Strategic Management Journal
Strat. Mgmt. J., **37**: 22–44 (2016)
Published online EarlyView in Wiley Online Library (wileyonlinelibrary.com) DOI: 10.1002/smj.2454
Received 29 August 2013; Final revision received 20 January 2015

UNDERSTANDING NETWORK FORMATION IN STRATEGY RESEARCH: EXPONENTIAL RANDOM GRAPH MODELS

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Research summary *: This article uses Exponential Random Graph Models (ERGMs) to advance strategic management research, focusing on an application to board interlock network tie formation. Networks form as the result of actor attributes as well as through the influence of existing ties. Conventional regression models require assumptions of independence between observations, and fail to incorporate endogenous structural effects of the observed network. ERGMs represent a methodological innovation for network formation research given their ability to model actor attributes along with endogenous structural processes. We illustrate these advantages by modeling board interlock formation among Fortune 100 firms. We also demonstrate how ERGMs offer significant opportunities to extend existing strategy research and open new pathways in multiparty alliances, microfoundations of interorganizational network formation, and multiplexity of ties among actors.*

Managerial summary*: Social networks are increasingly important in the business world, not only between individuals but also between organizations. Firms can obtain information, resources, and status through their external network connections, and understanding how these outside ties form is an important goal of strategy research. Our paper helps advance this effort by introducing a new tool for social network analysis, Exponential Random Graph Models (ERGMs) to the management and strategy fields. We provide an example of this method, demonstrating how social network ties form between companies when they hire common directors to their boards. Executives can benefit from this research through a greater understanding of how corporate relationships are built with allies as well as among competitors.*

INTRODUCTION

The ubiquity of networks among industries, firms, and individuals has attracted significant research attention as evidenced by the sheer volume of studies that draw on network concepts and methods (Borgatti *et al.*, 2009). One of the key themes to emerge from organizational research on social networks is that firms are embedded in sets of relationships and interactions (Granovetter, 1985) that determine both their actions and outcomes (e.g., Ahuja, Polidoro, and Mitchell, 2009; Stern, Dukerich, and Zajac, 2014). Prior research has examined numerous properties of networks, including structural cohesion (Moody and White, 2003) and small-worldness (Uzzi and Spiro, 2005; Watts, 1999) as well as what kind of ties are likely to form

Keywords: social networks; empirical methods; board interlocks; network formation; network analysis
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between actors and which actors will become more central (e.g., Burkhardt and Brass, 1990; Shipilov and Li, 2012). At the same time, a better understanding of how and why organizational networks emerge is critically important to determine how different network structures offer distinctive benefits or constraints to firms embedded in them (Ahuja, Soda, and Zaheer, 2012; Salancik, 1995; Stuart and Sorenson, 2007).

Network formation may be driven by multiple interdependent social processes acting simultaneously (Hedström and Swedberg, 1998; Lusher, Koskinen, and Robins, 2013). Networks may emerge through a process whereby actors seek partners with specific characteristics (e.g., homophily) or in response to opportunities made available by their partners' reciprocal behaviors (Blau, 1964; Park and Luo, 2001), leading to changes in the network structure (Contractor, Wasserman, and Faust, 2006). Alternatively, network ties may result from locally emergent structures (Gulati and Gargiulo, 1999; Lusher *et al.*, 2013; Zaheer and Soda, 2009), in which relationships among actors are influenced by the presence (or absence) of other ties in the network. For example, in the context of the global cellular phone industry, Google's choice to partner with Samsung and HTC around the Android operating system and initially promote it through the Verizon carrier network in the United States was strongly influenced by the existing relationship that Apple had formed with AT&T. Google's decision illustrates an endogenous network structural effect—the choice to form network ties with Samsung, HTC, and Verizon extends beyond simple considerations of their characteristics and involves a calculated response to the ties already formed by AT&T. Observed network structure may thus result from the combination of distinct, simultaneous processes that may be interdependent and structurally emergent (Lusher *et al.*, 2013) and co-evolve in a complex manner (Stuart and Sorenson, 2007; Zaheer and Soda, 2009).

Prior strategy research has rarely examined the complex combinations of processes that simultaneously shape the structural characteristics of a given network. Traditional network analysis uses regression methodologies that are based on the assumption that tie formation between two actors is independent of the other ties and actors in the network. However, this assumption can be problematic for many networks, in which new tie formation is an interdependent process influenced by both the characteristics of the actors and of their existing ties (Ahuja *et al.*, 2012; Contractor *et al.*, 2006; Provan, Fish, and Sydow, 2007). Strategy network researchers often address this problem by using matched pair samples, rare events methods, or other advanced techniques in random effect logistic regression models. However, these approaches offer only a partial solution. Moreover, conventional statistical methodologies are unable to account for the endogenous structural effects that the existing relationships between two firms have on the formation of ties to a third firm (Contractor *et al.*, 2006). In the example of the global cellular phone industry, existing relationships among Google, HTC, and Samsung are likely to influence Microsoft's subsequent choice to partner with Nokia. As a result, without modeling such endogenous structural processes, researchers run the risk of inappropriately attributing observed network tie formation to firm- or dyad-specific characteristics (e.g., characteristics of Microsoft or Nokia in our previous example), although such effects may be confounded by underlying interdependent structural processes (e.g., the existing relationships among Google, HTC, and Samsung).

The goal of this study is to highlight a relatively new analytical approach that allows scholars to examine multiple interdependent social processes involved in network formation. We focus on a class of social network methodologies called Exponential Random Graph Models (ERGMs) to demonstrate how they permit better specification of the processes underlying network formation (Frank and Strauss, 1986; Pattison and Wasserman, 1999; Snijders *et al.,* 2006). Broadly stated, ERGM analysis examines tie formation at the network level, accounting for potential cross-dependencies, emergent network structures (such as consortia or clusters of allied firms within an industry), and other effects that cannot be addressed through conventional approaches, which focus primarily on dyadic relationships. Thus, while ERGMs can model many of the co-variates included in traditional regressions, they provide additional insights that increase our understanding of how network structures form. In the example of the global cellular industry, ERGMs could provide insight into the likelihood that any two firms will form a tie, *given* the existing ties between other firms in the industry.

Currently, only a small number of organizational studies have utilized ERGMs (e.g., Faraj and Johnson, 2011; Lomi *et al.*, 2014). In this article, we

DOI: 10.1002/smj

extend this research and demonstrate how ERGMs can be effectively employed for a much broader set of research questions to study strategy network phenomena. We suggest that ERGMs can be used to explicitly capture the effects of endogenous local structures, and more generally, to understand the antecedents and mechanisms involved in network formation. Broadly stated, this category of research can be expressed through two questions: (1) How do observed network structures emerge, and (2) What are the underlying social processes that lead to the emergence of these observed structures? With their distinctive advantages, ERGMs not only extend prior research, but also open up new research opportunities to enhance our understanding of strategy topics such as multipartner alliances, microfoundations of interorganizational network formation, and multiplexity (multiple types of ties) in social relationships.

To demonstrate the benefits of ERGMs, we provide an example examining board interlocks among Fortune 100 firms and develop models to illustrate the comparison of traditional logistic regression methodologies to ERGM techniques. Prior research has examined different firm- and dyad-specific factors of interlock tie formation, yet few studies examine endogenous structural processes underlying the formation of board interlock networks (Harrigan and Bond, 2013). Thus, we first examine whether there are any structural processes that shape the board interlock network. We also test whether the influence of firm-, dyad-specific factors examined in prior research persists after explicitly accounting for these structures. Our results show that endogenous structural processes such as reciprocity ("returning the favor" by exchanging board interlock invitations) and triad closure (the greater likelihood of a tie forming between two actors when each is already tied to a third actor) play a significant role in shaping this network. These results provide insights not offered by other regression techniques and indicate that interlock formation may partially stem from broader social phenomena. At the same time, when we control for local network structural effects using ERGMs, some of the firm-specific characteristics that have most often been studied in the past using conventional techniques prove to be less consequential. For example, prior research has produced inconsistent results regarding the relationship between profitability and interlocks (Mizruchi, 1996). Our findings help clarify this issue, revealing little evidence that directors of large or profitable firms are more likely to be invited for a directorship at other firms when network structural effects are taken into consideration. Our application shows that the use of ERGMs provide not only rigorous empirical evidence for advancing scientific research, but also opportunities for further theorizing the social embeddedness view of board interlock formation as suggested in prior research (Withers, Hillman, and Cannella, 2012). Furthermore, we offer potential extensions of existing strategy research that could be made using ERGMs in domains such as alliances among multiple firms, microfoundations of interorganizational network formation, and different types of concurrent ties among actors.

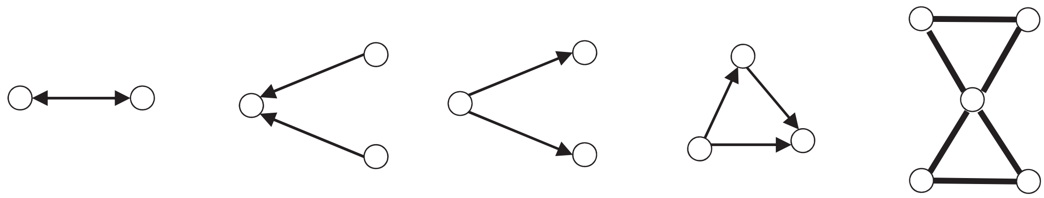
NETWORK FORMATION

Current approaches in strategy research

Existing research in the strategy area has focused on numerous actor and dyadic characteristics that influence tie formation between organizations. At the actor (firm) level, a variety of firm-specific characteristics such as technical capability or organizational reputation have been shown to be important predictors of a firm's propensity to form ties with other firms, for example through alliances (e.g., Ahuja, 2000; Gu and Lu, 2013). In a directed network, sender's and receiver's characteristics may influence the likelihood of a tie being formed.

Existing research has also illustrated how the observed network structure may be driven by characteristics of the dyad, showing how a relational attribute between two parties can influence the formation of ties. As an illustration, homophily suggests that firms with similar characteristics are more likely to have ties with one another than with other firms (McPherson, Smith-Lovin, and Cook, 2001). However, homophily may sometimes limit the benefits of connection in terms of information or resources available in the network; thus, actors may partner with others who are different from them. For example, past research has shown how dyad-specific characteristics such as differences or similarities in firms' resource endowments or their relative position with respect to markets, technologies, or geographic location are important factors influencing tie formation (Diestre and Rajagopalan, 2012; Rothaermel and Boeker, 2008). Finally, network ties emerge as a result of other types of shared ties between actors, that is, multiplexity. For

DOI: 10.1002/smj



(a) Reciprocity (b) Popularity (c) Activity (d) Triad closure (e) Brokerage

Figure 1. Different types of network structures and associated endogenous processes

example, the presence of collaborative R&D relationships between firms may subsequently influence the formation of different kinds of ties such as customer-buyer relationships (Powell, Koput, and Smith-Doerr, 1996; Shipilov and Li, 2012). Similarly, characteristics of interlocking ties between individual board members influence subsequent alliance formation between their affiliated organizations (Gulati and Westphal, 1999).

Endogenous structural processes

While network formation is influenced by firm-specific and dyad-specific characteristics such as those highlighted above, networks can also emerge through broader social processes such as endogenous effects driven by the internal processes of the focal network (Lusher and Robins, 2013; Robins, 2009). For example, individual actors may act separately from each other without any knowledge of or intention to shape the broader network while still being influenced by each other's simultaneous actions (Gulati and Gargiulo, 1999; Uzzi and Spiro, 2005; Watts, 1999). In such cases, network ties are the result of endogenous processes influenced by existing network ties rather than as a result of actor attributes or other exogenous factors. Scholars have suggested five broad types of endogenous structural processes that influence network formation (Lusher and Robins, 2013), as illustrated in Figure 1.

Reciprocity (a) is the most basic, yet one of the most important, tendencies in social interactions (Blau, 1964). It explains tie formation through "returning the favor," reciprocating an earlier interaction with a network actor. The structure of the network can also be influenced by the number and direction of an actor's ties. Popularity (b) illustrates the process by which already-popular actors may become even more popular, analogous to the well-known "Matthew effect" in social science (Barabási and Albert, 1999; Merton, 1968), often described as "the rich get richer." For example, in interorganizational networks, firms with more extensive alliance ties are more likely to engage in future alliances, subsequently influencing their visibility and attractiveness as a potential partner (Podolny, 1993; Podolny and Stuart, 1995). Ties may also more likely be generated by actors that are simply very active in seeking new network connections, represented as Activity (c) in Figure 1. The network patterns associated with Popularity (b) and Activity (c) are often called "star" terms because of their star-like structures; specifically, "in-two-star" describes popularity with two incoming ties toward the central node, and "out-two-star" refers to activity with two outgoing ties from the central node in a directed network. In an undirected network, there is no need to differentiate the direction, and we would refer only to a general "two-star" term. (Note that there can be multiple ties outgoing/incoming to the central node; we depict only the simplest forms for purpose of illustration.) In network terms, a triad represents the structure of ties between any set of three actors, with Triad Closure (d) indicating that two actors are likely to form a tie if they are each tied to a separate common actor, creating a triangle connecting all three actors (Wasserman and Faust, 1994). "A friend of my friend is my friend" is an intuitive example of triad closure, which is also referred to as the transitive influence on the formation of a tie between unconnected actors. Research suggests that firms may engage in triad closure to obtain resources from multiple collaboration partners to counter the move of a competitor or to protect their own interests in an interorganizational network (Gomes-Cassares, 1994; Madhavan, Gnyawali, and He, 2004). Finally, ties may occur by the network process of Brokerage (e) where an actor connects others who are not directly connected. There are particular advantages that brokers enjoy, as Burt (1992) discusses in terms of the power and

DOI: 10.1002/smj

influence obtained by actors in a brokerage position, shown as the central node of Figure 1(e).

Network formation is the result of numerous processes that interact and operate simultaneously (Contractor *et al.*, 2006; Hedström and Swedberg, 1998; Lusher *et al.*, 2013). Strategy research on networks and ties has largely focused on how a firm's characteristics or dyadic-specific attributes influence tie formation. More complex, endogenous structural effects such as reciprocity, triad closure and brokerage have rarely been empirically investigated in a systematic fashion, although the notion that firms' decisions to create ties are influenced by others' behaviors is a central premise of network research. This omission has important implications for research on network formation. Failure to account for these endogenous structures may result in model misspecification, attributing significant effects to firm- or dyad-specific characteristics that may be confounded with structural processes independently driving the network (Cranmer and Desmarais, 2011; Goodreau, Kitts, and Morris, 2009; Harrigan and Bond, 2013). In contrast, properly accounting for these structural effects may aid theory development, allowing us to identify combinations of social processes underlying the emergence of network structures (Contractor *et al.*, 2006). In the next section, we discuss why conventional regression models may be an inadequate tool for network formation research and introduce recent methodological advancements, ERGMs, as a better alternative.

NETWORK METHODOLOGIES

Conventional regression methodology for network formation research

Past network research in strategy has generally employed regression models such as logit or probit to study network formation among firms, with a focus on testing the effect of firm or dyadic co-variates (e.g., technical capability, resource complementarity) or some network characteristics (e.g., centrality) on tie formation (Chung, Singh, and Lee, 2000; Gulati, 1995; Gulati and Gargiulo, 1999). However, for a number of reasons, these approaches impose significant limitations when examining network formation. Standard statistical methods are based on assumptions of independence, which are problematic for network data that are inherently interdependent (Wasserman and Faust, 1994). Past research has attempted to address this issue by employing corrections such as the clustering of standard errors or the creation of separate control variables to correct for autocorrelation among observations (Lincoln, 1984; Stuart, 1998), or it has treated the problem as a sampling issue and tackled it by using elaborate weighting methodologies (Barnett, 1993; Gulati, 1995). These techniques may provide an insufficient solution to the study of network formation, given the dependence of observations in relational data that make it impossible to correctly cluster standard errors or to appropriately control for oversampling (Greene, 2008).

More importantly, standard regression methods are generally not capable of incorporating various local network structures such as triads stemming from either endogenous structural effects or dyadic effects (e.g., homophily between firms with similar attributes) because they are not independent of each other (Wasserman and Pattison, 1996). Thus, when conventional statistical models are used for network formation research, they are likely to suffer from model misspecification, even with the inclusion of firm- or dyad-specific co-variates. Causal inference about the influence of specific factors may be incorrect given this confounding effect of the endogenous structural processes (Cranmer and Desmarais, 2011; Goodreau *et al.*, 2009; Lusher *et al.*, 2013). In sum, although standard statistical approaches are useful for research from the perspective of the individual firm (i.e., ego-centric perspective), they are inappropriate to study network formation when we have the goal of examining the multiple processes that operate concurrently to generate a global network.

Exponential random graph models

Exponential Random Graph Models (ERGMs) are well suited to address the limitations of traditional regression methodologies. ERGMs are a class of statistical models for social networks which account for the presence (or absence) of network ties (Robins *et al.*, 2007a; Snijders *et al.*, 2006; Wasserman and Pattison, 1996). Relative to traditional regression models, ERGMs provide a superior approach to study network formation by explicitly modeling endogenous dependencies that may shape networks along with exogenous factors such as actor- or dyad-specific characteristics (Lusher *et al.*, 2013; Robins *et al.*, 2007a). ERGMs model ties as being interdependent, resulting in a

DOI: 10.1002/smj

variety of local network configurations (as represented in Figure 1). These network configurations are consequential patterns that may reflect important social processes such as reciprocity or clustering that simultaneously affect the formation of a global network. The formation of ties and network structures is tested for statistical significance relative to what might be expected through random tie formation, conditioned on other effects in the model. ERGMs do not require the assumption of independence between network ties and avoid the need for a matched sample design or the bias correction techniques for rare events that have been used in prior network research.

ERGMs can incorporate different types of network configurations and estimate their effects on network formation. For instance, ERGMs can describe the likelihood of the formation of reciprocal ties or whether a tie between two actors, already tied to a common third actor, is more likely to be observed (i.e., triad closure) in an overall network, *conditioned* on the structure of the network. Given that structural outcomes such as triad formation have been shown to be interdependent, such an inference is problematic for standard statistical methods (Wasserman and Faust, 1994).

Moreover, ERGMs can accommodate any number of binary, categorical, or continuous actor- or dyad-specific co-variates as well to see whether they are associated with the formation of network ties. ERGMs can also be used to analyze different types of networks such as directed and nondirected networks, bipartite, and multiplex networks with various types of nodes and relationships (Lusher *et al.*, 2013; Robins, Pattison, and Wang, 2009; Wang, 2013; Wang *et al.*, 2013). Therefore, ERGMs provide a powerful, flexible tool to separate various social processes operating concurrently and evaluate the relative contribution of each on the formation of the observed network structure (Lusher *et al.*, 2013; Robins *et al.*, 2007a). At least in this aspect, these broader capabilities of ERGMs are in some ways analogous to the advantages of statistical analysis tools such as structural equation modeling (SEM), which allow researchers to simultaneously capture wider system-level effects. For example, as SEM expands from conventional cause-effect regression modeling to the concurrent analysis of more complex co-variance structures, ERGMs go beyond nodal and dyadic factors modeled in conventional logistic regression to capture diverse factors at the broader network level.

ERGMs trace their origins to influential work by Frank and Strauss (1986) who applied spatial statistical approaches to networks and proposed Markov random graph models to directly address the issue of interdependence. The models became widely known as *p** models from the seminal work by Wasserman and Pattison (1996), which broadened the use of this approach to network analysis. A number of subsequent advances, including adaptations for local "neighborhood" network structures (Pattison and Robins, 2002) and methods for overcoming the problem of model degeneracy (Hunter and Handcock, 2006; Robins *et al.*, 2009; Snijders *et al.*, 2006) have helped develop ERGMs into a viable tool for analyzing real world network data.

Recently, ERGMs have begun to be adopted in a wide range of social science disciplines, including sociology, demography, communications, and political science (e.g., Atouba and Shumate, 2010; Cranmer and Desmarais, 2011; Goodreau *et al.*, 2009; Wimmer and Lewis, 2010). A small, yet growing number of recent organizational studies using ERGMs demonstrates the potential of the methodology as a useful tool for modeling multiple social processes, though these techniques have seldom been applied to empirical research focused on strategy questions. We provide a summary of recent studies using ERGMs in organizational research in Table S1, along with a description of how they apply ERGM techniques.

STATISTICAL INFERENCE THROUGH ERGMS

Statistical framework and dependence assumptions

ERGMs have the following form

$$\Pr\ (\mathbf{X} = \mathbf{x}) = (1/k)\ \exp\left[\sum_{A} \eta_A z_A(\mathbf{x})\right], \qquad (1)$$

where X_{ij} is a random variable that represents a tie between actor *i* to actor *j* ($X_{ij} = 1$ if there is a tie from actor *i* to *j*, and 0 otherwise). These ties are represented in an $n \times n$ adjacency matrix (n = number of actors in the network) denoted as **X**, and **x** denotes a matrix of realized ties in the network. When ties are nondirectional (edges), **X** is symmetric. When ties are directional (arcs), $X_{ij} \neq X_{ji}$. The *A* refers to different network configuration types. The $z_A(x)$ terms

DOI: 10.1002/smj

are model co-variates, denoting any set of A network statistics calculated on **x** and theorized to affect the probability of this network forming. Examples of z statistics are the number of ties, the number of ties between firms with a shared nodal characteristic, or the number of closed triads and so on. Equation 1 may be modified by replacing $z_A(x)$ with $z_A(x, P)$ to accommodate additional co-variate information P such as firm- or dyad-specific characteristics. The η_A coefficients are unknown parameters to be estimated, and they determine the effect of the network statistics included in the model for the observed network. The k stands for the quantity from the numerator summed over all possible networks with n actors. It constrains the probabilities to sum to 1. Simply put, ERGMs place more or less weight on networks with certain features, as determined by η_A (i.e., parameters), and z_A (network statistics). The equation above can also be expressed in terms of the conditional log-odds (logit) of individual ties:

$$\text{logit}\left(\mathrm{P}\left(\mathrm{X}_{\mathrm{ij}} = 1 \mid n, X_{ij}^{c}\right)\right) = \sum_{A} \eta_A \delta z_A(x), \quad (2)$$

where X_{ij}^c denotes the rest of the network other than the single variable X_{ij}, and δZ_A is the amount by which z_A changes when X_{ij} is changed from 0 to 1. The presence of X_{ij}^c in the conditional statement in the left-hand side of the equation represents the mutual dependence of ties, showing how ERGMs explicitly accommodate interdependent observations. This alternative specification also clarifies the interpretation of η_A vector, the coefficients of interest. If forming a tie increases z_A by 1, then all other things being equal, the log-odds of that tie forming increase by η_A.

To implement ERGMs, it is important to understand the dependence assumptions that define the ways in which the observed ties may be related (Brandes *et al.*, 2013; Pattison and Robins, 2002; Robins *et al.*, 2007a). A particular dependence assumption determines the different types of network configurations to be included in a model (Lusher *et al.*, 2013; Robins *et al.*, 2007a). The simplest dependence assumption is that all possible distinct ties are independent of one another; they occur randomly with a certain fixed probability. A second assumption is that dyads are independent of one another. For example, reciprocity in a directed network is a form of dependency assumption where the two possible directed ties within a dyad are dependent on each other. This assumption is sometimes referred to as "dyadic independence" because there are no other effects outside the dyad that influence the formation of ties, and so the dyads are independent of each other. However, these two assumptions are usually implausible in most of the observed social networks (Snijders *et al.*, 2006). For example, if we believe that ties do not depend on each other, there would be no local network configurations formed such as stars or triangles other than a reciprocated tie. A more realistic assumption is Markov dependence (Frank and Strauss, 1986), where ties may depend on the presence of a common actor. For example, the relationship between A and B may well be dependent on the presence or absence of a relationship between B and C. As explained in the following section, models exclusively based on the Markov dependence assumption do not represent the observed network data well due to the problem of model degeneracy (Handcock, 2003a, b). Finally, the most common assumption is the "social circuit model", in combination with Markov dependence (Pattison and Robins, 2002). In this model, some dyads are conditionally dependent on the presence of other ties, even without a common actor (see Koskinen and Daraganova, 2013a, b) for more comprehensive explanations on the different types of dependence assumptions).

Model estimation

Parameters in ERGMs were initially estimated using maximum pseudo-likelihood (Strauss and Ikeda, 1990), yet this approach tends to perform poorly, particularly with dyad-dependent models. Instead, Markov Chain Monte Carlo maximum likelihood estimation (MCMC-MLE) procedures have been used (Geyer and Thompson, 1992; Snijders, 2002). Monte Carlo estimation simulates a distribution of random graphs using starting values of parameter estimates generated by pseudo-likelihood, and it repeats the process to get refined values by comparing simulated distributions of graphs with the observed data (Snijders, 2002). The benefit of the MCMC-MLE approach is that with an infinite number of draws from the distribution of network configurations, it gives estimates equivalent to the MLE and provides reliable standard errors while including dyad-dependent terms (for a review, see Wasserman and Robins, 2005). Currently, the MCMC-MLE approach is the default for most software packages. One drawback associated with the use of this procedure is that

DOI: 10.1002/smj

resulting networks generated by parameter estimates with Markov dependence assumptions were often degenerate—that is, the model produced estimates that created a graph with no ties at all or a complete graph with ties connecting every node. This problem of model degeneracy is primarily due to poor model specification and often occurs among networks with a high level of triangles (Handcock, 2003a, b). Scholars have developed a series of new network specifications called social circuit dependence (Pattison and Robins, 2002) that significantly curtail such issues (Hunter and Handcock, 2006; Robins *et al.*, 2009; Snijders *et al.*, 2006). Thus, in our application, we adopt these new specifications to examine structural effects, following prior research (Goodreau *et al.*, 2009; Wimmer and Lewis, 2010).

APPLICATION

To illustrate the capabilities of ERGMs and their application in the field of strategy, we examine the phenomenon of board interlocks, interorganizational ties that are formed between firms sharing executives on their boards of directors (Mizruchi, 1996). Prior research has identified a variety of factors that influence dyadic interlock tie formation (Beckman, Haunschild, and Phillips, 2004; Mizruchi and Stearns, 1988; Pfeffer and Salancik, 1978), yet few studies explicitly account for the influence of endogenous structural processes—that is, the existing set of board interlocks—in the formation of future interlock ties (Harrigan and Bond, 2013). Thus, we explore whether the influence of firm- and dyad-specific characteristics persists while structural effects are taken into account.

Sample and data

We chose to focus our study on the network of interlocks formed between the boards of directors of U.S. firms belonging to the Fortune 100 in 2005 to predict the subsequent formation of interlock ties among these companies from 2006 to 2010. Long-established research has argued that director ties among the most important firms in the U.S. economy result in the formation and persistence of a corporate elite (Mills, 1956; Palmer, Friedland, and Singh, 1986), who act to ensure the maintenance of their privileged position in the economy as well as offering a platform for the diffusion of information and new managerial practices (Davis, 1996; Haunschild, 1994; Haunschild and Beckman, 1998; Mizruchi, 1996). We use 2005 as the reference year for firm and dyadic attributes and track the subsequent formation of interlock ties between companies in our sample during the period of 2006–2010. The Sarbanes-Oxley legislation passed in 2002 led to substantive changes in board composition and membership. Our study period lags this change and captures boards after changes made in response to the legislation related to the availability and willingness of directors to sit on multiple boards (Green, 2005; Linck, Netter, and Yang, 2009). Following prior research (Beckman *et al.*, 2004), we omit privately held organizations such as insurance firms from our sample to ensure the consistency of financial information in our analysis, resulting in a final sample size of 95 firms.

We capture a new board interlock tie for each instance in which a director or executive of a firm accepts a directorship with another firm in the sample. We draw interlock data from the GMI Ratings corporate governance database (formerly known as the Corporate Library), a third-party resource tracking board membership in publicly traded U.S. firms. The resulting binary ties recorded among all potential dyads are then assembled into a 95×95 binary sociomatrix (essentially, a grid listing all firms on the vertical and horizontal axes, capturing the presence or lack of board interlock ties for each possible dyadic combination of sample firms) to be analyzed by ERGMs. This is a directed network, given that the focal firm essentially initiates a tie by inviting a director from another firm to serve on its board. We observe a total of 129 new interlock ties formed between sample firms during the 2006–2010 period of our study.

We also collected data on our independent variables from a variety of additional sources. Data for firm size and all financial measures were obtained from COMPUSTAT. Alliance data were obtained through the SDC Platinum database.

Variables and measures

The dependent variable in our study is tie formation through board interlocks among the 95 sampled firms. Our key independent variables examine the effect of board characteristics at different levels of analysis—firm characteristics, dyad–co-variates, and structural effects—on subsequent board ties.

Firm level characteristics

Prior research on boards of directors has emphasized the role that firm characteristics play in determining what interlock relationships may form. Research has shown that geographic proximity is an important determinant for network formation of corporate interlocks (Kono *et al.*, 1998). We examine the influence of geography by modeling whether a tie is more likely between firms located in the same *State,* while accounting for geographic levels of tie formation. Empirically, we include a series of indicator variables for the 10 states most commonly represented in our data, which cover 74 percent of our sample population. The remaining firms are grouped into the reference category. We also include a term to capture homophily effects of colocation in a common state. This approach is analogous to including both main effect and interaction terms in a regression. The main effect in this case is to control for the propensity of firms located in a particular geographic region to make ties, whereas the interaction effect tests whether firms located in the same region are more likely to make ties with each other, over the variance explained by the main effect. We include *Firm size* by measuring the number of employees in each firm as reported in the reference year of 2005. Managers and directors of successful firms may be more likely form ties (Davis, 1993; Withers *et al.*, 2012); thus, we include *Profitability* of a company by measuring its ROA, again in 2005. We include *Market uncertainty*, which has been shown to influence a firm's propensity to pursue interorganizational relationships as it seeks to lessen its dependence and alleviate environmental uncertainty (Pfeffer and Salancik, 1978). We measure this variable as the average monthly volatility across all companies in the focal firm's industry using four-digit SIC code (Beckman *et al.*, 2004). Prior experience in external interorganizational relationships may influence a firm's motivation to make additional ties (Beckman *et al.*, 2004; Yue, 2012). Therefore, we also include a measure of the *Number of prior alliances* in which each firm engaged during the period from 2001 to 2005.

Dyad level characteristics

The presence of existing relationships among firms can influence their subsequent tie formation. Thus, we examine whether firms in our sample had any previous interlock ties with each other before the period of our study. *Prior interlocks* is operationalized as a binary sociomatrix valued as 1 for the presence of one or more prior ties between a pair of sample firms and 0 otherwise. We draw from the GMI Ratings corporate governance database, using 2001–2005 as the reference period for this variable. We also examine whether firms that are similar in size may be more likely to make interlock ties with each other. *Size difference* is a dyadic co-variate consisting of the absolute difference in firm size operationalized by the number of employees for each firm.

Structural effects

Structural processes can also be important drivers of board network formation, but empirical examination of such effects has been largely absent in prior board interlock research. To facilitate understanding of each of the structural terms we include in the model, we provide a graphical presentation of each structural term in Figure 2. We follow in the path of prior research suggesting that models should include at least a parameter for density, some control over the degree distribution and triad closure to properly capture the features of the network in general (Robins and Lusher, 2013; Robins *et al.*, 2009; Snijders *et al.*, 2006). We include the following set of structural effects that may occur independent of firm or dyad characteristics. *Reciprocity* captures the tendency of a tie being reciprocated from j to i when firm i has an existing tie to firm j; in our study, it represents the likelihood that firm i that already has a director of firm j on its board will subsequently place a member of its board on the board of firm j. Ties are directional, with one actor initiating them and another receiving them. In the interlock context, the initiator is the firm that puts another firm's director on its own board while the firm that originally had the board member is the receiver. We use two measures to capture the differences between senders and receivers. Popularity and activity spread (star-like configurations) capture the tendency of network centralization in the in- and out-degree distributions (Pattison and Robins, 2002). *Popularity spread* measures how often a firm's director is invited for a directorship from multiple firms, while *Activity spread* captures how often a firm initiates an interlock tie by inviting a director from other firms. Triads represent an important intermediate level in

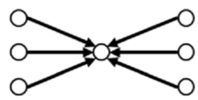
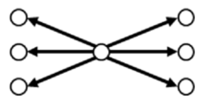
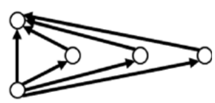
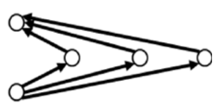
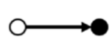
Parameter	Diagram	Social Process	statnet term
Purely structural effects			
Arc		Baseline tendency for interlock tie formation	edges
Reciprocity		Firm A's tendency toward inviting a director of firm B whose director is already on Firm A's board	mutual
Popularity Spread		Tendency toward variation in the degree to which a manager of firm A is invited to sit on multiple boards.	gwidegree
Activity Spread		Tendency toward variation in the degree to which firm A invites a director from multiple firms to sit on its board	gwodegree
Generalized transitive closure		Tendency for the closure of transitive triads (when firm A's board has a director from firm B, and when firm B's board has a director from C, firm A is more likely to invite a director from firm C)	gwesp
Multiple Connectivity		Tendency for the formation of multiple 2-paths connecting firms in the board interlocking network	gwdsp
Actor relation effects (black nodes indicates actor with attribute)			
Sender (firm size) Sender (profitability) Sender (prior alliance activities) Sender (uncertainty)		Tendency of firms with a certain level of size, profitability, prior alliance activities or facing a certain level of uncertainty to invite a director from other firms	nodeocov (firm size) nodeocov (profitability) nodeocov (prior alliance activities) nodeocov (uncertainty)
Receiver (firm size) Receiver (profitability) Receiver (prior alliance activities) Receiver (uncertainty)		Tendency of firms with a certain level of size, profitability, prior alliance activities or facing a certain level of uncertainty to be invited by other firms	nodeicov (firm size) nodeicov (profitability) nodeicov (prior alliance activities) nodeicov (uncertainty)
Homophily (state)		Tendency of managers from firms located in the same geographic location to sit on common boards	nodematch (state)
Covariate network			
Prior interlocks		Tendency for a dyad of firms that had prior interlocking ties to make a new tie through board interlock	edgecov (prior interlocks)

Figure 2. Summary of structural effects included in the ERGM estimation for board interlocks

DOI: 10.1002/smj

network analysis between the individual dyads and larger network structures (Madhavan *et al.*, 2004; Wasserman and Faust, 1994). In our context, triad closure refers to the likelihood that a board interlock will form between two firms that both have existing ties with a third firm. We capture this effect using the term *Generalized ransitive closure* (other forms of triad closure may be modeled in a directed network—Robins *et al.* (2009) provide greater detail on these alternative terms). Finally, *Multiple connectivity* captures a tendency for the formation of nonclosure structures where two actors are connected by multiple paths: in our context, in which firm A and firm B are indirectly connected through other organizations that share board interlocks with the two firms. Research suggests that inclusion of this term permits refined inferences about transitivity effects because a triad closure contains other lower-order configurations such as popularity and activity spread (Robins *et al.,* 2009).

We use new specifications to incorporate these structural effects (Goodreau *et al.*, 2009; Hunter, 2007; Wimmer and Lewis, 2010) and to overcome the problem of model degeneracy discussed earlier. Popularity spread and activity spread are included by using geometrically weighted in-degree distribution (GWID) and geometrically weighted out-degree distribution (GWOD), respectively. They model the shape of the in- and out-degree distribution. A large, positive coefficient for these parameters suggests a network with high-degree nodes. The GWID statistic models a tendency toward variation in the degree to which firm A's director is invited to join multiple external boards. The GWOD statistic indicates, on the other hand, a tendency toward variation in the degree to which firm A invites directors from multiple external firms to join its board. Basic triangles are included in ERGMs by a geometrically weighted shared partner (GWESP) statistic. This term indicates a general tendency for network closure of transitive triads (i.e., when firm A has a board interlock with firm B, and firm B has an interlock with firm C, A is more likely to form an interlock tie with C). Finally, multiple connectivity is included by geometrically weighted dyad-wise shared partner distribution (GWDSP) statistics. This statistic models a tendency for the formation of multiple two-paths connecting firms in the board interlock network.

Adding structural effects to the examination and estimation of board interlock formation provides several distinct advantages. A co-variate–only model without structural terms tends to overestimate the effect of firm- or dyad-level characteristics, whereas a full model that includes the structural terms can specifically estimate the unique effects of those factors. As a result, estimates of the effects of firm and dyadic co-variates may be smaller in the full model than in the co-variate–only model. We also predict that the full model will fit the observed network better than the co-variate–only model because at least some of the structural effects such as reciprocity and triad closure are important social processes influencing board interlock formation. We estimate our models using MCMC-MLE in the ERGM package, a part of the statnet suite of packages for R (Hunter *et al.*, 2008b). There are other useful software packages available for ERGM analysis, such as the PNet suite of programs for ERGMs (Wang, Robins, and Pattison, 2009) or SIENA-*p** in StOCNET (Snijders *et al.*, 2008).

Analysis and results

For the main descriptive statistics of the network of board interlocks, the probability that any pair of firms has a board interlock tie at some point during the study period is 1.4 percent (i.e., network density = 0.014). The average degree is 2.72. The standard deviation of out-degree (1.57) is slightly greater than that of in-degree (1.33). Thus, the sample firms are more heterogeneous in terms of initiating ties (i.e., inviting new directors who currently sit on the boards of other firms) than in terms of receiving ties.

The results of the ERGMs are shown in Table 1. Model 1 includes firm characteristics and dyad-specific co-variates without any structural terms. It is important to note that when ERGMs include only firm- or dyad-specific characteristics, the results are the same as what would be obtained from conventional logistic regression analysis frequently used in prior research (Koehly, Goodreau, and Morris, 2004). Thus, Model 1 provides a benchmark for comparison to the model with structural terms included. Model 2 adds a variety of structural terms explained earlier, along with the firm characteristics and dyad-specific co-variates.

We first consider whether a full model with the structural terms shows improvement with respect to model fit based on Akaike's Information Criterion (AIC) (Akaike, 1998). The smaller the value of AIC, the better the model fits the data. The AIC of Model

Table 1. Formation of board interlock in Fortune 100 firms

Parameter	Model 1 co-variates–only (no structural term)	Model 2 co-variates and structural term
Purely structural effects		
Arc	−13.23***	−10.39***
Reciprocity	—	2.72***
Popularity spread	—	−0.07
Activity spread	—	−0.57
Generalized transitive closure	—	0.83***
Multiple connectivity	—	−0.12+
Actor relation effects		
Sender (firm size)	0.49***	0.35***
Sender (profitability)	8.46***	6.25**
Sender (prior alliance activities)	0.002	0.002
Sender (market uncertainty)	1.56	1.61
Receiver (firm size)	0.23**	0.15+
Receiver (profitability)	4.81*	3.42
Receiver (prior alliance activities)	0.001	0.001
Receiver (market uncertainty)	−3.17+	−3.01+
Homophily (state)	1.08***	0.79***
Homophily (firm size)	−0.09	−0.05
Co-variate network		
Prior interlocks	0.74**	0.59*
Akaike information criterion (AIC) goodness of fit	1,264	1,196

+$p < 0.1$; *$p < 0.05$; **$p < 0.01$; ***$p < 0.001$.

2 is substantially smaller than Model 1, suggesting that systematic network properties are important in producing the observed network of board interlocks in our sample.

We are interested in the underlying processes of tie formation or how the observed network could have been formed (Lusher *et al.*, 2013). Thus, in addition to model selection criteria such as AIC, we also employ graphical evaluations of goodness of fit to visualize the match between the predicted and observed networks in Figure 3(a, b) (Goodreau *et al.*, 2009; Hunter, Goodreau, and Handcock, 2008a). Each plot compares the observed data to 100 randomly generated simulated networks obtained from the fitted models we examined. This allows the researcher to gain a visual sense of model fit by observing how well the distribution of plotted points of networks randomly generated from the fitted models match the actual observed network (represented by the dark line) in terms of key structural properties of the network such as the proportion of incoming or outgoing ties to other actors. We show the logit of relative frequency on the y-axis for greater ease of interpretation.

The first and second plots in Figure 3(a, b) represent the out-degree distribution (the number of connections a focal node has sent to other nodes) and in-degree distribution (the number of connections a focal node has received from other nodes). Model 2 fits slightly better than Model 1 with the dark line of Model 2 passing through the median point of the box plots for the range, yet Model 1 also does a relatively good job of producing networks that reflect the actual degree distribution. The third plot shows the distribution of the triad census, which captures 16 different forms of triads (see Holland and Leinhardt, 1970, for details on the 16 triad forms). While Model 1 underestimates several types of triangle structures in the observed network (suggesting a relatively poor fit), Model 2 appears to provide an improvement with simulated numbers of each type of triad closely following the pattern of the observed network. The fourth plot in Figure 3(a, b) shows the distribution of shared partners (number of third-party interlock ties in common between a given pair of firms), which indicates the level and scale of clustering. Here, we also see a noticeable difference between Models 1 and 2. By directly modeling the local structure with the inclusion of a term for shared partners, the plot illustrates that Model 2 provides a good fit between the simulated and observed networks. In contrast, Model 1 appears to be more divergent in terms of this network characteristic. Finally, the fifth

DOI: 10.1002/smj

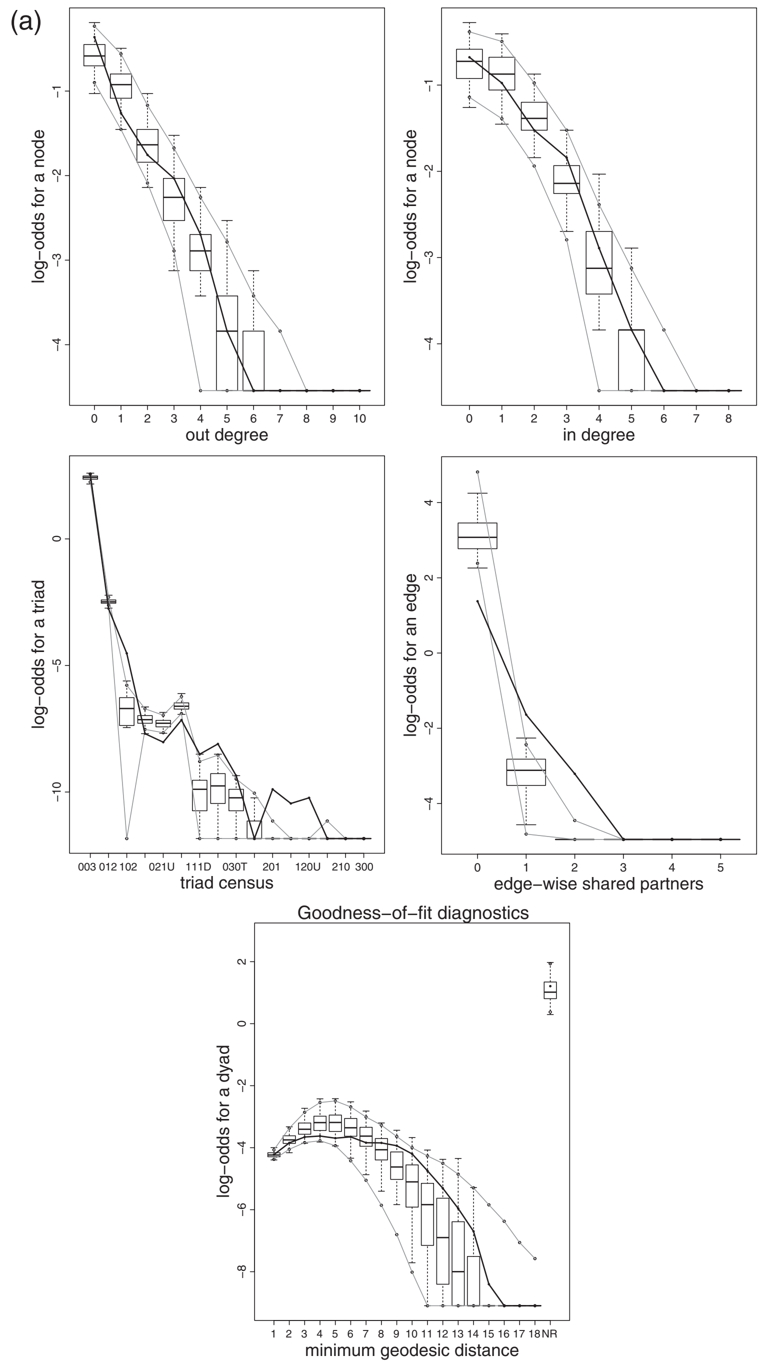


Figure 3. (a) Goodness-of-fit diagnostics for Model 1 (without structural effects). The dark solid line represents a given statistic from the observed board interlock network. The boxplots represent the same statistic from the 100 simulated networks; they include the median and interquartile range. The light-gray lines represent the range in which 95 percent of simulated networks fall. The Y-axis is expressed as a loglikelihood to facilitate interpretation. In summary, Model 1 without any structural effects shows a lack of fit, particularly in terms of “triad census” and “edge-wise shared partners” model statistics, as evidenced by the gap between the dark solid line and the trend of the boxplots. (b) Goodness-of-fit diagnostics for Model 2 (with structural effects). Compared to Model 1, Model 2 with structural effects shows a noticeable improvement of model fit by explicitly capturing additional structural effects through the GWESP and GWDSP terms included in the model. In each network statistic, the pattern of the boxplots from simulated networks are largely in line with the dark solid line from the observed network.

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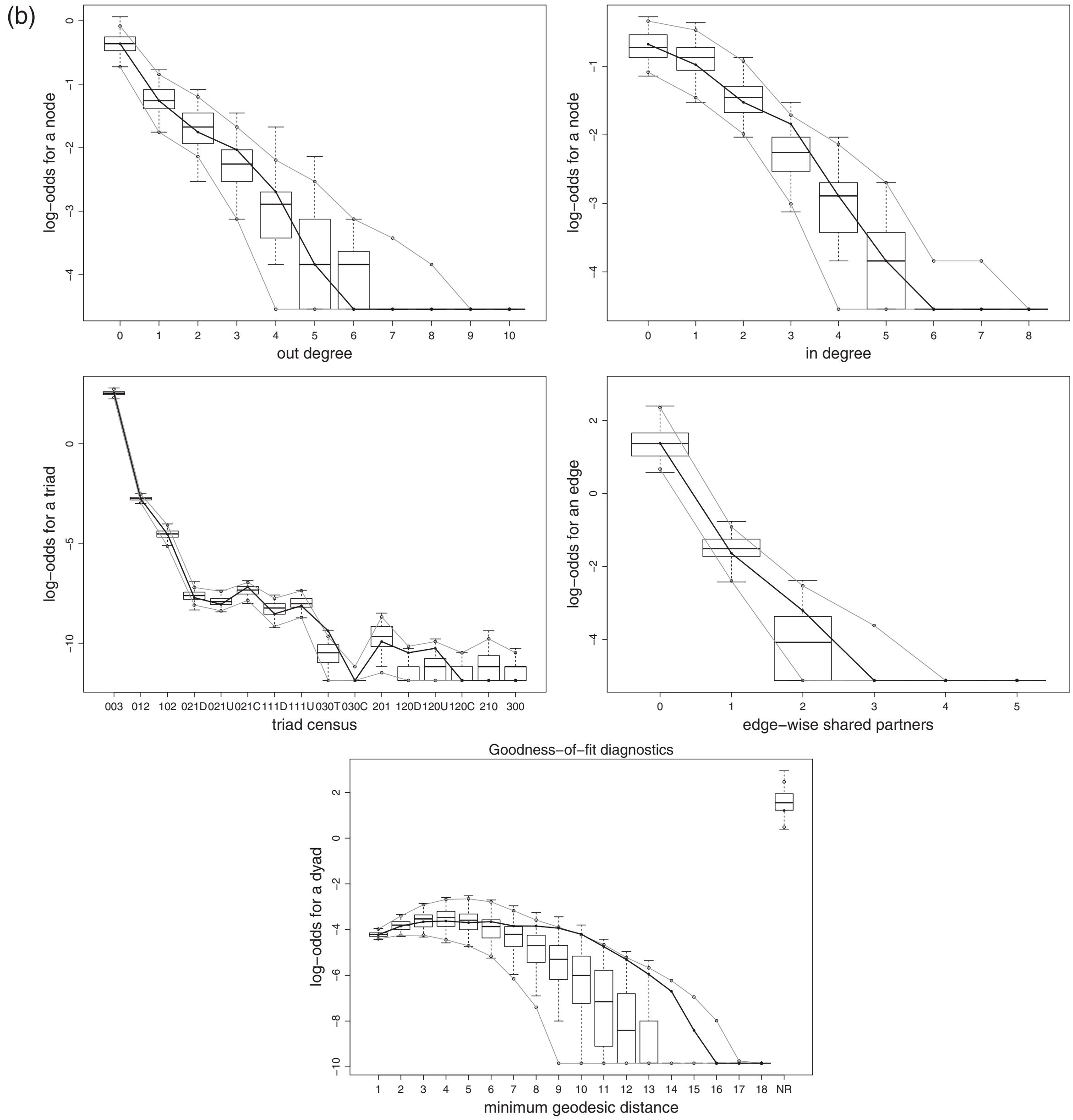

Figure 3. Continued.

plot examines a higher-order network statistic, the distribution of geodesic distances, tabulated across all actors. Geodesic distances represent the pairwise shortest distances between firms. Both Models 1 and 2 appear to provide a relatively good for the lower range of the plot, yet beyond the middle point the observed distribution diverges from the model prediction. Note that geodesic distance is a global property of the network (Goodreau *et al.*, 2009), and our models (both Models 1 and 2) do not include a specific structural term to capture this property because we do not propose specific examples of factors in the interlock context that would explain global network properties. Thus, although we provide the plots for geodesic distances as one of the ways to graphically demonstrate model fit, it is not surprising to see little improvement of Model 2 over Model 1 for this particular network characteristic. Depending on the goals of their study, researchers may explicitly capture this higher-order property in

DOI: 10.1002/smj

their models (Morris, Handcock, and Hunter, 2008, provide a discussion of ERGM terms related to this property).

Because Model 2 provides a better fit with the observed data, we further examine the model coefficients in order to assess the drivers of board interlock formation. In ERGMs, a positive coefficient suggests greater prevalence of a given configuration in the network than that which would be expected, conditional on the other effects in the model, whereas a negative coefficient indicates that the configuration occurs less often than expected (Lusher *et al.*, 2013). Returning to the results in Table 1, the negative, significant coefficient of *Arc* in Model 2 suggests that interlock ties occur relatively rarely, especially if a given pair of firms is not part of a higher order structure such as a star or triad. The *Arc* term in ERGMs is equivalent to an intercept term or a grand mean in regression or ANOVA, indicating the baseline propensity for tie formation in the network (Strauss and Ikeda, 1990; Wasserman and Pattison, 1996). The *Reciprocity* term represents the strength of reciprocity within dyads. The coefficient of *Reciprocity* in Model 2 is positive and highly significant, suggesting that firms are likely to reciprocate board membership with each other (e.g., a director/executive of firm A is more likely to hold a directorship in firm B whose director/executive has already been on firm A's board). The popularity spread and activity spread terms account for dispersion in the in- and out-degree distribution in the network. The coefficients for both terms are not significant. The positive, significant coefficient on the *Generalized Transitive Closure* term indicates that controlling for the tendency to reciprocate ties and for multiple connectivity, board interlock ties tend to take place in transitive structures. The results also imply that clusters in this network are driven by groups of overlapping triangles rather than clusters of firms that are either particularly popular or active. In terms of firm-specific characteristics, the positive, significant coefficient for *Sender* (*Firm size*) suggests that, when structural effects are accounted for, large firms are more likely to invite directors to join from other firms. The results also suggest that high performing firms (positive, significant coefficient for *Sender* [*Profitability]*) are more likely to invite external directors to join their boards, conditional on the other effects in the model. The positive, significant coefficient on *Homophily* (*State*) suggests that firms located in the same states are more likely to make interlocking ties with each other. Finally, firms are more likely to make interlock ties when they have shared interlock ties previously (positive, significant coefficient for *Prior interlocks*).

In fact, the comparison of Models 1 and 2 shows the striking change in terms of the effects of some co-variates. The coefficient associated with *Receiver* (*Firm size*) is highly significant in Model 1 ($p < 0.01$); however, it is only marginally significant in Model 2. In other words, after explicitly accounting for endogenous structural effects, the significance of the tendency to invite directors of large firms to join external boards is substantially reduced. The magnitude of the coefficient is also decreased. Similarly, the influence of *Receiver* (*Profitability*) also loses significance. While some firm-level characteristics (*Firm size* and *Profitability* in initiating board interlock ties) and dyad-level characteristics (homophily [*State*], prior interlocks) are shown to be influential in Model 2, the comparison of Models 1 and 2 shows a general pattern that the magnitude of coefficients and their significance level diminish with the inclusion of structural effects, as we anticipated. From a theoretical standpoint, these findings may support the notion that social processes related to reciprocity or information obtained through common third-party ties (i.e., transitivity) actually explain variation in interlock tie formation that would otherwise be attributed to target firm characteristics of prominence and success.

Overall, these results suggest that a variety of structural processes have unique explanatory power for board interlock tie formation among the largest, public U.S. firms, indicating that network formation models that fail to control for endogenous processes provide only a partial picture of the dynamics in this network. This analysis emphasizes the importance of simultaneously accounting for network–self-organizing processes as well as other firm- and dyad-specific co-variates in order to gain an accurate understanding of the complicated mechanisms of network formation, a task uniquely suited to ERGM techniques.

DISCUSSION

Network formation is the result of critical social processes driven by numerous factors. While prior research has employed traditional regression methods to empirically examine network

DOI: 10.1002/smj

formation, we propose the use of ERGMs as a superior alternative that offers several advantages. The primary advantage of ERGMs is that they allow accurate specification of multiple processes that simultaneously influence the creation of an observed network structure. In particular, ERGMs allow the incorporation of purely endogenous structural processes such as reciprocity, triad closure and higher-order dependencies while accounting for other actor and dyad specific attributes. In addition, ERGMs do not require the assumption of independence that underlies conventional models, enabling researchers to analyze complex relational data, and disentangle concurrent effects in a rigorous manner. Using ERGMs, strategy researchers may construct hypotheses of distinct social processes and test them directly to evaluate their relative contribution to network formation (Robins *et al.*, 2007a).

We provided a brief overview of recent network research, discussed some of the limitations of current methodological approaches and elaborated the basic concepts underlying ERGMs and how they offer unique strengths for studying network formation. Our application example demonstrates the advantages of ERGMs, uncovering interesting findings that would not have been possible using conventional techniques. For example, there has been little empirical research explicitly examining the influence of endogenous structural processes on board interlock formation even though social network theory has been a dominant theoretical lens in the literature (Withers *et al.*, 2012). ERGMs provide a useful tool to address these processes, and our results show that the board interlock network is in part a function of endogenous structural processes such as reciprocity and triad closure. Our examination of board interlocks using ERGM demonstrates how the failure to account for multiple processes or simultaneously include endogenous structural effects can lead to incorrect or incomplete inferences regarding the role of factors influencing network tie formation. We find that the influence of firm- and dyad-level characteristics diminishes substantially in magnitude and significance after accounting for structural effects, making an important contribution to our empirical analysis. Our results also help resolve the inconsistent findings regarding the influence of firm profitability on interlock formation, providing evidence that profitability may not play a significant role when network structural effects are considered.

Despite their advantages, ERGMs do have specific limitations as an empirical methodology for network analysis. One limitation is that they can only be used to model binary outcomes—the presence or lack of ties among actors in a network. Consequently, when ties vary in strength, they must be dichotomized in order to be analyzed using ERGMs. In our application, we operationalized ties using board interlocks. It is rare for multiple directors or executives of a given firm to overlap in their directorships in another specific firm simultaneously. As a result, the creation of a binary variable is appropriate for our sample and research question. For other applications where there is important variance in the value of the tie, researchers may want to first consider the distribution of the values and understand how the operationalized variable can be dichotomized (e.g., values either above or below the median for the overall sample). Another limitation of ERGMs, particularly the MCMC-MLE procedures we used in our examples, is that they can be computationally intensive, requiring substantial computational resources (especially with large-scale data). Furthermore, model degeneracy—cases in which the fitted model does not offer a good fit to the observed data due to model misspecification (Handcock, 2003a, b)—remains a challenge. However, recent (and continuing) development of these models has resulted in new network specifications that have limited the problem of model degeneracy and facilitated the adoption of the methodology (Robins *et al.*, 2007b). We employed these new network specifications in our empirical study and our predicted model provided a generally good fit to the observed data without the problem of model degeneracy, as shown in Figure 3(b).

Potential use of ERGMs in strategy research

Several features of ERGM methodology provide significant opportunities to extend strategy research in meaningful ways. First, the ability of ERGMs to directly account for tie dependencies in network data allows more precise analysis of the effect of factors that have been examined in prior research. Because ERGMs do not assume independence among observations and account for endogeneity, they can be used to test theories of tie formation to establish rigorous empirical evidence, a critical ingredient to develop models that are not only appealing, but also scientifically valid (Colquitt and Zapata-Phelan, 2007). For example, much prior research has examined the influence of organizational resources on alliance formation. While firms with more resources have more opportunities to form ties, their greater level of resources may also eliminate the need for collaboration through alliance.

To try to understand the competing effects of resources, some researchers have proposed an integration of both perspectives, resulting in a curvilinear relationship between resources and alliance formation (e.g., Gu and Lu, 2013). Of course, firms may also be more likely to form ties because of their extensive histories of alliance formation (i.e., activity) or their popularity as an alliance partner from the perspective of other potential partners. In such analyses, it may be important to first establish whether organizational resources have any independent effect beyond other factors that may simultaneously influence the formation of an observed network. ERGMs can test the main effect of organizational resources while explicitly controlling for numerous forms of structural effects. Because ERGMs avoid the need to use a matched sample design or analysis of only a subset of firms by modeling tie formation across the entire network, the inferences drawn as a result of the empirical analysis are significantly improved.

ERGMs may also help us better understand different types of local network patterns that generate the observed structure of the overall network. For example, brokerage is an important phenomenon that directly relates to network formation and structure. Research has demonstrated that status and centrality influence the formation of structural holes (Zaheer and Soda, 2009) and that firms that are in brokerage positions with heterogeneous partners are more likely to sustain their network position (Yin, Wu, and Tsai, 2012). ERGMs offer important advantages over conventional methods to extend research into brokerage and other structural effects by modeling brokerage directly.

ERGMs' flexibility to model exogenous firm- and dyad-specific attributes as well as endogenous structural effects allows researchers to hypothesize among competing explanations for network formation to isolate the specific effects of interest in their study with enhanced methodological rigor. To highlight and demonstrate how ERGMs may be used to extend past strategy research, we provide a summary of recent strategy work on tie formation in Table S2 with some specific comments on the potential use of ERGMs to extend each work.

ERGMs also open up a host of new and interesting questions that can advance strategy research. For example, ERGMs allow for the study of multipartner alliances that involve three or more actors (Das and Teng, 2002; Lavie, Lechner, and Singh, 2007; Li *et al.*, 2012). While multiparty alliances have become more prevalent recently, especially in high technology industries where different groups of firms may work together, relatively little is known about their formation (Li *et al.*, 2012). Given the empirical complexities inherent in the study of multipartner alliances, scholars have called for the development of methodologies that can more effectively investigate these types of structures (Rosenkopf and Padula, 2008). Because ERGMs can directly model local network structures such as triad and multipartner connectivity while accounting for other types of endogenous effects and exogenous factors, they provide a useful tool to better understand the antecedents of multipartner alliance formation.

Another promising area for the use of ERGMs is research on the microfoundations of interorganizational network formation. Prior research has highlighted the important role of existing ties among individuals for the subsequent formation of ties between their firms (Gulati and Westphal, 1999; Rosenkopf, Metiu, and George, 2001). For example, in an entrepreneurial setting, new startups are often founded by individuals who were previously employed by industry incumbents and subsequently left them to begin independent ventures (Klepper, 2001; Phillips, 2002). Thus, founders' employment relationships with their previous employers may have an important influence on the types of ties they form between their new ventures and the parent firms. ERGMs are well suited to study these situations as they allow for analysis of ties at two levels—where the network is represented simultaneously through a set of ties between individual actors and as a set of ties between organizations. This permits the modeling of both sets of characteristics, and their reciprocal effects on each other, simultaneously. Such modeling approaches ensure the preservation of the dualistic nature of the structure rather than constraining relationships into one form of tie or another (a network of firms or a network of individuals) (Harrigan and Bond, 2013). This methodological improvement is important because research focused on only individual or firm attributes, while simultaneously ignoring social processes behind network formation, may overestimate the impact of each of these attributes in isolation. ERGMs provide a more accurate assessment and understanding of the relative importance of different factors leading to network formation at the firm and individual levels.

Past network research in strategy has often assumed that all ties formed between actors reflect a single type of relationship. However, actors often maintain qualitatively different relationships to other actors connected with them both directly and indirectly (Baker and Faulkner, 2002). In fact, many interesting research questions in strategy involve firms engaged in multiple types of ties where the influence of such ties may span different networks (e.g., Shipilov and Li, 2012). For example, two firms may have an R&D alliance with each other while at the same time both being suppliers to a third firm (Gimeno, 2004; Gulati and Gargiulo, 1999). Given the flexibility of ERGMs to accommodate different roles for each organization as actor attributes and different types of relationships as dyad-co-variate or exogenous networks, ERGMs provide an opportunity to examine the influence of tie multiplexity on the formation of networks among organizations (Wang *et al.*, 2013). In the discussion section, we highlight recent extensions of ERGM techniques that enable the study of multiplex ties in strategy research.

Extensions of ERGM methodology

ERGMs are primarily used with cross-sectional data and do not model longitudinal effects in a manner directly analogous to conventional panel regression techniques. However, endogenous structural processes can still be examined and demonstrated over time using ERGMs with cross-sectional data (Lusher *et al.*, 2013). For example, to detect whether homophily has an influence on the network, researchers can observe the network at different points in time and observe whether ties were being formed among actors sharing similar characteristics. As a result, analysis using ERGMs with cross-sectional observations still offers important insights regarding the effect of homophily on the formation of the given network. Nonetheless, networks evolve and are subject to change, and more insight will be gained from longitudinal network data. Recent developments have created new opportunities for longitudinal analysis of organizational networks using newer ERGM techniques. For example, longitudinal ERGMs incorporate parameters for dynamic change, focusing on network ties (Snijders and Koskinen, 2013). This approach has been demonstrated in the study of changes in friendship networks (Igarashi, 2013) and could be meaningfully applied to a variety of time-based network phenomena in strategy, such as the creation and dissolution of alliance ties or changes in board interlocks. Note that while ERGMs are primarily tie-oriented models, stochastic actor-oriented models (SAOM) focus on actor characteristics in network dynamics (Snijders, 2001; Snijders and van Duijn, 1997). Depending on the research questions explored, SAOM may be better suited than a tie-based approach for studies focused on actor-driven theory and social processes (Lusher *et al.*, 2013).

Many interesting questions in strategy research involve firms' simultaneous participation in multiple relational networks, connecting them to external organizations through different types of ties. ERGM techniques have recently been extended to address the dynamics of such multiplex ties (Wang, 2013). This allows the exploration of social processes unique to multiplex networks, including the co-occurrence of multiplex ties, reciprocity across different types of ties, and entrainment, in which the presence of one connection leads to the formation of a different type of tie. Zhao and Rank (2013) illustrate the capabilities of multiplex ERGM methods in an organizational setting, studying networks of advice and employee satisfaction within bank branches. They find evidence of cross-network entrainment and reciprocity in these relationships, processes that could not be tested through conventional network analysis methodologies. The occurrence of multiplex ties is quite common in strategy network research, given that firms may be linked through alliances, board interlocks, trade associations, or other types of concurrent ties. Recent work in strategy has begun to explore such concurrent network effects (Ranganathan and Rosenkopf, 2014; Shipilov *et al.*, 2014; Wang *et al.*, 2014). Multiplex ERGM techniques can enhance this stream of work, providing a sound methodology for capturing the influence of cross-network relationships and offering a more realistic understanding of the many linkages that may form between organizations.

DOI: 10.1002/smj

Another potentially useful extension is multilevel ERGMs, which allows the simultaneous examination of networks among individuals at one level, organizations at another level, and cross-level networks between the organizations and individuals. This methodology can be particularly useful if one may be interested in how interdependencies among different levels of networks influence network formation. For example, Wang *et al.* (2013) examined a collaboration network of French cancer scientists and their affiliations with research laboratories using multilevel ERGMs, demonstrating how modeling of each network at the level of the researcher, lab, and ties among researchers and labs provides a more comprehensive understanding of network formation.

Another model closely related to ERGMs is the Autologistic Actor Attribute Model (ALAAM) (Robins, Pattison, and Elliott, 2001). This technique is designed to model behaviors of individuals as a function of an underlying network structure that is treated as exogenous. Although it is a social influence model that focuses on the attributes of nodes, whereas ERGMs are a social selection model for network structure, ALAAM follows similar logic to that of ERGMs. Further development in these and related techniques will permit researchers to better understand network structure and its influence of the practices and characteristics of network members (Daraganova and Pattison, 2013) in areas such as the diffusion and contagion of firm actions and practices in strategy research (e.g., Davis, 1991; Strang and Soule, 1998).

In conclusion, ERGMs represent an important technique that will allow strategy researchers to empirically examine a wider host of phenomena that have heretofore been inaccessible using conventional methodological techniques. As the connectedness among individuals, organizations, and societies continues to increase, a better understanding of how network structures emerge is critical to our knowledge of network mechanisms and outcomes. ERGMs allow scholars to build on the considerable foundation of existing network research while advancing our understanding of networks even further. Our discussion of the use of ERGMs demonstrates how strategy research focused on the emergence of networks can be more appropriately examined using ERGMs. We hope to stimulate more interest in ERGMs among strategy scholars and help to realize the promise of ERGMs to advance our understanding of the genesis of organizational networks.

ACKNOWLEDGEMENTS

We are grateful to David Gomulya, Steven M. Goodreau, Dennis Park, Miruna Petrescu-Prahova, Kevin Steensma, Dan Wang, and Mike Withers for their helpful comments and feedback on the manuscript.

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SUPPORTING INFORMATION

Additional supporting information may be found in the online version of this article:

Table S1. Research using ERGMs in organizational, nonstrategy research

Table S2. Prior strategy research on network formation and possible extensions using ERGMs