ONLINE APPENDIX

Appendix A: Robustness Analyses

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

Second, we varied the starting conditions of the simulation. We specifically extended the set of initial networks to two other stylized networks: (a) the regular network in which every firm is connected to four other firms, and (b) the small-world network in which most firms are connected to four other firms but 10 percent of the firms are connected at random (Watts and Strogatz, 1998). Furthermore, in addition to the Erdős–Rényi random network used in the paper, we also tested four alternative random networks with variable degree distributions. These included (a) a normal degree distribution with a mean of 4 and a standard deviation of 4, (b) a log-normal distribution with a mean of 4 and a standard deviation of 4, (c) an exponential distribution with $\lambda = 2.5$, and (d) a power-law distribution with $\gamma = 2.5$. All these models produced similar results to those reported in the paper.¹

¹ In addition to reaffirming the robustness of our main model, changing the initial degree distribution also allowed us to validate our assumptions with respect to the costs of interorganizational ties. Our theory postulated that one reason firms might choose between open and closed ego networks relates to the benefits and costs of these distinct positions, which might vary across industries. Yet interorganizational partnerships could also involve other types of costs, such as the costs of managing and coordinating across different collaborations. By considering other degree distributions, one can account for these various types of costs indirectly. For example, a normal degree distribution implies that firms could realize certain benefits and synergies from multiple ties but only provided that their number does not exceed the mean value of four. Beyond this threshold level, the partnership costs would start to rise and would eventually exceed the benefits. The power-law distribution, in turn, implies an exponential increase in
Third, we considered a model with greater behavioral heterogeneity of firms in the industry. Our main model assumed that firms in a given industry would choose between open and closed ego networks with a certain probability $p$, equal for all firms. This specification offered the best fit to the data. In alternative specifications, we assumed that $p$ is not fixed but varies randomly across firms. We considered five different specifications of this model using a normal distribution of $p$ with a fixed mean between 0 and 1 and a standard deviation that varied from .1 to .5 (in .1 increments). Introducing this additional behavioral heterogeneity to the model did not affect our results.

Fourth, we revisited our assumptions regarding firms’ visibility across the wider network. The assumption we made in the main analysis was that the extent to which an ego can observe potential alters is inversely proportional to network distance. One possibility to extend this model is to restrict ego’s visibility to a certain maximum range, beyond which no alter can be “seen.” To implement a limited range of visibility, we specified an alternative model in which the ego can observe only those alters who are up to $d_{\text{max}}$ links away from the ego. We tested values from $d_{\text{max}} = 2$, which corresponds to the shortest distance between any two unconnected firms, to $d_{\text{max}} = 10$, 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 showed the same pattern of covariance between network connectedness and community structure but with absolute values of both properties substantially lower than those observed in the data. Such a poor fit was evident particularly for the automotive industry, chemicals, and new materials, in which firms were found to pursue more-closed ego networks. For this set of industries, we found that the maximizing model on average underestimates the observed levels of network connectedness by about 75 percent and of community structure by about 60 percent.
Sixth, we considered an alternative mechanism by which firms can dissolve their existing ties. To reflect the contractual nature of interorganizational partnerships, in the main analysis we assumed that partnership duration is a function of time. In the alternative model we tested whether, in addition to the passage of time, tie dissolution can be driven by firms’ desire to create a more-open or a more-closed ego network. We found that such a model yields substantially poorer fit to the data over low to medium \( p \) values, producing networks with substantially lower levels of connectedness (on average 50 percent below the main results) and weaker community structures (on average 80 percent below the main results). As a result, we were unable to validate this model against our six empirical networks.

Seventh, rather than measuring network connectedness through the variation in component sizes, we specified connectedness as the fraction of dyads that are accessible to one another via an existing network path of some length. This alternative measure strongly correlated with the original measure of connectedness used in the paper (at over .8), and the main results remained unchanged.

Finally, we verified our model against two other models of network formation established by prior research: (a) a model in which firms select between entirely new alters and the alters they know through previous ties (e.g., Beckman, Haunschild, and Phillips, 2004; Baum et al., 2005) and (b) a model in which firms follow the strategy of preferential attachment by favoring highly central actors (e.g., Barabási and Albert, 1999; Powell et al., 2005). We first checked whether these models are supported empirically. We found that our data provide some support for the first model but not the second one, offering no evidence of preferential attachment among firms. This insight is consistent with recent work on the dynamics of interorganizational networks, which showed that firms are unlikely to be unconditionally attracted to central partners (Powell et al., 2005; Gulati, Sytch, and Tatarynowicz, 2012). We then checked the validity of the first model, which distinguishes between new and familiar partners, and found that it underestimates the empirical levels of network connectedness by about 60 percent and community structure by about 65 percent. This suggests that when compared with other agent-based models of network emergence, the model proposed in this paper provides a realistic account of firms’ collaborative behaviors with broad relevance across different empirical contexts.
Appendix B: Stability of the Emergent Industry-wide Networks

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

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

$$
c_i = (n-1) \left[ \frac{1}{n-1} + \left( \frac{1}{n-1} \right)^2 \right]^{\frac{1}{2}}
$$

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

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

Because $K \ll N$, $1 + K/(N-K) \to 1$. By substituting, we could simplify equation (2) to:

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

By solving the above for $K$, we got:

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

Equation (4) captures the relationship between the total number of network components ($K$) and the constraint of any given firm ($c_i$). To derive the association between network connectedness ($C$) and constraint, we substituted $K = 1/C$ and solved for $C$:
This suggests that network connectedness decreases proportionally to firms’ constraint (0 ≤ c_i ≤ 1). The precise rate at which connectedness decreases is given by the derivative of C with respect to c_i:

\[
\frac{dC}{dc_i} = -\frac{1}{Nc_i^2}
\]  

Expression (6) captures the relationship between the stability of network connectedness (dC/dc_i) and the stability of firms’ ego networks. It suggests that once firms obtain their optimal constraint levels such that no further improvements are possible, then (ceteris paribus) the connectedness of the entire network should stabilize as well. To understand when this happens, we explored how long it takes for a typical firm to obtain an optimal constraint level. To this end, we assumed that each firm must replace all of its initial ties assigned to it at t = 0. Because the likelihood of forming a new tie is .15 at any time and a typical firm is initially assigned four unique ties, replacing these ties with new ones will roughly take 4/.15 ≈ 27 time steps. The most critical changes in the firm’s ego network should thus occur approximately over the first 20 to 30 time steps of the simulation.

We validated these analytic conclusions with our model, as shown in figure B1. Panel (a) plots firms’ average constraint levels in a typical clan (\(\text{frac}_{p=0} = .9, p = .1\)), a typical community (\(\text{frac}_{p=0} = .7, p = .3\)), and a typical convention network (\(\text{frac}_{p=0} = .2, p = .8\)) over time. Panels (b) and (c) plot the related changes in network connectedness and community structure at the system level. Results confirm the analytically derived relationship between stable constraint levels and stable industry-wide network properties, both of which emerge just over the first 20 to 30 time steps of the simulation.

Equation (3) leads to similar conclusions with respect to the relationship between firms’ average network constraint and the network’s community structure. Consider a simple network with K interconnected network communities (rather than K components), in which community structure Q increases proportionally to K. Following the same reasoning as that above, we can express the stability of community structure as a function of c_i, namely \(Q'(c_i) = N / (1+c_i)^2\).
Figure B1. Relationship between the stability of firms' ego networks (a) and the emergent global network properties (b and c).

(a) Stability of network constraint

(b) Stability of connectedness

(c) Stability of community structure
Appendix C: Dynamics of Network Formation

(a) Clan network

(b) Community network

(c) Convention network
Appendix D: Network Formation and Knowledge Diffusion*

(a) Clan network  
(b) Community network  
(c) Convention network

* Red indicates knowledge adopters.
Appendix E: Transient Bridges

(a) Transient bridging tie between Daihatsu and Balkancar (the automotive industry, 1989)

(b) Transient bridging tie between BP and Ube Industries (the new materials industry, 1992)
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