DOES EVIDENCE OF NETWORK EFFECTS ON FIRM PERFORMANCE IN POOLED CROSS-SECTION SUPPORT PRESCRIPTIONS FOR NETWORK STRATEGY?

JOEL A. C. BAUM,1* ROBIN COWAN,2,3 and NICOLAS JONARD4

1 Rotman School of Management, University of Toronto, Toronto, Canada
2 BETA, Université de Strasbourg, Strasbourg, France
3 UNU-MERIT, Maastricht University, Maastricht, The Netherlands
4 Faculty of Law, Economics and Finance, University of Luxembourg, Luxembourg City, Luxembourg

Strategic prescriptions drawn from pooled cross-sectional evidence of firm performance effects are not necessarily warranted. This is because firm characteristics can influence both the mean and variance of firm performance. Strategic inferences are warranted if empirically observed effects reflect increases in mean firm performance. If they reflect increases in firm performance variance, however, such inferences are warranted only if the increased odds of achieving high performance compensate sufficiently for the concomitantly increased risk of realizing poor performance. Our simulation study, which contrasts firm performance effects in pooled cross-section and within-firm over time, counsels caution when basing strategic prescriptions on pooled cross-sectional studies of firm performance in general, and in the case of network effects in particular. Copyright © 2013 John Wiley & Sons, Ltd.

INTRODUCTION

At the intersection of network and strategy literatures, researchers are concerned with how patterns of strategic alliances create network-based advantages for well-connected firms. Researchers have examined whether firms should occupy densely interconnected “closed” network positions, which afford coordination and integration benefits by facilitating the ease of exchange and commonness of information among firms (Coleman, 1988, 1990), or sparsely connected “open” network positions, which confer access and control benefits through conveyance of diverse information and resources, and brokerage opportunities (Burt, 1992; Granovetter, 1973).

Despite empirical evidence remaining somewhat equivocal, the idea of “network effects” on firm performance is now uncontroversial, and attention is focused increasingly on the identification of conditions under which open or closed network positions are more or less advantageous (e.g., Ahuja, 2000; Baum et al., 2012; Burt, 2000, 2001; Rowley et al., 2000). What remains uncertain, however, is whether the evidence of “network effects” supports the commonly inferred prescriptions offered in these studies for “network strategy,” where the former is typically based on empirical estimates from panel or pooled time-series-and-cross-section data showing that firms occupying a particular type of network position at time $t$ outperform firms that

Keywords: strategic alliances; interfirm networks; network effects; network strategy; firm performance; computer simulation

*Correspondence to: Joel A. C. Baum, Rotman School of Management, University of Toronto, 105 St. George St., Toronto, ON, MSS 3E6, Canada. E-mail: jbaum@rotman.utoronto.ca

Copyright © 2013 John Wiley & Sons, Ltd.
do not at time $t+1$, and the latter is based on the inference that firms sustaining the type of network position shown to be beneficial in pooled cross-section will outperform those that do not over the longer term.

Although such an inference is intuitively appealing and common, in this paper we explicitly assess its validity. We focus on firm performance effects of open and closed network positions, both because they are the main focus of influential contemporary empirical work on network effects and because of their distinct firm performance implications. In particular, recent empirical research (e.g., Ahuja, 2000; Gilsing et al., 2008; Lavie and Rosenkopf, 2006; Powell et al., 2005; Rothaermel and Deeds, 2004; Rowley et al., 2000) suggests that open network positions facilitate exploratory (nonlocal) search, while closed network positions facilitate exploitive (local) search. A point not much discussed in the literature, but that we take up here, is that open positions, because they expose firms to more diverse sources of information and knowledge, are also likely to increase the variance of a firm’s performance distribution whereas closed positions are likely to decrease it. Moreover, we argue that environmental conditions, reflected in the skewness of the population-level performance distribution or, equivalently, the reward to exploration-versus exploitation-oriented activities, moderate the relationship between network position and firm performance distributions.

As a result, we expect that open and closed network positions will have different effects on short- and long-term firm performance, depending on the skewness of the population-level performance distribution (see for example Holland, 1975; March, 1991).

Our approach is simulation based. This enables us to examine the effects of open and closed network positions in different environments and whether, in different environments, which we characterize by the skewness of population-level performance, observations on cross-section effects can be used to make inferences about firm strategies. After first formulating our theoretical predictions linking firms’ network positions and performance variation, we develop a simulation model designed to characterize interfirm innovation networks and outcomes. As we demonstrate, the model replicates both behavioral (e.g., repeated ties) and structural (e.g., sparsely connected; locally clustered) properties of “real world” networks, as well as pooled cross-section performance effects that mirror those obtained in empirical network studies. Subsequently, we turn our attention to network strategies and, specifically, to two questions: (1) are network positions associated with high performance in pooled cross-section also beneficial when sustained in the long run and (2) how do environmental properties, specifically innovation regimes that govern the skewness of the population-level performance distribution, affect the veracity of network strategy inferences drawn from network effects observed in pooled cross-section?

**NETWORK POSITION AND FIRM PERFORMANCE**

Although network theorists agree that “better-connected” firms gain a competitive advantage, there is disagreement regarding what “better-connected” actually means. Coleman’s (1988) closure argument implies that firms are better off occupying densely interconnected, closed network positions in which their partners are also partners. Burt’s (1992) structural hole argument, in contrast, prescribes that firms embed themselves in sparsely connected, open network positions comprised of disconnected partners. Rather than arguing the superiority of one network position over the other, Burt (2001, p. 45) suggests a contingency approach to reconcile this disagreement: “Closure and hole arguments are not as contradictory as they might seem . . . The ambiguity stems in large part from the different roles that social capital plays in the study populations with which each is justified.”

Open and closed network positions afford distinct benefits that are useful for different purposes, and understanding their effects requires consideration of the conditions under which firms benefit from possessing the distinct benefits they afford.

Consistent with this view, recent studies have pursued contingency approaches in which the benefits of open and closed network positions depend on environmental conditions and task purposes (Ahuja, 2000; Baum and Ingram, 2002; Gilsing et al., 2008; Lavie and Rosenkopf, 2006; Rothaermel and Deeds, 2004; Rowley et al., 2000). These approaches conceive the appropriate choice of network position to turn on their differential value to firms emphasizing exploitative and exploratory learning modes. Exploitation involves using and
refining existing knowledge to improve organizational functioning by reducing variability in the quality or efficiency of current strategies, competencies, technologies, and procedures. The solution space is well defined, and search is local and highly specific. Exploration, in contrast, entails processes of concerted variation and experimentation to identify emerging innovations and alternative future options, new ways of doing things and new things to do. The solution space is ill-defined, search is wide, and a premium is placed on newer, more diverse information.

The distinct information requirements of exploitation and exploration suggest different prescriptions regarding appropriate network position. Open network positions comprised of disconnected, nonredundant partners, are ideal for gaining access to diverse sources of information and knowledge, facilitating identification of emerging opportunities and threats, alternative future options, and the location of complementary knowledge (Mitsuhashi, 2003; Powell et al., 1996). In dynamic, uncertain environments requiring large investments in exploration, sparsely connected, open network positions are therefore expected to be advantageous. Closed network positions comprised of highly interconnected partners, in contrast, inhibit firms’ access to broader, divergent, distant, and less familiar approaches critical to exploration (Uzzi, 1996, 1997). The access to redundant, validating, and refined information that closed positions afford is essential, however, to meeting the requirements of exploitation (Dyer and Singh, 1998; Van de Ven, 1976; Walker et al., 1997). In stable, certain environments requiring large investments in exploitation, closed network positions are thus expected to be advantageous.

The previous arguments offer clear predictions regarding the value of open and closed network positions in different environments and for different task purposes. They also suggest one critical further implication that remains largely unexplored. Specifically, that because open network positions permit access to broader, more diverse, possibly complementary sources of information and knowledge, firms occupying them can be expected to have higher variance performance distributions than firms in closed network positions. As a consequence of this variance-augmentation effect, in cross-section, firms occupying open network positions should typically outperform firms occupying closed network positions. This is seen most clearly in March’s (1991) seminal analysis of the effects of firm characteristics on the mean and/or variance of firm performance. March’s argument is very general: when observing a population of firms at any point in time, the highest-performing firms will tend to be those having the highest variance in their performance. Thus, in cross-section, the correlation between firm performance and variance-increasing firm characteristics will tend to be positive. In our context, this means a positive (negative) correlation between the openness (closedness) of a firm’s network position and performance in cross-section. Indeed these predictions match both theoretical arguments and empirical findings in pooled cross-section studies of network effects on firm performance (e.g., Ahuja, 2000; Gilsing et al., 2008; Lavie and Rosenkopf, 2006; Rothaermel and Deeds, 2004; Rowley et al., 2000).

March’s analysis also indicates, however, that cross-sectional and long-run performance effects of firm characteristics can be contradictory. Indeed, in the long run, firm performance is determined by the mean rather than the variance of performance. And thus a firm with a high variance, which appears high-performing in cross-section, may in fact perform poorly in the long run. March’s reasoning is supported by a small number of studies providing evidence that the mean and variance of performance do not necessarily move in the same direction (e.g., Cavarretta, 2008; Denrell, 2003; Miner et al., 2003). Taken together, these observations and evidence suggest the possibility of a negative correlation between the openness of a firm’s network position and performance in the long run. The short- and longer-term implications of firms attempting to manipulate their performance distributions via their network positions may thus disagree.

The magnitude of this disagreement between short- and long-run performance effects, we contend, is contingent on the properties of the population-level performance distribution, and specifically its right skewness. Though this specific feature is absent from March’s (1991) original analysis, right-skewed distributions of aggregate firm performance are commonly observed (e.g., Andriani and McKelvey, 2009; Powell, 2003), and this feature can be easily incorporated by observing that March defined the “high variance firm” relative to the population. If aggregate, population-level performance is only slightly skewed, then...
Figure 1. Effects of increasing right-skewness of population-level performance distributions. Note: Log-normal distributions with constant mean of 1 (vertical line) and increasing right-skewness moving from thick black line ($\sigma = 0.2$) to thin black to gray line ($\sigma = 1.0$). Holding mean performance in the population constant, increasing right-skewness raises both the density of the right tail of the distribution and the mass near zero. As a result, increasing right-skewness increases the likelihood that, at any given point in time, the firms with the highest-performance variance are the best performers in the population. But it also exposes high-variance firms to an increased risk of poor performance, which can result in low mean performance over time.

A high-variance firm can have a fairly low variance in absolute terms. If population-level performance is highly skewed, the high-variance firm has a high variance in absolute terms. In either case, given a skewed distribution, the penalty for intermittently achieving one of a small number high performance outcomes is a large mass of low performance outcomes, but in the case of a highly skewed population-level performance distribution, this penalty (i.e., the risk of low vs. high performance) will be much larger than in the case of population-level performance being only slightly skewed. In the language of March’s analysis, markedly right-skewed performance distributions demand that the tension between exploitation and exploration be carefully considered, since increased performance variance may often raise firms’ risk of low performance more than their chances of achieving high performance, and thus reduce their mean performance. Figure 1 visually illustrates this phenomenon.

As preliminary evidence in support of the above reasoning, consider a fixed population of firms each endowed with a variant of some characteristic, $c_i \in [1, C]$ (level of diversification, R&D intensity, network position, . . . ) that preserves the mean but affects the variance of the firm’s performance distribution. The population-level performance distribution is the aggregation of individual firm performance distributions, and the upper bound, $C$, controls its skewness, which increases with $C$. Each period, one firm is drawn, and it receives a random, binary payoff, either high or low. With this simple model we can see how correlations in cross-section can be different from related correlations over the long run.

Figure 2 shows the resulting correlations between firm performance and characteristic $c_i$ using (1) each period’s payoff as the observation (cross-section) and (2) each firm’s total payoff as the observation (long-run). As expected (mean performance is identical for all firms), in the long run firm performance and characteristic $c_i$ are uncorrelated. In cross-section, however, firm characteristics do matter: larger payoffs are associated with larger values of $c_i$, the variance-increasing characteristic. And the cross-section correlation between firm performance and characteristic increases with the right-skewness ($C$) of the population-level performance distribution. Thus at any point in time, the highest-performing firms tend to be those having the highest variance performance outcomes (as in March, 1991), and this correlation increases with the right-skewness of the population-level performance distribution. Yet, because increased performance variance also exposes firms to a greater risk of very poor performance, the two effects cancel each other out over time, resulting in identical performance for all firms, regardless of their characteristic (and thus variance).

In summary, the foregoing arguments suggest that open network positions are associated with a higher variance in underlying (firm-specific) performance distributions than closed network positions. At any given point in time, the value of this variance-augmenting feature of open network positions—improved odds of being a high performer—increases with the right-skew of the population-level performance distribution. Over time, however, the penalty for improved odds of high performance is a concomitant increase in the risk of performing poorly. And this penalty increases with the right-skew of the population-level performance distribution as firm performance variance raises the risk of low performance more than it raises the odds of high performance, reducing mean firm performance. Correlations between
open network positions and firm performance in pooled cross-section should thus increase with the right-skewness of the population-level performance distribution, while for within-firm mean performance over time the correlations should decline. For closed network positions, the correlations should be reversed.

Table 1 summarizes our theoretical predictions. Note that the predictions are opposite not only between open and closed network positions, but also between performance in pooled cross-section and over time within each network position, complicating inferences for firm strategy from evidence in pooled cross-section.

THE MODEL

In this section we develop a model aimed at elaborating the arguments presented above. Our focus is on network strategies, drawing inspiration from the literature on the sources of value of open and closed network positions. We follow this literature in framing our model in the context of firms alllying in order to innovate and formalize the exploration–exploitation spectrum by focusing on the properties of innovations that take place. Specifically, an environment rewarding exploitation is characterized by innovations of similar importance, as if drawn from a distribution with relatively low skewness. By contrast, in an environment rewarding exploration, innovations differ widely, most being small and of little impact but a few being large and highly disruptive, as if drawn from a very skewed distribution. With this formalism we capture very simply the effects of the population-level innovation regime on the benefits of exploration and exploitation as means of innovation.

A brief verbal sketch of the model is the following. Firms ally for the purpose of innovating. The decision to ally is guided by the expected profitability of the alliance, itself a function of firms’ positions in knowledge space and the nature of the technological regime. All alliances produce learning, which brings the partners closer. In addition, some alliances produce innovations. An innovation disrupts the activities of all other (noninnovating) firms, forcing them to rearrange their activities and deploy new knowledge: noninnovating firms are relocated in knowledge space, thereby changing the value of their (potential) partnerships, and the innovating firm receives a value equal to the total displacement of other firms in knowledge space. These dynamics are repeated for a fixed number of periods. In the following sections we operationalize these assumptions, taking each element of the process individually.

Innovation rates and learning

A fixed population of firms indexed by $i$ is located in a two-dimensional metric knowledge space taken to be the unit square $[0, 1]^2$, with periodic structure (i.e., the unit torus). Each firm is characterized by a knowledge endowment in the form of a pair of positive real numbers, $0 \leq v_{i,1}, v_{i,2} \leq 1$, which defines the firm’s location in knowledge space. At the outset, firms occupy locations distributed uniformly over the unit torus. Time is discrete.

We treat innovations as stochastic and independent across firms. Each alliance represents one
R&D project. An alliance being in essence an institution for knowledge sharing, a firm selects partners in order to access the knowledge it needs to (potentially) make that project successful. Each firm thus engages in knowledge sharing with each of its alliance partners, and each alliance formed by the focal firm contributes additively to the probability that this firm succeeds (for simplicity, we assume that firms undertake no R&D outside alliances). The marginal contribution of a particular alliance to the firm’s project portfolio is its success rate, which in turn depends on the characteristics of the alliance.

The role of complementary knowledge in successful innovation implies that partners will be neither too close together nor too distant in knowledge space. Specifically, the success rate for any alliance depends of the “goodness of fit” of the alliance, which is modeled as a single-peaked function of the Euclidean distance in knowledge space (with a maximum distance $d^*$) between the alliance partners in knowledge space. Research has indeed showed that, in a variety of contexts, alliance and merger formation and success depend on partners’ relative knowledge endowments. This feature is commonly formalized using “distance in knowledge space”, which is measured in a variety of ways. This work also indicates that the probability that a pair of firms forms an alliance is concave in their distance in knowledge space (e.g., Ahuja and Katila, 2001; Mowery et al., 1996, 1998; Rothaermel and Boeker, 2008; Schoenmakers and Duysters, 2006; Stuart, 1998).

Notably, because the knowledge space is a metric space, this need for proximity will induce some amount of local correlation in the decisions to ally, yielding both the repetition and clustering commonly observed in “real world” firms’ partnering decisions (Baum et al., 2010). Formally, we employ a bell-shaped (Gaussian) function to map knowledge-distance to one-period success rates, $\lambda_{ij}$, according to

$$\lambda_{ij} = f(d_{ij}) = \frac{\lambda}{\sigma} e^{-\frac{(d_{ij} - d^*)^2}{2\sigma^2}},$$

(1)

where $d_{ij}$ is the distance in knowledge space between $i$ and $j$:

$$d_{ij} = \left[ \sum_{l=1,2} \left( \frac{1}{2} - \frac{1}{2} - \left| v_{i,l} - v_{j,l} \right| \right) \right]^{1/2},$$

(2)

and $\lambda \ll 1$ is a scaling parameter which we use to control the maximum success probability. Firm $i$’s overall success rate is $\lambda_i = \sum_{ij \in g} \lambda_{ij}$, where $g$ is the network of existing alliances during the period we consider, and $ij \in g$ expresses that $i$ and $j$ have an alliance. The population-level arrival rate of innovations is $\lambda = \sum_i \lambda_i$. Provided success rates are small enough ($\lambda_{ij} \leq \lambda \ll 1$), any firm’s overall success rate $\lambda_i$ is also small, and thus the population-wide arrival rate of innovations $\lambda$ is less than one, in which case at most one firm succeeds in any period. We impose parameter values such that this constraint is satisfied.

Learning, by contrast, affects any firm engaged in alliances. If firms $i$ and $j$ ally, they learn from each other and so move closer together in knowledge space, affecting their suitability as partners in subsequent periods (Mowery et al., 1998; Uzzi, 1997). We model this movement as a linear partial adjustment process

$$v_{i,1}^t + 1 = \alpha v_{j,1}^t + (1 - \alpha) v_{i,2}^t + (1 - \alpha) v_{j,2}^t,$$

(3)

where the parameter $\alpha \in (0, 0.5)$ measures absorptive capacity in the industry.
Dislocation following an innovation

Following an innovation the knowledge landscape changes, altering the value of different types and combinations of knowledge. We assume that an innovation by firm \( i \) disrupts the status quo for all other firms. Firms respond by deploying new knowledge in their activities, and so an innovation changes where firms are located in space. The extent to which a noninnovating firm is affected by an innovation is determined both by its proximity to the innovating firm and by the size of the innovation. We operationalize this by assuming that, following an innovation, noninnovating firms are dislocated in the knowledge space as a function of their distance to the innovator, \( i \). Any firm \( j \) is relocated, uniformly at random within a disc centered on \( i \)

\[
r^j = \theta \cdot r_{\text{max}} \left( 1 - \sqrt{2}d_{ij} \right), \tag{4}
\]

where \( d_{ij} \) is the Euclidean distance in knowledge space between \( i \) and \( j \), \( r_{\text{max}} \) is the maximum possible dislocation, \( \sqrt{2}/2 \) is the maximum possible distance between firms, and \( \theta \) measures the size of the innovation. Firms are affected by an innovation as a linear function of their distances to the innovating firm. The magnitude of this distance effect, however, depends on the size of the innovation, \( \theta \). Innovation size is drawn from a binary random variable with expectation equal to 1 and variance and skewness which we control with the parameter \( C \). By changing the skewness of the innovation size distribution, we control the nature of the innovation regime in which firms operate, and thus the skew of the population-level performance distribution (Abernathy and Utterback, 1978; Tushman and Anderson, 1986).

Define realized dislocation of firm \( j \) as \( \delta_j \). Total dislocation following an innovation is thus

\[
V_i = \sum_{j \neq i} \delta_j \tag{5}
\]

The expected magnitude of the dislocation of firm \( j \) being \( r_j/2 \), total expected dislocation, used by firms to calculate expected value of an alliance, is

\[
E[V_i] = \sum_{j \neq i} E[r_j] = E[\theta] \cdot \sum_{j \neq i} r_j / 2 = \sum_{j \neq i} r_j / 2 \tag{6}
\]

Strategic alliance formation

The value to firm \( i \) of a particular alliance \( ij \) is the marginal contribution of that particular alliance to the firm’s expected profit, net of alliance cost \( k \). The marginal contribution of alliance \( ij \) to the success rate of firm \( i \) is \( \lambda_{ij} \). We assume that innovations do not compete in any aftermarket, so firms can treat each alliance decision independently from all others, both their own and other firms’. If firm \( i \) innovates, the value of that innovation is the sum of the dislocations it imposes on all other firms, as in Equation 5. We can thus write the expected value of alliance \( ij \) to firm \( i \) as

\[
\pi_i^{ij} = \lambda_{ij} \cdot E[V_i] - k \tag{7}
\]

which is the product of \( \lambda_{ij} \), the marginal contribution of alliance \( ij \) to the success rate of firm \( i \), and the dislocation firm \( i \) expects to impose on other firms, \( E[V_i] \), net of alliance cost, \( k \). Alliance \( ij \) forms (or is maintained) if expected profits are positive to both \( i \) and \( j \). Rewriting, the alliance condition is thus

\[
\lambda_{ij} \cdot E[V_i] \geq k \quad \text{and} \quad \lambda_{ij} \cdot E[V_j] \geq k \tag{8}
\]

As a consequence, the single-period outcome of the strategic alliance formation game is easily characterized: there is a unique (pairwise stable) equilibrium in which all pairs of firms \( ij \) and only those pairs for which the condition in Equation 8 holds form (or continues) an alliance.

However, in a dynamic industry, we also observe that knowledge portfolios, alliances, and network structure all change over time. At the population level, network structure is shaped by (current) knowledge stocks of the firms comprising it. But the network structure is instrumental to innovation. Innovations in turn force firms to respond and to redeploy their knowledge, possibly using different knowledge in reaction to the new market conditions created by the innovation. Thus innovations change firms’ position in the knowledge space, forcing them to use different knowledge than they had done previously. So at the population-level, network structure and knowledge profile coevolve.

Numerical implementation

Although characterization of the single-period equilibrium of the model is straightforward, the
behavior of the model over time does not lend itself to analytical solution. We therefore resort to numerical simulation, with the following settings.

The industry consists of 100 firms located on the unit torus. We set the optimal partner distance, \( d^* \), equal to 0.025, a small value that represents a broadly defined industry such that, between absorptive capacity and the need for novelty—the opposing forces widely taken to produce the inverted-U relationship between knowledge distance and alliance formation—absorptive capacity dominates. We set the parameter that decreases the success probability of firm-pairs deviating from the optimal distance, \( \sigma \), at 0.025, a small value expressing low tolerance for deviations from \( d^* \). The upper bound to the success rate of alliances (achieved by participants at the optimal distance) is \( \lambda = 0.004 \). The maximum possible dislocation following an innovation, \( r_{\max} \), is set to 0.05. As for dislocation itself, when firm \( i \) dislocates firm \( j \), the direction of motion of firm \( j \) is an angle drawn uniformly at random in \([0, 2\pi]\), and the distance of \( j \)'s dislocation, \( \delta_j \), is drawn from a uniform distribution \( U[0, r_j] \), with \( r_j \) given by Equation 4. Absorptive capacity is set to \( k = 0.01 \). Finally, the cost of forming and maintaining an alliance is set to \( k = 0.000001 \).

These parameters produce a relatively sparse, though locally clustered, network with an average degree near five (i.e., network density 0.05) and an industry-wide arrival rate of innovations of about 0.3 (i.e., on average, one innovation every third period). The network is sparse enough for network effects to materialize, and the innovation arrival rate is slow enough to permit substantial network inertia and frequent repeated alliances. Indeed, over 90 percent of alliances repeat from one period to the next regardless of simulation parameter values.

The innovation regime (the extent to which exploration rather than exploitation is rewarded) is controlled through the skewness of the distribution of innovation sizes (see Equation 4). Each time an innovation takes place, its size, \( \theta \), is drawn from a binary random variable taking the two values \( H \) and \( L \), with \( H > 1 > L \), and probabilities \( (p_H, 1 - p_H) \), where \( p_H = ((1 - L)/(H - L)) \). Setting \( H = 1.01C \) and \( L = 0.01C \), the innovation size has constant mean for any value of \( C \), and a variance increasing with \( C \) (equal to \( 0.0101C^2 + 1.02C - 1 \)). Innovation size is therefore a mean-preserving random shock with tunable variance, skewness, and higher moments that indirectly control the population-level performance distribution. Holding mean innovation size constant permits us to focus on the effects of variance in firm performance and right-skewness of the population-level performance distribution.

We consider 500 random values of \( C \) between 1 and 30 to cover a wide range of innovation regimes. We run the alliance formation/innovation process for 10,000 periods, discarding the first 500 to avoid any spurious effects arising from the initialization. Numerous explorations around the values we use here produced little variation in the results.

Several remarks are in order regarding the foregoing specifications. (1) The knowledge space is bounded. If it is not, firms separate in the space until they are too dispersed for any alliances to form. Using a simple, nonperiodic unit square, the general results are preserved, though firms gravitate to the boundaries of the square. (2) Our “goodness of knowledge fit” function is Gaussian. This is chosen purely for familiarity; we explored many other functional forms, and the results are preserved, provided the function is single peaked. (3) Following innovation, firms are dislocated to a disc. This is not crucial; any bounded region provides the same general results. (4) We also assume that dislocation is undirected in the knowledge space: firms are as likely to move toward the innovator as away. Imposing the assumption that firms move away from the innovator does not change the results. (5) We assume a binary distribution function for innovation size, controlled by the parameter \( C \) through particular functional forms. We have explored a variety of alternative forms, and the results are preserved. Moving toward more continuous distributions (such as the log-normal) attenuates the observed effects. The results thus seem to depend on the starkness of this function. (6) The model contains a number of parameters: alliance cost; maximum success probability; the effect of knowledge distance on success probability. These jointly determine the density of the network (and as a consequence, several other properties). We restricted our explorations of the parameter space to regions where network density is around 5 percent to reflect the fact that empirically observed networks are sparse. Within that subregion of the space, the results are generally robust.
RESULTS

We examine some aggregate properties of the alliance network before turning to a more detailed analysis of the relationship between firms’ network position and their performance.

The network: snapshots and dynamics

As a first step in the analysis, we display in Figure 3 two representative networks captured in period \( t = 1,000 \) in two runs of the model, one having a low-skewness innovation regime (left panel, \( C = 5 \)), and the other with a high-skewness regime (right panel, \( C = 20 \)). Standard network descriptive statistics are given.

This figure provides a first intuition about the effect of skewness (in the innovation size distribution) on network structure. The effect is dynamic rather than static, as alliance decisions are based solely on expected profits, disregarding higher moments of the performance distribution. Put another way, given firm locations, the alliance decisions are independent of \( C \) (recall that mean innovation size remain constant across all values of \( C \)). However, innovation interacts with learning. Over time, the effect of the latter is to bring firms closer in knowledge space. The low-skewness regime has frequent innovation of roughly constant magnitude. Innovations tend to disrupt current structures, and so they will counterbalance forces of learning, which drive agglomeration in knowledge space, and thus cluster in the network. The high-skewness regime, in contrast, has many very small innovations whose effects are much weaker than the learning effects, and only rarely large ones. So firms will tend to be closer in the knowledge space in a high-skew regime, with higher average degree and clustering, and consequently more connected components and shorter distance among reachable pairs (within the smaller, denser components).

These intuitions are confirmed by Figure 4, which displays average degree and average clustering for the final 500 periods in two representative histories of the network, again one for low-skew (left panel, \( C = 5 \)) and the other for high-skew (right panel, \( C = 20 \)) innovation regimes. As firms ally, learn, innovate, and are dislocated by other firms’ innovations, the locations of firms over the knowledge space change, and so the alliances formed change, expressing a coevolution between knowledge endowments and network behavior.

In both cases we observe that network activity (degree and clustering) rises and falls over time. However, the patterns differ markedly for low- and high-skewness innovation regimes. In the low-skew regime, fluctuations remain of comparable magnitude over time. In the high-skew regime, there is, in general, very little movement from one period to the next, and the effect of learning dominates. Firms in a given connected component get closer in knowledge space, forming more alliances (also among partners of a given firm) as global convergence takes place toward the center of gravity of the set of connected firms. Innovation size is typically so small that its effect is overwhelmed by the learning process. But, infrequently, a very large, disruptive innovation occurs and dislocates many firms. Degree and
clustering then fall significantly, before routinized learning again takes command.

We can use this observation to interpret the parameter $C$, characterizing the innovation regime. We would expect, in an era or industry where exploitation dominates, that in each period there is some small, incremental innovation. Most innovation attempts are successful and of comparable, albeit limited, significance. In a period of exploration, however, we would expect that innovation attempts tend to be unsuccessful. Every now and then, however, there will be a success, and it can be sufficiently significant to cause major disruptions in the industry.

**Network position and firm performance**

Our overarching concern is whether prescriptions for firm strategy can be derived straightforwardly from empirical findings in pooled cross-section. In the context of interfirm alliance networks, this is framed in terms of open versus closed network positions. In this section we tackle this issue directly. There are two ways to think about the relationship between firms’ network positions and their performance. In the first, the locus is the innovation: what determines the size of an innovation? This is the pooled cross-section approach. In the second, the locus is the firm: what determines the size of a firm’s innovative performance? This is the within-firm, over-time approach, which is relevant for strategic prescriptions. We ask both questions and examine whether the answers are consistent with or, as we predict, opposite to, each other and thus whether or not evidence of network effects in pooled cross-section data supports prescriptions for network strategy over time.

For comprehensiveness, we consider two measures. Betweenness centrality measures the openness of a network position. Betweenness centrality of firm $i$, $b_i$, is defined as the sum, over all possible pairs $k, l \neq i$, of the proportion $p_{k,i,l}$ of shortest paths between $k$ and $l$ that run through $i$, i.e., $b_i = \sum_{k,l \neq i} p_{k,i,l}$. Betweenness is large when a firm connects two otherwise disconnected (or distant) parts of a network. Such a firm occupies a fairly unique, open position in terms of accessing and controlling access to a broad set of diverse resources. Low betweenness, by contrast, signals a more common structural position wherein the source of social capital is redundancy and commonality of neighbors. A firm with low betweenness occupies a closed network position. An alternative, constraint, is a more direct measure of closure. Constraint of firm $i$, $C_i$, is defined as $C_i = \sum_{j \neq i} \sum_{q \neq i,j} (a_{i,j} + a_{i,q} a_{q,j})^2$, where $a_{i,j} = 1$ if $i$ and $j$ have an alliance and 0 otherwise. Constraint increases when the degree of the focal firm decreases, the number of distance-two neighbors decreases, and the clustering of the focal firm’s neighborhood increases (Burt, 1992). We use both measures and observe the consistency of our results.
Earlier, we argued that in pooled cross-section open network positions would become more beneficial to firms as the skew of the distribution of possible performance outcomes increased, whereas over time the opposite would hold. We assess the veracity of this prediction by examining the correlation between firms’ betweenness and innovation size. To observe network effects in pooled cross-section, each time a firm innovates, we record the profits of the innovating firm (i.e., total dislocation imposed on other firms minus the cost of its alliance portfolio this period), and the betweenness of the innovating firm. We thus have innovation-centric data. To observe “network strategy” effects, we follow each firm over its entire history and, at the end of the simulation record for each firm, total profits over this history (i.e., the total dislocations it has imposed on other firms through its innovations minus the total cost it has incurred in making alliances) and the average of its betweenness measured every period. Here we have firm-centric data. Correlations between innovation size and betweenness on the one hand and total profits and betweenness on the other allow us to compare pooled cross-section and within-firm long-run relationships. To observe how these relationships are affected by the skewness of possible performance outcomes, we use as the abscissa the observed skew of the population-level distribution of firm profits. That is, for each value of the parameter $C$, which controls the innovation regime, at the end of each simulation run, we calculate the skew of the distribution of observed firm profits. We display Spearman correlations against this variable in the left panel of Figure 5.

To provide an alternate view of the results, we present the data a second way. The cross-section analysis essentially asks about innovations: “What are the properties of big (versus small) innovations?” By contrast, the strategy analysis asks about firms: “What is the performance of high (versus low) betweenness firms?” We can address those questions directly by comparing large and small innovations, or open-positioned and close-positioned firms. In the first instance, we compare the betweenness of the top and bottom halves of the innovation size distributions. In the second instance, we compare total profits for the top and bottom halves of the population of firms ranked by betweenness. To perform these comparisons and assess their statistical significance, we use a simple difference of means test. We report the value of the $t$-statistic, plotted against the observed skew of the observed distribution of firm profits, on the right panel of Figure 5.

What we observe in the left panel of Figure 5 is that, in pooled cross-section, open network positions (measured by betweenness) are positively correlated with firm performance. Further, this correlation increases with the skewness of the population-level distribution of observed firm profits. By comparison, in the long run, while the correlation is positive for low-skew profit distributions, it falls as the skewness of firm profits increases and becomes negative when skew is high. The right panel, displaying the
difference of means test for of top-versus-bottom halves of the population, tells the same story. In cross-section, with innovation-centric data, there is clearly a statistical difference: large innovations are strongly associated with firms holding open positions and this association grows as the skewness of firm profits increases. Over the long run, using firm-centric data, though, effects are less clear. Statistically, it would be difficult to argue that high-profit firms have more or less open than closed positions. We note, though, that if there is a trend, the effect of population-level performance skewness on the relationship between open positions and profit is of opposite sign to that seen in cross-section. Consistent with the predictions above, then, the results indicate that the effects of network position on firm performance in pooled cross-section and over time are contradictory and that evidence of network effects in pooled cross-section data does not straightforwardly support prescriptions for network strategy over time.

To examine the effects of closed positions more directly, we replicate the analysis using constraint to measure firms’ network positions. The results, presented in Figure 6 are analogous to those in Figure 5 for betweenness. The left panel shows correlations between performance and constraint, plotted against the skewness of the population-level profit distribution. The right panel shows t-statistics for the difference in means: in pooled cross-section we compare the constraint of the top and bottom halves of the innovation size distributions; for the long run, we compare total profits for the top and bottom halves of the population of firms ranked by constraint. As expected, the correlation patterns are reversed from those for betweenness. And, again, the results are consistent with our theoretical predictions.

The simulation results are consistent with the link drawn between network positions and learning modes suggesting that closed positions reduce firm performance variation, while open positions increase it. To assess the alignment of this characterization with the outcomes experienced by our simulated firms, we computed correlations of firms’ profit variance with betweenness and constraint. To observe how these relationships are affected by the skewness of the population-level performance distribution, we again use the skew of the observed distribution of firm profits as the abscissa. The correlations are presented in Figure 7.

The left panel shows that the correlation between firm profit variance and betweenness is positive but decreasing as the skewness of the observed firm performance distribution increases initially and stabilizes at 0 for skewness > 2.5. The right panel shows that the correlation between firm profit variance and constraint, oppositely, is negative but increasing as the skew of the observed firm profit distribution increases initially and stabilizes at 0 for skewness > 2.5. Thus, for skewness < 2.5 the profit variance correlations are consistent with the theoretical expectation that closed positions characterized by high constraint, lower firm performance variance, while open positions,
Figure 7. Relationships of variance in firm profits with firm betweenness (left panel) and firm constraint (right panel), by skewness of the observed population-level distribution of firm profits.

characterized by high betweenness, raise it. For skewness > 2.5, the disruptiveness of the innovation regime (controlled by the parameter $C \in [1, 30]$) results in all firms experiencing similar performance variance and this reduces the correlations with network position to zero. Firms’ profit variance converges as $C$ increases because the probability of large innovations declines, while the probability of small innovations increases. The result is that small innovations become more frequent but are too small to differentiate the profitability of innovators from noninnovators, while large innovations become large but are too infrequent to differentiate the profitability of firms over time.

Indeed, our findings revealed substantial discrepancies in correlations between network position and firm performance in pooled cross-section and within-firm, over time. When we observe pooled cross-section outcomes, our results follow precisely the predictions and findings found in the empirical literature. When we observe within-firm performance over time, however, the relationships between network position, firm performance, and environmental conditions are reversed.

The discrepancies in firm performance in cross-section and over time appear to result from the different ways in which open and closed network positions generate value. Open positions facilitate broad search for emerging innovations and future options vital to exploratory search, while closed positions yield access to the redundant and validating information essential to exploitive search. As a result, closed positions are likely to reduce firm performance variation, whereas open positions are likely to increase it. In cross-section, as March (1991) observes, the correlation between firm performance and variance-increasing (decreasing) firm characteristics, such as open (closed) network positions will tend to be positive (negative).

We have argued that this tendency is particularly strong when the population-level performance distribution is markedly right-skewed. The long-term effect of sustaining open and closed network positions on firm performance also depends on the skewness of the population-level performance distribution. If the distribution is right-skewed, with only a small number of high-performance outcomes available relative to poor ones, by increasing the variance of its performance, a firm improves its chances of achieving one of the

DISCUSSION AND CONCLUSION

The model we have presented contains a very simple mechanism by which firms form alliances—firms seek partners whose knowledge endowments complement their own. By this mechanism a network forms, firms learn from each other and occasionally innovate. The model mimics central features of observed real-world networks. In terms of structure, the model generates sparse, clustered networks of small diameter; that is, they resemble small worlds often found in empirical studies. In terms of behavior, the model generates repeated ties and inertia. And, in terms of outcomes, the model generates network position effects consistent with observations in empirical studies: firms in open positions do well in turbulent environments; firms in closed positions do well in placid environments. This final point is slightly disingenuous, however.
high outcomes (and thus performs well in cross-section). But the increased odds of achieving the high outcome can be too small to counter the reduction in mean performance that results from the correspondingly higher odds of obtaining poor outcomes. The long-term performance of firms sustaining open network positions thus tends to decline with the right-skewness of the population-level performance distribution while, oppositely, the long-term performance of firms sustaining closed network positions tends to increase.

This mechanism is at work in the model and explains the correlations we observe. The model is designed to permit observations driven by the population-level distribution of performance. The possibility of large innovations (with high $C$) generates a right-skewed aggregate performance distribution in which firms occupying open network positions achieve higher performance in pooled cross-section. In contrast, when only incremental innovations are possible (with low $C$), variance-reducing closed network positions produce higher performance in cross-section. These results are consistent with arguments and pooled cross-section findings in empirical studies of network effects. Network strategy prescriptions drawn from the pooled cross-section correlations would thus counsel firms to adopt open network strategies in high-skew innovation regimes where population-level performance is also skewed. But the model shows that if we examine long-run strategies directly this prescription is exactly opposite to the behavior of firms successful in the long run. Analogously, network strategy prescriptions drawn from the pooled cross-section correlations would imply firms adopt closed network strategies in innovation regimes where population-level performance exhibits low-skewness, while this prescription again directly contradicts the behavior of firms successful in the long run. Our analysis thus identifies performance variability as a general mechanism that can account for observed empirical findings on network effects in pooled cross-section and also for their potential inadequacy as prescriptions for network strategy.

Although we have focused on the influential stream of research on network effects, the phenomenon we examine here is far more general and likely to apply broadly to firm characteristics (R&D intensity, corporate culture, diversification, top management team composition, etc.) that can affect firm performance through its variance rather than or in addition to its mean. Yet, theory and empirics have tended to focus more on mean performance. As a result, firm performance variability and its implications are often overlooked (Cavarretta, 2008; Denrell, 2003). Future research examining how key firm characteristics influence firm performance variability would thus complement the large body of work that has already examined their mean effects. Given the right-skewness commonly observed in distributions of aggregate firm performance (e.g., Andriani and McKelvey, 2009; Powell, 2003), such research may fundamentally alter our understanding of the relationship between firm strategy and performance.

We began with the observation that, while tempting and common, drawing network strategy implications from empirical evidence of network performance effects in pooled cross-section is not necessarily warranted. As we explained, this is because network positions—and firm characteristics more generally—may influence both the mean and variance of firm performance. Although strategic prescriptions are warranted if network effects observed empirically in pooled cross-section reflect increases in mean firm performance, if network effects instead reflect increases in firm performance variance, such prescriptions are warranted only if the increased odds of achieving high performance are sufficient to compensate for the concomitantly increased odds of realizing poor performance. Our analysis suggests that network effects may indeed reflect changes in firm performance variance and, moreover, that the increased odds of achieving high performance in cross-section may be insufficient to compensate for the accompanying increase in the odds of realizing poor performance over time. This suggests the exercise of caution in drawing implications for network strategies, and firm strategies more generally, from empirical evidence of firm performance effects in pooled cross-section.

ACKNOWLEDGMENTS

The detailed and helpful suggestions of several anonymous referees and expert editorial guidance afforded by Will Mitchell helped us to improve the paper considerably. We are also grateful to seminar participants at SDA Bocconi University, University of Lugano, Merage School of Business, University of California, Irvine, and Smeal College
of Business, Penn State University for their feedback and comments. This research was supported by grants from the Desautels Center for Integrative Thinking at the Rotman School of Management, the Social Science and Humanities Research Council of Canada, and Fonds National de la Recherche Luxembourg.

REFERENCES


Copyright © 2013 John Wiley & Sons, Ltd.

DOI: 10.1002/smj

