networks will vary across different technological regimes. To test this hypothesis, we used data on technology partnerships in the automotive, biotechnology and pharmaceuticals, chemicals, microelectronics, new materials, and telecommunications sectors. The breadth of our sample allowed us to capture significant variation in technological dynamism across different industries and thus positioned us well to examine whether and to what extent this variation could help explain the differences in firms' collaborative behaviors. In order to examine the micro-dynamics of network formation, we tracked partnerships formed in each industry from 1983 to 1999. Because collaborative partnerships were rare prior to 1980 (Hagedoorn, 1996), focusing on this period enabled us to provide a detailed account of the collaborative history of each industry. We obtained our data from the Collaborative Agreements and Technology Indicators (CATI) database, which is among the most well-established and frequently used sources of 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.

We followed the standard procedures of prior research in using these partnerships to map the industry-wide, global interorganizational networks. Over 95% of the partnerships were bilateral, and we treated them accordingly as dyadic network ties. 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 suggesting that interorganizational partnerships last on average for 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 constructed thirteen annual global networks for each industry.[1]

We anticipated that firms in technologically dynamic industries will be likely to form more open ego networks, while firms in technologically stable industries will be likely to form more closed ego networks. In line with prior research, we captured the technological dynamism of an industry by measuring its research-and-development intensity (RDI). This index captures the aggregate R&D spending of firms in an industry per year divided by the sum of firms' total assets (Chan et al., 2001). Extant research indicates that a technologically dynamic industry should exhibit high levels of RDI because its competitive dynamics are likely to be driven by innovation and technological change (Chan et al., 2001; Rosenkopf and Schilling, 2007). We obtained the data on firms' R&D spending

[1] It is worth noting 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 network 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 global network still showed some remarkable similarities to the system mapped here, includign high network connectedness (Ibid: Footnote 17) and some discernible community structure (Ibid: Footnote 13). We thank Jason Owen-Smith for providing us additional data that facilitated these comparisons.

from Compustat and Orbis. Table 1 shows the average RDI measured for the six industries in our sample. The values indicate noticeable differences in average industry-level technological dynamism.[2]

Table 1 about here

To differentiate between closed and open ego networks, we used 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 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 each other and decreases as they become more separated. Since the pursuit of closed ego networks involves forming ties to those partners who are directly connected to each other, firms that exhibit this behavior should obtain higher levels of network constraint. By contrast, firms that are forming ties to those partners who are not directly connected to each other should obtain lower constraint levels.

Based on the analysis of ego networks, we then estimated how likely an average firm in each industry is to pursue a more open (versus more closed) ego network. In measuring these behaviors, we focused only on those firms that had formed at least one new tie in any year. Doing so allowed us to focus on the behavior of the individual firm, rather than change in the surrounding network. For each focal firm, we first estimated the firm's probability of forming a more open ego network in any year (p_i). Figure 2 illustrates this procedure. Suppose that from t = 0 to t = 3, A had 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 network was p_A = (0+0+1)/3 = 0.33. Using the same procedure, we estimated B's and C's propensities as p_B = 0.66 and p_C = 0, respectively.

[2] In additional analyses, we verified these results for a larger sample of industries. Specifically, we used data from Booz & Company's "Global Innovation 1000" series on R&D spending of 1,000 public companies over 2005-2011 to derive the average levels of RDI for our six industries in that period as well as for software & internet, aerospace and defense, and consumer-goods sectors. We found a consistent rank ordering of industries in terms of their technological dynamism.

Figure 2 about here

Following this estimation, we checked the distribution of p_i values for firms in each industry against a number of commonly known distribution functions. Our results indicated that the best fit is provided by using two discrete parameters: (a) the fraction of firms with zero probability of forming more open ego networks at any time ($frac_{p=0}$), and (b) the average probability that the remaining firms will form more open networks (p). Both parameters are reported in Table 1. We then explored the correlation between firms' average propensities to form more open ego networks and industry-level RDI. The results are summarized in Table 1: the correlation between RDI and $frac_{p=0}$ is -0.99, $p < 0.001$; the correlation between p and RDI is 0.75, $p < 0.1$. This result supports our first hypothesis that predicted more open ego networks for industries with greater levels of technological dynamism.

In additional analyses, we explored whether these differences in firms' collaborative behaviors could be attributed to an industry's degree of maturity rather than its technological dynamism. First, we specified a regression model in which we estimated the effect of an industry's RDI on a focal firm's collaborative behavior while controlling for the effect of industry maturity directly. Our dependent variable was *Constraint change*, defined as $c_{i,t}$ - $c_{i,t+1}$, where $c_{i,t}$ and $c_{i,t+1}$ represent the firm's network constraint in years t and t+1, respectively. A positive value indicated the pursuit of a more open ego network while a negative value indicated the pursuit of a more closed network. Our analysis again focused on those firms that had formed at least one new partnership in any given year. Independent variables included *Industry-level RDI* defined as the R&D intensity of an industry in year t, and *Industry maturity* defined as the 5-year average yearly growth rate in the number of firms in the 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 number of firms operating in the industry in year t (e.g., Klepper and Graddy, 1990; McGahan and Silverman, 2001). Lower growth rates typically characterize more mature industries that face diminishing market opportunities and increasing consolidation. In contrast, higher growth rates are typically associated with younger industries. We obtained the yearly counts of firms operating in each given industry from the CRSP database. In the model, we also controlled for a range of other possible determinants of firms' collaborative behaviors, all lagged by one year with respect to the dependent variable (see Table 2 for a full list of control variables).

Table 2 about here

Given the nested structure of the data, we used a multilevel mixed-effects regression model to mitigate 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 estimated at Level 1 and random intercepts specified at the firm level (Level 2) as well as the industry level (Level 3). Our additional analyses indicated that adding random coefficients at any level does not improve model fit. Table 3 reports the descriptive statistics and correlations for the independent and control variables. The mean VIF of 1.83 suggested that multicollinearity is not a serious concern (Belsey, Kuh, and Welsch, 1980). The results in Table 4 show that the effect of *Industry-level RDI* on a firm's propensity to form a more open ego network is positive and significant ($b = 1.769, p < 0.01$). This evidence confirms Hypothesis 1 and the earlier findings of our correlation analysis. Notably, this effect holds even when accounting for the effects of industry maturity (the coefficient estimate for *Industry growth rate* is statistically insignificant), firm-level R&D expenses, firm size and financial condition, as well as the firm's current levels of network constraint.[3]

Tables 3 & 4 about here
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[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 harder for firms to pursue more open network positions. Our analyses revealed that the empirical networks analyzed in this study are characterized by statistically similar density levels, which rules out the possibility that our results could be driven by network density.

Variation in Global Network Structures

In line with Hypothesis 2, we investigated whether and to what extent the empirically established differences in firms' collaborative behaviors could explain the variation in global industry-wide networks. As noted earlier, we assessed the variation in global networks using the properties of network connectedness and community structure (Figure 1). We defined network connectedness as $C = \sum_k (n_k / N)^2$, where n_k is the size of the k-th network component and N is the size of the network. This index captures how many components exist in the network and how they vary in size. Its possible values range from close to 0 for a highly disconnected network that contains many smaller components, to 1 for a fully connected network that consists of a single large component.

To measure community structure, we used the clustering method proposed by Girvan and Newman (2002), which represents a particularly robust approach to community detection.[4] In order to find the optimal partitioning of the network into communities, this method utilizes a measure of *modularity* 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* average number of ties within communities estimated from a baseline network that connects firms at random while preserving the same number and distribution of ties as in the observed network. This method thus helps evaluate to what extent the observed community structure is statistically different from that found at random. However, since the number of possible community partitionings increases exponentially with network size, in partitioning our networks we utilized an optimization algorithm based on simulated annealing (Guimerà and Amaral, 2005). This method quickly finds the maximum value of modularity

[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 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.

associated with the best community partitioning of a given network and is particularly efficient for medium-sized networks, such as those in our data (Danon, Diaz-Guilera, Duch, and Arenas, 2005).

Table 5 reports the values of network connectedness and community structure along with the size, average degree, and density of each network in our data, averaged over the study period. As expected, we found the six networks to exhibit rather distinct global forms, ranging from highly connected (biotechnology and pharmaceuticals, microelectronics, telecom) to highly disconnected systems (automotive, chemicals, new materials); and from strong (biotechnology and pharmaceuticals, chemicals, new materials) to medium community structures (automotive, microelectronics, telecommunications). Somewhat unexpectedly, we also found that the anticipated tradeoff between network connectedness and community structure does not apply to all industries: the network in biotechnology and pharmaceuticals had both high connectedness and strong community structure.[5]

Table 5 about here

To recapitulate our findings so far, our statistical analyses indicated that firms' collaborative behaviors differ across industries, in line with the variations in industries' technological regimes. We also found that there are substantial differences in the observed global, industry-wide networks with respect to their connectedness and community structure. Hypothesis 2, in turn, leads us to explore whether these global differences in network structure can be attributed to the observed variations in firm behaviors. Answering this question requires an agent-based simulation model for two reasons. First, conducting agent-based simulation essentially allows us to perform a series of experiments, where actual firm behaviors can be compared with numerous counterfactuals, many of which are not observed in our data. Doing so can position us to better understand the often complex and non-linear linkages that relate local actor behaviors to the emergence of global systems in social and

[5] Additional analyses confirmed that the observed structural differences among industry-wide networks persist over time.

economic settings (Schelling, 1978). Second, through experimenting along the entire continuum of firms' collaborative behaviors from closed to open ego networks, we can also gain a better understanding of the possible transitions among different global network forms and of their resultant typology. Therefore, an agent-based model can provide deeper insight into how strongly the observed network forms differ from one another, as well as how strongly they differ from other possible network forms that may not be observed in empirical data (Bonabeau, 2002).

Agent-based Model of Interorganizational Network Emergence

We simulated the process of network emergence by starting from a random Erdös-Rényi network with a fixed number of N firms and k ties per firm on average, where any two firms were connected with the same probability k/(N-1) (Erdos and Renyi, 1959). This approach offered several advantages (for a range of 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 among firms provided an uncontaminated testing ground for exploring how the simulated firm behaviors could transform and shape the emergent global network structures. Second, an Erdös-Rényi network also helped us approximate the empirically observed variation in partnership counts among firms in a given industry (Rosenkopf and Schilling, 2007).[6] We applied constant network size and network density to keep consistent analytic conditions across different simulations.

The global network emerges as firms form new ties with one another, thereby realizing their preferences for more open or 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

[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 would perhaps be able to 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 structure that may equally affect firms' collaborative behaviors (Rosenkopf and Schilling, 2007). According to our results, for example, the strength of community structure varies from medium to strong between different contexts. Our model, which limits firms' focus to their ego networks (rather than broader communities) thus allows for extending the analysis to a wider spectrum of interorganizational networks with variable degrees of community structures.

this process works. Suppose that A is the ego; B, D, and E are A's current contacts; and C, F, G and H are A's potential alters. A first ranks the alters according to its *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 tie to a given alter ($c_{A,t+1}$=[0.46, 0.48, 0.66]). In our example, the greatest negative change in ego's network constraint is associated with alter G ($c_{A,t+1}$ = 0.46); the greatest positive change is associated with alter C ($c_{A,t+1}$=0.66). Depending on ego's preference for a more open or more closed ego network, A should thus partner either with 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 largest *decrease* in network constraint for the ego. The ego's probability to pursue an alter associated the largest *increase* in constraint was thus 1 - p. To ensure some degree of matching between the preferences of the ego and the alter, a tie would be formed only if it was consistent with the alter's preference structure as well.[8] Otherwise, the ego would pursue the next best option. We set the same level of p for all firms in an industry and used this modeling approach to distinguish a given industry from another collaborative setting characterized by a different level of p. However, even though all firms in an industry were thus subject to the same average propensity to pursue a more open ego network, in practice the model featured substantial behavioral heterogeneity among firms because of the stochastic nature of this process, which allowed individual firms to act differently than the average firm. In addition, each firm could also be exposed to different local

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

opportunities in terms of the availability and access to potential alters (cf. Ibarra, Kilduff, and Tsai, 2005). Taken together, these factors ensured close representation of a real-world industrial setting.

Building on prior work, we also included a range of other behavioral mechanisms to ensure a highly realistic model. First, since organizational agents are unlikely to observe the entire social space around them, we assumed that the ability of an ego to observe any potential alter declines as a function of network distance (Friedkin, 1983). Formally, the probability that i could observe j was specified as $1/(d_{ij}-1)$, where d_{ij} was the number of links along the shortest network path between i and j. Should j be entirely unobservable to i by virtue of residing in a different network component, we assumed that the connection 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 where both isolates and unconnected components can sometimes join the core of the network.[9]

Second, we assumed that two partners can terminate their existing tie and that the likelihood of termination varies with the duration of a relationship. In modeling this process, we built on prior research indicating that partnership terminations are often time-consuming and costly, and that partners typically avoid premature terminations before their contract expires (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 normal distribution for the duration of ties with the mean of 10 and a standard deviation of 2 time steps. With the simulation length of 100 time steps, our analysis thus extended over 10 full partnership rounds by firms.[10]

Third, to preserve constant network density over time, we set the number of ties terminated in each time step equal to the number of new ties created by firms in that time step. We formalized

[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 from new partnerships and to reenter the network (Powell et al., 2005).
[10] It may be helpful to apply these modeling choices to the dynamics of real interorganizational ties, where two simulation steps may correspond to one year in the data. This means that 10 time steps correspond to 5 years, which constitutes the typical lifespan of a interorganizational tie in our empirical sample. Our entire analysis should thus be regarded as equivalent to tracing the evolution of a real interorganizational network over the period of 50 years.

this process by first selecting two random subsets of firms that were chosen independently of each other but could overlap. Both subsets had the same size set to 15% of the entire network, which 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 existing tie per time step. Finally, we also provided additional model realism by allowing firms to connect to entirely new partners as well as to their current or past partners.

Results: Empirical Validation Against Data

We aimed to validate the model by exploring how closely it represents real collaborative behaviors of firms observed across different industrial settings. A useful validation test entails examining whether —when supplied with the actual collaborative behaviors of firms—the model reproduces roughly the same levels of network connectedness and community structure as those found in the real world (Davis et al., 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 create 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 the simulated networks with their corresponding empirical values (see Table 1). For each industry, we conducted 100 simulations to ensure that the results are not affected by stochastic variation, and recorded the average levels of connectedness and community structure along with their standard deviations.

We then compared those values statistically with the corresponding properties obtained from real interorganizational networks using z-scores. Specifically, for network connectedness we used $z_C = [C - E(C)] / \sigma_C$, where C is the connectedness of the empirical network, while E(C) and σ_C are the average and standard deviation of connectedness measured for the simulated network (Szell, Lambiotte, and Thurner, 2010). For community structure, we used $z_Q = [Q - E(Q)] / \sigma_Q$ where Q is the modularity of the empirical network, while E(Q) and σ_Q are the average and standard deviation of simulated modularity. Results (Table 6) reveal close empirical correspondence of the simulated networks, indicating that our model is valid (Davis et al., 2007).[11]

Table 6 about here

Results: Topological Transitions and Variation in Global Networks

To understand the link between firms' behaviors and the emergent global networks more precisely, we extended our agent-based simulation across the entire range of conceivable values of $frac_{p=0}$ and p. We obtained those 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 $101 \times 101 = 10{,}201$ analytic cases. To achieve a more realistic representation of an interorganizational setting, we again followed our descriptive results and those of prior research in specifying the key parameters of the model (Rosenkopf and Schilling, 2007). This involved modeling a medium-sized network of 200 firms, with an average of 4 ties per firm (see Appendix 2 for alternative specifications). For each set of p values, we simulated the network for 100 time steps to ensure stability in the emergent global properties (see Appendix 1 for a formal analysis). To mitigate stochastic variance, we repeated the simulation 100 times for each analytic case and recorded the average levels of network connectedness and community structure. The complete analysis thus involved 1,020,100 different simulation runs.

We summarize the findings in Figure 4 using two-dimensional heat maps. The results are consistent with the basic intuition of our second hypothesis, which suggests that as firms' propensity for open ego networks increases, the emergent global networks should become more connected and should exhibit weaker community structures. Two results are particularly striking, however. First, Figure 4a indicates that a sharp initial increase in network connectedness occurs over a relatively

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[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 global networks. We therefore additionally tested a range of alternative models of network formation among firms. We report the results in the robustness section.

narrow range of p values, thus resembling a rapid phase transition toward a globally connected network form (Holme and Newman, 2006). Second, Figure 4b documents that community structure follows a more stable pattern over p; it is noteworthy, however, that the initial increase in p is accompanied by growing (rather than declining) community structure. This appears somewhat at odds with our second hypothesis, which predicted that in sufficiently sparse systems the formation of open ego networks should weaken (rather than strengthen) community structure.[12]

To gain a better understanding of exactly when the changes in p result in different global network forms, Figure 5 examines the transitions in connectedness and community structure over the entire scale of p values. Using a representative set of scenarios with low $frac_{p=0}$, medium $frac_{p=0}$, and high $frac_{p=0}$, we first fitted a series of Bézier curves to smooth out the average results obtained across different simulations (Farin, 1997). Using their first-order derivatives, we then assessed at precisely at which p values the fitted curves indicate key inflections in network connectedness and community structure.[13] The results suggest a rather complex, non-linear pattern of co-variance that occurs along the same set of inflection points ($p = 0.15$, $frac_{p=0} = 0$; $p = 0.22$, $frac_{p=0} = 0.35$; and $p = 0.34$, $frac_{p=0} = 0.70$ for both properties). Within this pattern of co-variance, there are certain intervals that are characterized by rather intuitive transitions, such as the rapid growth of a highly connected system at low p values and the subsequent decline in community structure at medium-to-high p values. However, the results also indicate that a simple linear trade-off effect between network

[12] One way to understand these results is to explore where the observed changes in community structure may come from: the inside or the outside of the main network component. As firms create more open ego networks, the initial boost in community structure may come from the outside and be the result of integration of other, smaller network components into the main component. However, given only weak firm propensities toward open ego networks, this process is unlikely to fully absorb other components and eliminate any emergent community structure. Instead, the integrated components may continue to exist inside the main component as distinct network communities. But once the transition toward a connected network is over, firms' opportunity to pursue more open ego networks by connecting to outside components may diminish. Instead, firms may be increasingly required to pursue open ego networks by connecting across the separate network communities that exist inside the main component. These dynamics may thus form the basis of an initial rise and a subsequent decline of community structure, as observed in our results.

[13] These analyses are not reported but are available upon request.

connectedness and community structure does not occur at all levels of p. Instead, the plots show a concurrent rise in *both properties* at low p and a stable pattern of connectedness at medium-to-high p.[14]

Figure 4 about here

Figure 5 about here

Results: General Typology of Emergent Global Networks

Based on the above results, we identify three distinct archetypes of global networks that emerge as a result of varying firm preferences towards more open versus more closed ego networks. These network archetypes are characterized by significant differences in network connectedness and community structure (see also Figure 6). The first network archetype is characterized by low connectedness and medium-to-strong community structures. Because this configuration is reminiscent of a set of clans with strong in-group ties and almost no ties to other groups, we call it a *clan network* (Figure 6a). In our results, clans were 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 strong community structure. It is noteworthy that this structure corresponds to an intermediate network form linked to the critical non-linearities that were uncovered by our agent-based model. In view of the sparsely interconnected and dense network communities that populate this system, we call it a *community network* (Figure 6b). Our analysis indicated that community networks are associated with firms' moderate propensities towards forming more open ego networks. For example, in the set of

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

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 is characterized by high connectedness and medium-to-weak community structures.[15] Notably, this structure features more disorder than the previous two, bearing some resemblance to a large public gathering or a convention; we therefore call it a *convention network* (Figure 6c). In our results, convention networks were associated with strong firm propensities towards more 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 models (Table 7), we found that this typology represents a set of statistically significant differences in network 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 visualized in Figure 6d.[16]

Figure 6 about here

Table 7 about here

In a representative application of our typology, we explored which network archetypes characterize the six industries in our data. Given that the networks in automotive, chemicals, and new materials were found to combine low-to-medium connectedness with strong community structures, and that this configuration seemed to be the result of relatively weak firm propensities towards more open ego networks, we can classify these systems as *clan networks*. In turn, the networks in biotechnology and pharmaceuticals, microelectronics, and telecommunications were all found to

[15] Our description of a *convention network* as a network with weak community structure is consistent with some other work on network cohesion including, for example, the work of Moody and White (2003), which defined cohesion as the presence of *multiconnectivity* among a group of actors. According to this view, cohesive social groups are the ones that manage to withstand separation even in the face of losing multiple in-group ties. Although it is possible that an entire global network could display such a property by virtue of offering sufficient tie redundancy to withstand separation, the convention networks we traced in our model were not sufficiently dense to provide such system-level cohesion.

[16] 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).

combine high connectedness with strong community structures and were driven by moderate firm propensities towards open ego networks. Hence we can classify them as *community networks*. To illustrate this classification, in Figure 7 we provide two real-world images of (a) a clan network in new materials in 1994, and (b) a community network in telecommunications in 1994. Broadly speaking, these results suggest that *clan networks* may be associated with technologically 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. We address this finding in the discussion section.

Figure 7 about here

DISCUSSION

This study was motivated by the recognition that global networks in different social and economic settings vary in terms of their structural properties, and that this variation can be consequential for a range of collective outcomes. With this insight in mind, we set out to explore the antecedents of the differences in global network structure. Our methods combined agent-based simulation models with empirical analyses of interorganizational partnership networks in six industries. The study showed that firms' collaborative behaviors vary with the technological dynamism of their industry, and that this variation leads to the emergence of three distinct global network archetypes.

Overall, our findings represent an important step toward an environmental contingency theory of network formation, which proposes a close association between the characteristics of the environment in which actors reside and the processes of network formation among actors. We thus suggest that organizations may be responding to environmental demands not only in terms of their internal organizational design (Lawrence and Lorsch, 1967), but also in terms of their collaborative behaviors with other organizations. The main findings of the study are twofold. First, we found that in technologically dynamic industries firms on average tend to pursue more open ego networks. In contrast, in technologically stable industries firms on average tend to pursue more closed ego networks. This effect likely indicates that firms in technologically dynamic industries may favor the pursuit of novel and non-redundant knowledge and resources over the preservation of existing resources, which is best enabled by open ego networks. In technologically stable industries, in turn, firms may favor the preservation of their existing resource base over access to new knowledge and resources, which is best enabled by closed ego networks.

Second, we found that the variations in firms' collaborative behaviors closely explain why and how the interorganizational networks that emerge in different industries vary in terms of their global topology. Specifically, our results indicated that even though the local differences in firms' behaviors may seem rather subtle, they still result in entirely different global network forms that exhibit distinctive levels of network connectedness and community structure, and which emerge from complex interactions between firms' behaviors and global network structure. With respect to this non-trivial finding, our results indicated that technologically stable industries are characterized by the emergence of *clan networks* that feature weak network connectedness and medium-to-strong community structures, while technologically dynamic industries are characterized by the emergence of *community networks* that feature high network connectedness and medium community structures.

Interestingly, while our model indicated the emergence of a third network type, a *convention network* that exhibits high connectedness and weak community structure and is linked to high firm propensities toward open ego networks, such a network was not found in our data. One possible explanation is that firms might be driven toward closed ego networks by a number of potent forces. For example, the formation of closed ego networks could correlate with geographic proximity, which could enable firms to draw on the economic efficiencies and the institutional support mechanisms of a regional cluster (Krugman, 1991; Marquis, 2003). Alternatively, firms could agglomerate into dense network communities based on structural similarities and homophily (Powell et al., 2005). Finally, forming closed ego networks could be driven by inertia and the comfort of familiarity, which might overshadow the economic imperatives of collaboration (Li and Rowley, 2002).

The same forces might also serve to align firms' private goals with the shared goal of creating a global network that 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 reduce the 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 the environment. By this logic, firms might be increasingly adapting their collaborative behaviors to respond to the requirements of value creation present in their industry. Should one network type be better suited to satisfy these requirements (e.g. a *community network*), it may be more likely to form and be sustained over time than others. Though our theory focused on the requirement of knowledge transfer among firms, future research could extend this logic to a wider range of systems and outcomes (e.g., Powell et al., 2005). In some systems, for example, environmental adaptation could reflect the need to minimize the costs of forming new ties or the need to avoid network failure (Jackson and Wolinski, 1996; Schrank and Whitford, 2011).

The Implications of Global Network Types for Collective Outcomes

To manage the scope of the study, we have deliberately limited our analyses to firms' collaborative behaviors and the resulting variation in global, industry-wide network forms. Of course, underlying this focus is an assumption that variation in global networks is consequential for a range of collective outcomes. We briefly explored the validity of this assumption in our supplementary analyses, where we modeled a simple process of knowledge diffusion across an industry. In line with prior research, we considered a basic process of diffusion where the probability of knowledge transfer between two firms is a function of (a) existence of a network tie between them, and (b) their familiarity and trust in each other (Rogers, 2003). We modeled firms' familiarity and trust using the total number of their current and past direct ties and the fraction of ties held to the same third parties, respectively (Gulati, 1995). We considered a realistic model of network diffusion where new knowledge diffuses in parallel with the process of network emergence (Cowan, 2005).[17] We subsequently evaluated how quickly and broadly knowledge can diffuse across such an emergent global network.

Our results indicated that, among the three archetypes of networks analyzed in this study, community networks have the greatest capacity to sustain the diffusion dynamics. 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 system. Second, they also help firms develop a higher degree of familiarity and trust in each other, which is enabled by the structure of dense and cohesive network communities. Clan networks provide a relatively strong community structure as well, but they fail to offer enough global range to facilitate knowledge access. Thus, in comparison with community networks, clan networks inhibit diffusion.

Interestingly, we found that clan networks tend to perform better at spreading new knowledge among firms than convention networks. Given that firms are significantly more isolated from one another in a clan than in a convention network, we expected to see the opposite result (cf. Davis and Greve, 1997; Westphal, Gulati, and Shortell, 1997). In additional analyses, we found that clan networks provide a highly dynamic network setting that assures sufficient access to new knowledge via temporary ties that span different network components (see Online Supplements 2-3). Over time, these transient bridges may serve as effective substitutes for permanent connections, mitigating the negative effects of low network connectedness that characterizes a clan network.

[17] Modeling the dynamics of network formation independently from the dynamics of diffusion is consistent with the bulk of empirical work on 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 global network on diffusion outcomes. Of course, in some diffusion scenarios, the dynamics of network formation could be shaped by actors' desire to access knowledge via newly formed ties. Future work could examine such complex dynamics between network structure and diffusion in more detail.

One example of a transient bridging tie in our data was the joint venture created in 1989 by the Japanese automaker Daihatsu and Balkancar, a state-owned Bulgarian manufacturer of large utility vehicles. The goal of this partnership was to exchange knowledge and pool resources to produce the first Japanese-Bulgarian truck. Though the partnership got off to a good start and managed to enable substantial knowledge transfer, it got dissolved as political turmoil swept across Eastern Europe in the early 1990s. The two companies have not collaborated since, and ties between the members of their respective network communities have been equally rare. Another example of a transient bridge was the 1992 alliance between BP and the Japanese new materials specialist Ube Industries. Their goal was to transfer knowledge and technology with hr goal to develop a new line of low-density plastics. The contract expired in 1997 and no subsequent agreements between the two firms have been registered. Given that the network communities to which both firms belonged remained separated over time, this transient bridge also stands out for its role in supporting knowledge flows across wide parts of the interorganizational network (see Online Supplement 3).

Existing studies treat network connectedness as the key determinant of network diffusion (Coleman, Katz, and Menzel, 1957; Watts and Strogatz, 1998; Cowan, 2005). Our study and the examples above, however, suggest that global access does not necessarily require high levels of *static* network connectedness. Even if the global network appears as being rather disconnected, this static image could mask the system's capacity to compensate through short-term transient bridging ties that can offer sufficient range, albeit over short periods of time. An important implication of this finding is that understanding collective outcomes may require reframing connectedness as a *dynamic* network property. As suggested by our additional results, understanding connectedness as a dynamic property can significantly enhance our conclusions with respect to the link between structure and diffusion.

Contributions to Studies of Social Systems

This paper offers several contributions to studies of social systems. First, we advance the study of social embeddedness of economic action (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 their social system. Our primary insight is that the variation in actors' network behaviors observed across different social and economic contexts helps explain the emergent variation in global networks, and we find that these differences are stable over time. Our work thus extends recent 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 global networks may show different structures not just over time but also across different contexts. More importantly, we relate these differences to varying behavioral tendencies of actors, such as the propensity to form open or closed ego networks, and demonstrate their linkage to different industrial settings, their levels of technological dynamism, and the associated requirements for value creation.

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

In particular, the typology of clan, community, and convention networks allows for a more precise classification of sparse global networks than do alternative typologies that use such measures as betweenness centralization, closeness centralization, degree centralization, and the small-world quotient (e.g., Uzzi and Spiro, 2005). First of all, our typology is applicable to a broader range of network structures, including highly fragmented structures for which many of these alternative measures are undefined. Since the emergent *clan*, *community*, and *convention networks* are differentiated in part by their degree of network connectedness, using our typology can allow scholars to precisely assess not only how global networks differ structurally but also how they shape actors' collective outcomes. Additional analyses we conducted showed that none of the alternative measures mentioned above could capture the emergent differences in global networks as precisely as the combination of network connectedness and community structure. The centralization metrics produced only two crude network forms, whereas 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 the alternative typologies in terms of explaining diffusion outcomes (by a factor of 1.8 to 8.8 depending on which alternative typology was used).

Third, the results of this study 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 firms' collaborative behaviors and the technological dynamism of their industry, which is essential for understanding the variation in global network forms. This connection helps reconcile some of the conflicting findings regarding how social networks emerge and how they affect actors' actions and outcomes (cf. Kilduff and Brass, 2010). For example, this study sheds more light on why closed ego networks may prevail in the technologically stable contexts such as the automotive industry or new materials (Gulati, 1995) but not in the dynamic context such as biotechnology and pharmaceuticals (Sytch and Tatarynowicz, 2014b). Our study also helps clarify why chemical companies have been found to benefit from closed ego networks (Ahuja, 2000), while 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. Though our goal has not been to examine how a firm's network position affects its performance, the findings of this study suggest that one way for future research to explore this link would be to account for baseline differences in the value-creation regimes across different industries.

Appendices

Appendix 1: Stability of the Emergent Global 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 equals the constraint of any given firm. For this condition to hold, we assume maximum density of ties within components.

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

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

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

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

Since K << N, 1 + K/(N-K) → 1. By substituting, we can simplify the above equation to:

$$c_i = \frac{K}{N-K} \qquad (3)$$

By solving the above for K, we get:

$$K = N\frac{c_i}{1+c_i} \qquad (4)$$

The above formula captures the relationship between the number of components K and the network constraint of any firm. To derive the association between network connectedness C and network constraint, we substitute K = 1/C and solve for C:

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

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

$$C'(c_i) = -\frac{1}{Nc_i^2} \qquad (6)$$

This formal result captures the relationship between stability of the global network (C') and stability of firms' ego networks. It suggests that once firms obtain their optimal constraint levels such that no further changes can be made, then – *ceteris paribus* – the emergent global network should stabilize as well.[18] To understand when this happens, we explored how long it takes for a typical firm to obtain an optimal constraint level. To do so, we assumed that the firm must replace all its initial ties, which were assigned to it at random at t = 0. Since the likelihood of forming a new tie is 0.15 and every firm is initially assigned 4 ties, replacing these ties will take 4/0.15 ~ 27 time steps. The most critical changes in the firm's ego network should thus occur over the first 20-30 time steps of the model.

We validate this conclusion through simulation and present the results in Figure 8. Figure 8a traces firms' average constraint levels in a typical clan network ($frac_{p=0}$ = 0.9, p = 0.1), community network ($frac_{p=0}$ = 0.7, p = 0.3), and convention network ($frac_{p=0}$ = 0.2, p = 0.8). Figures 8b-8c, in turn, plot the related changes in network connectedness and community structure, respectively. The results show that stable ego constraints indeed emerge just over the 20-30 time steps of the model and are closely related to the emergence of stability in global network properties.

Figure 8 about here

Appendix 2: Robustness Analyses

We conducted a number of additional tests to see if our results are robust to alternative parameters or model specifications. First, we tested some alternative values of network size and density. In our main analysis, we used the values that were supplied by our own data and were also consistent with prior work on interorganizational networks (Rosenkopf and Schilling, 2007). In additional tests, we extended our modeling to a broader range of network sizes (N = 2,000 and N = 20,000) and density levels ($2 \leq k \leq 6$). The results were similar to those reported in the paper. The only difference was when we applied an extremely low network density (k = 2). Under these conditions, the emergent network was too sparse to obtain global connectedness at any 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). While such extremely sparse networks are rare in the interorganizational setting, some studies have identified the occurrence of sparse networks in certain industries, such as footwear 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, such as (a) the regular network where every firm is connected to four other firms, and (b) the small-world network where most firms are connected to four other firms but 10% of the firms are randomly reconnected (Watts and Strogatz, 1998). Further, in addition to the Erdös-Rényi random network model used in the paper, we also tested a few alternative random models with variable degree distributions. These included (a) a normal degree distribution with the mean and standard deviation of 4.0, (b) a log-normal distribution with the mean and standard deviation of 4.0, (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 our main model.[19]

[18] 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 components), where community structure Q increases proportionally to K. Following the same reasoning as above, we can express the stability of global community structure as a function of stable ego networks as $Q'(c_i) = N/(1+c_i)^2$.

[19] 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 why firms might choose between open and closed ego networks is related the benefit and costs of these distinct positions, which may 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, we were able to account for these various types of costs indirectly. For example, a normal degree distribution implied that firms could realize certain benefits and synergies from multiple ties, however only as long as their number does not exceed the mean value of four. Beyond this threshold, the partnership costs would start to rise and would eventually

Third, we considered a model with greater behavioral heterogeneity of firms in an 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 empirical data. In an alternative specification, we assumed that p is not fixed but varies randomly across the population of firms. We considered five model versions using a normal distribution of p values with the mean set between 0 and 1 and the standard deviation increased from 0.1 to 0.5, in steps of 0.1. Introducing this additional behavioral heterogeneity did not affect our main 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 an ego's visibility to a certain maximum range, beyond which no alter can be "seen". To implement a limited range of visibility, we therefore specified an alternative model where the ego can observe only those alters who are up to d_{max} links away. We tested values from $d_{max} = 2$, which corresponds to the shortest possible 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 co-variance between network connectedness and community structure, but with absolute values of both properties substantially lower than those observed in our data. Such a poor fit was particularly evident in the case of the automotive industry, chemicals, and new materials, where firms were generally found to pursue more closed ego networks. For this set of industries, we found that the maximizing model on average underestimates the true level of network connectedness by about 75% and of community structure by about 60%.

Sixth, we considered an alternative mechanism by which firms could dissolve their existing ties. To reflect the contractual nature of interorganizational partnerships, in the main analysis we assumed that partnership duration is solely a function of time. In the alternative model, we also tested whether, in addition to the passage of time, tie dissolution could be driven by firms' desire to create a more open or more closed ego network. Yet, we found that this model yields a substantially poorer fit for lower p values, producing networks with substantially lower network 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 any empirical case.

Seventh, rather than specifying network connectedness as a variation in component sizes, we measured connectedness as a fraction of dyads accessible to one another via an existing network path of some length. This alternative measure turned out to be strongly correlated with the original measure 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 partners and the partners they already 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 partners over those with fewer ties (e.g., Barabási and Albert, 1999; Powell et al., 2005). We first checked whether both models are supported empirically. We found that our data provides some support for the first model but not the second, offering no

exceed the benefits. The power-law distribution, in turn, implied an exponential increase in partnership costs. Such an increase might eventually outweigh any benefits and synergies that firms could realize from having multiple ongoing ties.

evidence of preferential attachment among firms. This insight is consistent with some recent empirical work on the dynamics of interorganizational networks showing that firms are unlikely to be unconditionally attracted towards more central partners (Powell et al., 2005; Gulati et al., 2012). We then checked the validity of the first model that distinguishes between new and known partners and found that it substantially underestimates the true levels of network connectedness (by 60%) and community structure (by 65%) across our six empirical cases. This suggests that when compared to other established models of interorganizational networks, the model proposed in this study provides a highly realistic representation of firms' collaborative behaviors in various industrial 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. Full list of control variables used in the regression model.

Variable	Definition
Sales	Firm's sales in year t. Captures firm size (logged due to skewed distribution).
ROA	Firm's return on assets, defined as the ratio between the firm's net income and its total assets. Captures firm's financial condition in year t.
Firm-level RDI	Firm's R&D intensity, defined as the ratio between firm's R&D spending and its total assets in year t. Controls for the possibility that the formation of an open ego network could reflect the firm's own technological dynamism rather than the dynamism of an entire industry (logged due to skewed distribution).
Firm's network constraint	Firm's network constraint in year t. Accounts for the characteristics of the firm's current ego-network position.
Network size	Total number of firms present in the network in year t. Controls for the possibility that a larger interorganizational network could make it structurally easier for firms to pursue open ego networks.
Network average degree	Average number of network ties per firm in year t. Controls for the possibility that a sparser interorganizational system could make it structurally easier for firms to pursue open ego networks.
Industry concentration	Herfindahl–Hirschman index of industry concentration (Hirschman, 1964), defined as the sum of squares of the annual sales of the 50 largest firms in the industry. Captures the industry's competitive intensity in year t.
Year-level fixed effects	Set of 11 binary indicators for the observation year; 1987 is specified as the default year.

Table 3. Descriptive statistics and bivariate correlations matrix.

	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	*Firm's 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 growth rate*	0.030	0.019	-0.052	-0.024	0.066	0.093	-0.063	-0.251	0.473	0.058	1.000

Table 4. Three-level mixed-effects regression model with random intercepts.

	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)
Firm's 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-level fixed effects	Included
Industry-level RDI	1.769*** (0.585)
Industry growth rate	0.733 (2.113)
Observations	1,253
Log-likelihood	654.6

*Standard errors in parentheses; ***p<.01, **p<.05, *p<.10.*

Table 5. 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 6. 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 model 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 7. 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. Network connectedness and community structure.

(a) low connectedness (b) high connectedness (c) weak communities (d) strong communities

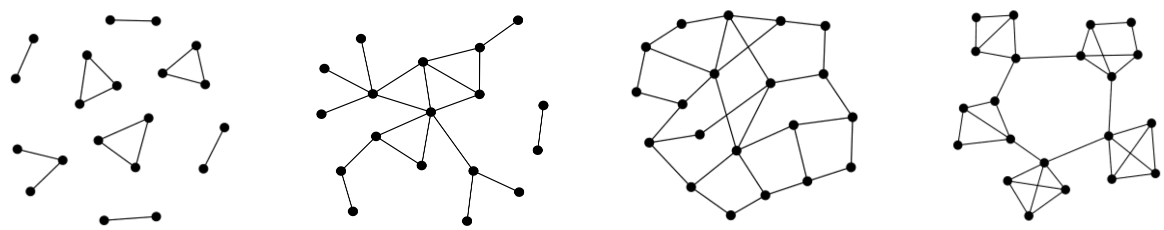


Fig. 2. Estimation of a firm's propensity to pursue open ego networks.

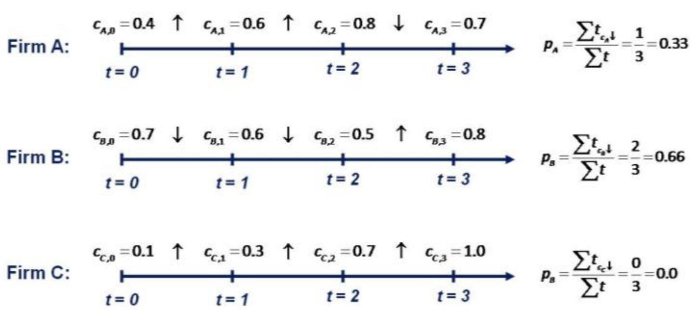


Fig. 3. The process by which network ties are formed (A is the ego, B-H are alters).

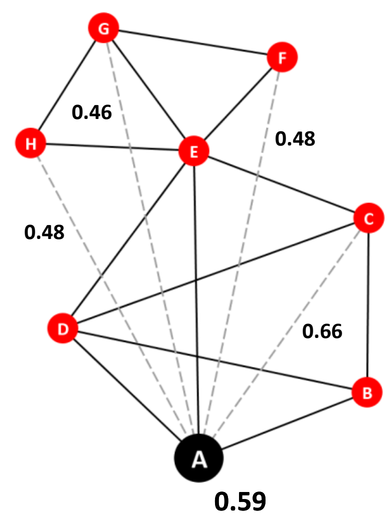


Fig. 4. Network connectedness and community structure produced by the simulation model at t = *100* time steps.

(a) network connectedness (b) community structure

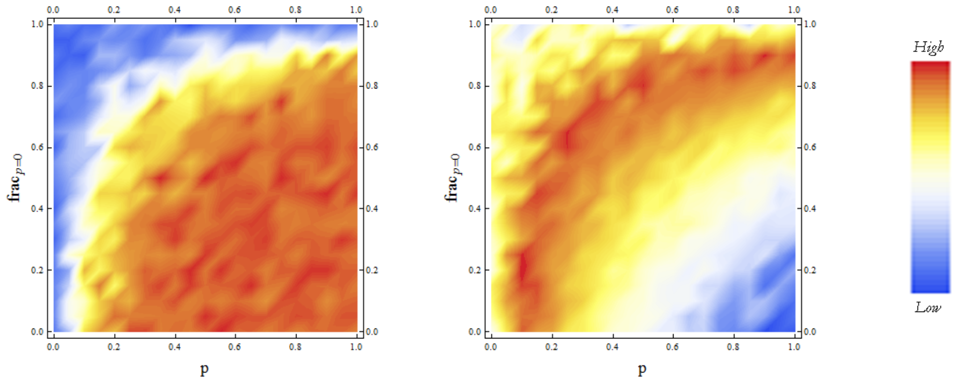


Fig. 5. Smooth Bézier curves capturing the critical transitions in network connectedness and community structure. The curves represent three distinct scenarios with low $frac_{p=0} = 0$, medium $frac_{p=0} = 0.35$, and high $frac_{p=0} = 0.70$, respectively.

(a) network connectedness (b) community structure

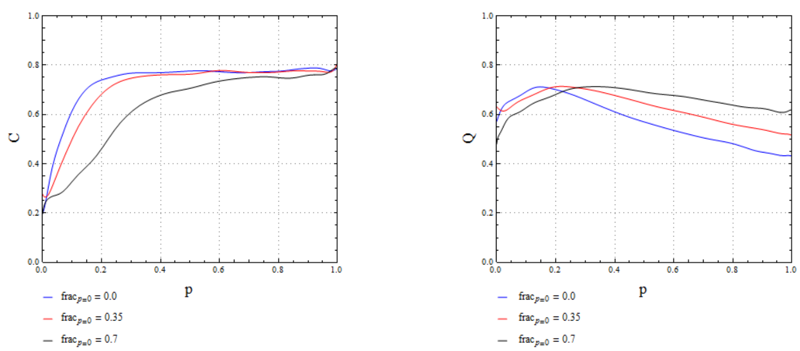


Fig. 6. Typical structure of a (a) clan network, (b) community network, and (c) convention network. Figure 6d summarizes the overall typology with respect to $frac_{p=0}$ and p.

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

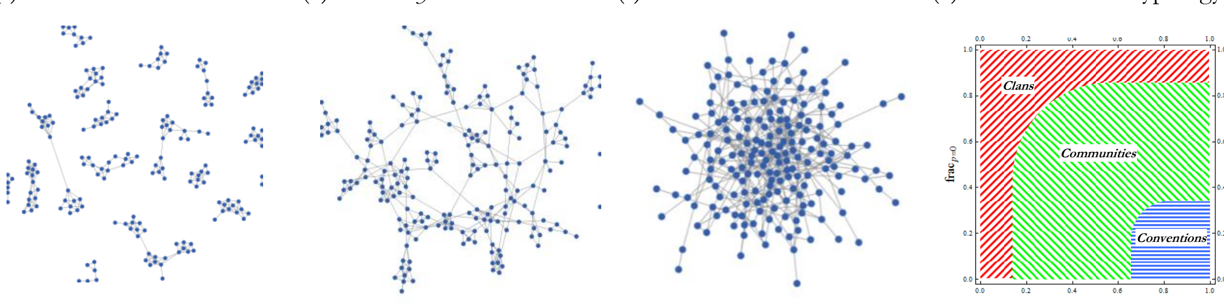


Fig. 7. Two representative images of a clan network and a community network obtained from the dataset.

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

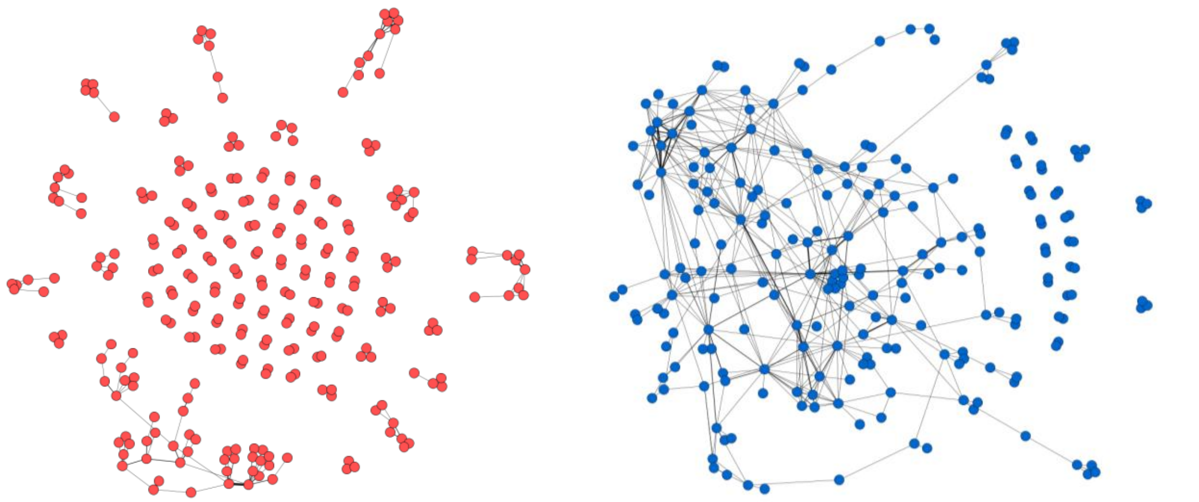
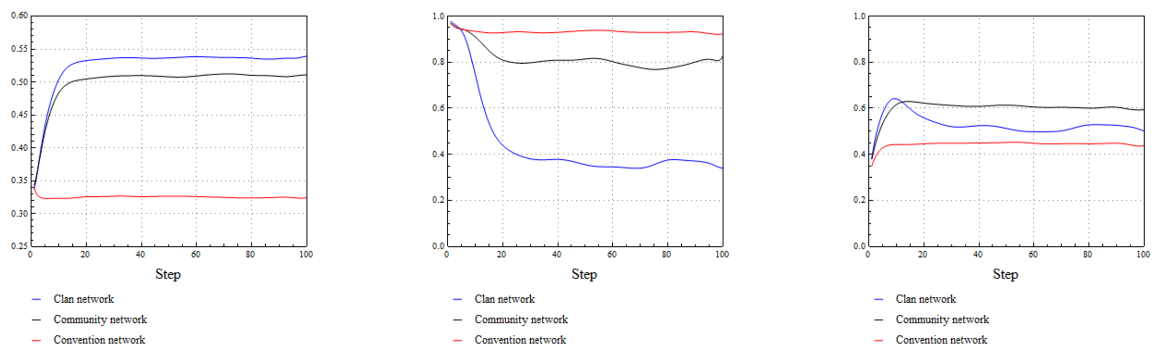


Fig. 8. Relationship between the stability of firms' ego networks (a) and the emergent global network properties (b-c).

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



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