KNOWLEDGE SHARING IN ORGANIZATIONS: A BAYESIAN ANALYSIS OF THE ROLE OF RECIPROCITY AND FORMAL STRUCTURE •

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Paper accepted for publication in the *Journal of Management*

(Special Issue on Bayesian Probability and Statistics in Management Research)

• The names of the Authors are reported in alphabetical order. Each contributed equally to the paper. We are grateful to the reviewers and the special issue Editors for their insightful comments and advice.

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ABSTRACT

We examine the conditions under which knowledge embedded in advice relations is likely to reach across intraorganizational boundaries and be shared between distant organizational members. We emphasize boundary-crossing relations because activities of knowledge transfer and sharing across subunit boundaries are systematically related to a wide range of desirable organizational outcomes. Our main objective is to understand how organizational and social processes interact to sustain the transfer of knowledge carried by advice relations. Using original fieldwork and data that we have collected on members of the top management team in a multiunit industrial group, we show that knowledge embedded in task advice relations is unlikely to crosscut intraorganizational boundaries, unless advice relations are reciprocated, and supported by the presence of hierarchical relations linking managers in different subunits. The results we report are based on a novel Bayesian Exponential Random Graph Models (BERGMs) framework that allows us to test and assess the empirical value of our hypotheses while at the same time accounting for structural characteristics of the intraorganizational network of advice relations. We rely on computational and simulation methods to establish the consistency of the network implied by the model we propose with the structure of the intraorganizational network that we actually observed.

***Keywords**:* Advice relations; Bayesian Models; Exponential Random Graph Models (ERGMs); Knowledge transfer; Organizational design; Organizational structure; Social networks.

INTRODUCTION

"Regardless of the time and effort devoted by management to designing a rational organizational chart and elaborate procedure manuals," Blau and Scott argue in their classic *Formal Organizations,* "this official plan can never completely determine the conduct and *social relations* of the organization's members" (2003:5. Emphasis added). This view still provides the broad canvas on which contemporary research portrays social networks within organizations (Brass, Galaskiewicz, Greve & Tsai, 2004).

During the fifty years since *Formal Organizations* (Blau and Scott, 1962), studies of social networks in organizations have progressively extended our understanding of the relational basis of a wide range of organizational outcomes previously associated with organizational design. Examples of such outcomes include technological change (Barley, 1990), learning (Borgatti & Cross, 2003), innovation (Burt, 2004), productivity (Reagan, Zuckerman & McEvily, 2004), and the development of new products (Hansen, 1999). One consequence of these studies is that the relevance of social networks for organizations is now generally recognized (Borgatti & Forster, 2003). Less generally and more recently recognized, however, is the relevance of *organizations* for understanding social networks (Argote & Kane, 2009; Dokko, Kane & Tortoriello, 2014; Kane, 2010; McEvily, Soda & Tortoriello, 2014). These recent studies suggest that a full understanding of the "company behind the chart" (Krackhardt & Hanson, 1993) cannot be reached if "the chart" itself is ignored. With few exceptions, however, the chart and what might lie behind it are rarely examined together.

In this paper we seek to advance this line of argument by examining how elements of formal organizational structure affect the propensity of individuals to share and exchange knowledge through informal advice networks. We build on prior work on knowledge sharing networks in organizations and extend it in at least three ways. First, we show how knowledge transfer activities across intraorganizational boundaries emerge from the interaction between formal relations of hierarchical subordination and informal advice seeking relations. Prior studies have established that knowledge exchange relations are more likely to be established within, rather than across the boundaries of organizational units (Argote & Ingram, 2000). We reproduce - but also go beyond - this established result by showing how formal (centralized) hierarchical relations and informal (decentralized) advice relations interact to determine the conditions that facilitate or hinder knowledge sharing and transfer across intraorganizational units. Second, we specify Exponential Random Graph Models (ERGMs), a newly derived family of statistical models for social networks that not only allow parameters of theoretical interest to be cleanly estimated, but also capture essential elements of the global network structure in which dyadic knowledge exchange relations are embedded (Snijders, Pattison, Robins & Handcock, 2006). We rely on computational and simulation methods to assess the adherence of the model to data. Prior studies have revealed how the network context shapes the probability of observing network ties between individuals located in different organizational units (Hansen, 2002; Tortoriello, Reagans & McEvily, 2012). No study we are aware of, however, has also examined how empirical estimates of theoretically relevant parameters are able to reproduce the observed global structure of the knowledge sharing network. Third, by taking a novel Bayesian approach to the estimation and evaluation of ERGMs, we provide a more reliable and systematic probabilistic assessment of the uncertainty surrounding the estimates of the parameters of theoretical interest (Caimo & Friel, 2011). We adopt Bayesian Exponential Random Graphs Models (BERGMs) to examine the posterior distribution of parameter estimates of the network effects that extant organizational research has frequently documented, but not systematically examined. To the best of our knowledge, this is the first paper in which Bayesian approaches to ERGM are brought to bear on problems of knowledge transfer and sharing within organizations. Our paper demonstrates the specific value added of a modern Bayesian approach to the analysis of knowledge transfer within organizations.

We situate our study in the context of a Bayesian network analysis of data that we have collected on advice relations between the 47 members of a top management team in an industrial group containing five distinct subsidiary companies. We emphasize task advice relations as an example of a social relation that is "influential in explaining the processes of knowledge creation, transfer, and adoption" (Phelps, Heidl & Wadhwa: 2012: 1155). We emphasize boundary-crossing relations because evidence is available on the association between knowledge sharing and transfer across organizational boundaries and a variety of desirable organizational outcomes (Argote, McEvily & Reagans, 2003; Burt, 2004). In this study, we clarify how organizational structure and formal relations of hierarchical subordination between individuals located in different organizational units interact with the emergent advice network to sustain knowledge transfer and sharing across intraorganizational boundaries. The study demonstrates how an explicit Bayesian reasoning applied to the statistical analysis of social networks contributes to a more complete understanding of the complex interdependence existing between hierarchical and social relations in organizations.

THEORETICAL BACKGROUND AND HYPOTHESES

Organizations and Social Networks

With a limited number of recent exceptions (Rank, Robins & Pattison, 2010) studies of social networks in organizations have implicitly treated participants as members of social groups, i.e., "Groups that are relatively small, informal and involve close personal ties" (Freeman, 1992:152).

This assumption typically leads to empirical studies of single interpersonal networks where organizational structure plays little or no role. Even the few studies examining multiple types of ties tend to focus almost exclusively on informal social relations (Lazega and Pattison, 1999 - but see Dahlander & McFarland (2009) for a partial exception).

The implicit tendency to consider organizations as informal social groups implies the empirically implausible assumption that informal relations in organizations are autonomous from the more formal elements that define organizations as structured social settings (Dokko et al., 2014). As McEvily, Soda, & Tortoriello (2014: 4) recently put it: “The surge in scholarly attention to informal social structure (…) has created a sort of amnesia about the role of formal elements in explaining the functioning, performance, and nature of organizations.” One consequence of this “amnesia” is that we can now rely on a detailed understanding of how, when and why social networks affect organizational outcomes such as innovation, knowledge transfer, product development, and innovative performance (Argote, McEvily, and Reagans, 2003; Hansen, 1999; Tortoriello & Krackhardt, 2010; Tsai, 2001; Tsai & Ghoshal, 1998). However, we still know relatively little about how organizations affect social networks and hence about how network in organizations differ from other kinds of social networks that have been extensively studied (Newman & Park, 2003). More specifically, we still know little about how formal relations of hierarchical dependence interact with informal social networks to shape knowledge sharing and transfer activities within organizations. Understanding and predicting the outcomes of this interaction is particularly important when knowledge and information have to be shared and transferred between organizational members who are both separated by administrative boundaries, as well as connected by relations of interpersonal subordination defined by corporate hierarchies linking individuals across different units. This is a common problem for matrix and multi-unit organizations similar to the one examined in this paper (Kleinbaum & Tushman, 2007; Nohria & Ghoshal, 1997).

Perhaps the most obvious implication of adopting organizations as settings for studying social relations is that formal hierarchical structures constrain interaction opportunities and frequency among organizational members (Marsden and Campbell, 1984). As we discuss in the next section this is particularly the case for social relations - such as advice relations - that are systematically associated with core processes of knowledge transfer, sharing and development within and across formal organizational boundaries.

Advice Relations in Organizations

Organizations routinely rely on their members' willingness and ability to mobilize their social capital for transferring capabilities (Zander and Kogut, 1995), sharing knowledge (Argote, Beckman, and Epple, 1990; Reagans and McEvily, 2003), diffusing best practices (Brown and Duguid, 2001), generating new ideas (Burt, 2004), and developing new products (Hansen, 1999). Advice relations play a central role in these and related cases where organizational participants expect to "get action" from their network partners (White, 1992).

Networks of task advice relations are generally understood as informal social conduits through which resources, knowledge and information flow within organizations (Podolny & Baron, 1997; Lazega, Mounier, Snijders & Tubaro, 2012; Nebus, 2006). In their phenomenology of advice, Cross, Borgatti & Parker (2001) argue that intra-organizational networks of advice relations are important as much as they are unavoidable because they relate directly to five fundamental organizational knowledge transfer and sharing activities. First, advice relations provide essential information relating to problems requiring integration of different kinds of knowledge and expertise. The presence of informal advice relations is not unusual because they are routinely activated during the course of regular organizational problem solving activities (Hansen, 2002). Second, advice relations provide meta-information about the location of relevant knowledge in organizations. Advice ties, therefore, produce richer and more complex information than the resolution of the problem at hand may require. Third, advice networks are not only the “pipes” through which material and symbolic resources flow, but also are also “prisms” that shape perception and meaning (Podolny, 2001). As a consequence, the network of advice relations in which organizational members are embedded affects their understanding of organizational activities and may help them to make sense of decision problems they face. Fourth, advice networks encourage exchange of opinions among individuals that may be working in different organizational units, divisions or functions (Argote, Beckman & Epple, 1990). Fifth, advice ties may help to garner legitimation and diffuse consensus for preferred solutions to contentious organizational issues (McDonalds & Westphtal, 2003).

The various organizational activities that advice relations support and facilitate are common, but tend to become problematic when they involve knowledge transfer and sharing between individuals separated by boundaries defined around organizational subunits (Argote, 1999; Hargadon & Sutton, 1997; Tsai, 2001). Knowledge transfer relations across the boundaries of organizational subunits are problematic at least as they are important. Reagans & McEvily (2003), for example, find that the presence of connections to diverse knowledge pools (network range) facilitates knowledge transfer within organizations. Kleinbaum & Tushman (2007) suggest that social networks play an essential role in initiating cross-line-of-business relations that support innovation in multidivisional firms. According to Cohen & Levinthal (1990: 133) “Interactions across individuals who each possess diverse and different knowledge structures will augment the organization's capacity of making novel linkages and associations -innovating- beyond what any individuals can achieve."

At least four main families of factors contribute to the difficulty of establishing and sustaining crosscutting ties within organizations. The first is that shared membership in organizational subunits provides enhanced opportunities and stronger incentives to form within-unit ties. This is the case because organizational subunits provide common social foci, or social settings (Feld, 1981; Pattison & Robins, 2002) that encourage the development of familiarity (Hinds et al., 2000), supply a repertoire of shared experiences (Marsden, 1988) and facilitate the shared interpretation of past events (March & Olsen, 1975). The second family of factors is related to the explicit objective of organizational design to confine major interdependences within purpose-built subunits (Thompson, 1967). The fragmentation of knowledge inherent in the successful implementation of organizational design solutions is systematically reinforced by staffing practices and internal resource allocation mechanisms (Dokko et al., 2014; Reagans & Zuckerman, 2001) that crystallize the boundaries of subunits and decrease their permeability to processes of assimilation and integration of heterogeneous resources (Tortoriello & Krackhardt, 2010). Third - and directly connected to the second - information and ideas are harder to exchange and integrate when the parties involved do not share a common knowledge base, or language (Reagans & McEvily, 2003; Tortoriello, Reagan & McEvily, 2012). Consequently, organizational units may experience considerable difficulty in understanding and absorbing knowledge and ideas generated elsewhere within the organization (Cohen & Levinthal, 1990). Finally, the fourth family of factors is inherent in the cost of supporting relations across boundaries. Hansen (1999) argues that such costs are induced by the time needed to cultivate relations across subunits and the attention necessary to process information generated in different and distant units. This subjective element of cost reduces further the permeability of subunit boundaries to knowledge and information that might be available in other subunits. Our first hypothesis summarizes this discussion, and provides the baseline for the predictions we develop next:

> *Hypothesis 1* (H1)*: Advice relations are more likely to be observed between members in the same organizational subunit than between members in different subunits.*

The image of organizations portrayed by Hypothesis 1 is that of a "cavemen world" described by Watts (1999: 102) where members live in dense isolated clusters (or "caves") of strong, frequent and redundant relations. Despite the clear-cut predictions implied by Hypothesis 1, organizations may be rarely decomposed into isolated caves: the formal boundaries of organizational units might contain the majority, but typically not all of the observed ties among their members (Cross & Cummings, 2003). As Brass et al. put it (2004: 801): "Ties between people in different units are especially intriguing, because they create ties between organizational units (…). When two individual interact, they not only represent an interpersonal tie, but they also represent the groups of which they are members." As we have discussed, ties between people in different organizational units are intriguing not only because they connect separate units but because they involve costs, risks, and uncertain benefits. What make these "distant" ties possible? Our attempt to address this question emphasizes reciprocity as a conflict resolution device (Powell, 1990), and as uncertainty reduction strategy that may be adopted to alleviate the problems associated with the various forms of information asymmetries that we have identified (Uzzi, 1996). Like "trust," reciprocity may be viewed as a: "(…) policy for handling the freedom of other human agents'' (Dunn, 1988: 73).

In the specific case of the advice network, Cross et al. (2001) suggest that reciprocity in advice relations within organizations is consistent with the interpretation of advice as an expression of social solidarity, rather than status differences. But reciprocity in advice may be expected also on the basis of more "local" (i.e., dyadic) considerations. Paraphrasing Fehr and Gachter (2000) reciprocity in advice relations may be viewed as a form of "conditional kindness" whereby advice is given under the expectation that it will be received. In network terms, this kind of restricted exchange may be one mechanism behind the assortativity (or positive degree correlation) that - according to Newman and Park (2003) - is one of the distinctive characteristics of social networks

By creating expectations of repeated interaction within the organization, reciprocity supports joint problem solving activities and arrangements, promotes trust (Uzzi, 1997), improves the understanding of complex problems (Tortoriello & Krackhardt, 2010), reduces the risk of opportunism (Coleman, 1988), and facilitates the transfer of private information and critical knowledge resources (Gulati et al., 2002). For these varied reasons, we would expect ties between individuals situated in different organizational units (distant ties) to be more likely if supported by general norms of reciprocity.

Hypothesis 2 (H2)*: Advice relations across of organizational subunits are more likely to be observed between reciprocating organizational members.*

Thus far, we have focused on reciprocity as a specific form of dyadic network dependence that may support knowledge sharing and transfer relations across organizational subunits boundaries. But reciprocity - a structural characteristic of social relations - is not the only factor that may affect cross cutting ties in organizations. More than anything else, organizations are hierarchical social systems explicitly designed to focus the attention of their members and shape their social interaction (March & Simon, 1958; Simon, 1962). How does the presence of hierarchical dependence affect the propensity of informal advice ties to share and exchange knowledge across the boundaries of organizational units? The limited number of available empirical studies (systematically and comprehensively reviewed in McEvily, Soda & Tortoriello (2014)) does not seem to offer a unique answer. Much seems to depend on how hierarchical dependence is actually represented (again see McEvily, Soda & Tortoriello, (2014: 18-19) on the different ways in which formal organization structure may be conceptualized).

In a study pre-dating much of current debate, Ibarra (1992) proposes a broad conceptual framework for articulating possible answers to our question. Her argument hinges on the well-established distinction between relations of formal hierarchical dependence (which she terms "prescribed") and formal social relations (which se terms "emergent"). She argues that the latter kind of relations are produced, in part, by the former as a natural consequence of the activities that interdependent individuals must perform to manage task uncertainty, make sense of their work experiences, and get work done. If this view of "formal" organizational structure as a possible source of social organization were correct, then we would expect the presence of interpersonal relations of hierarchical subordination to be positively associated with the presence of informal advice relations. Rank, Robins & Pattison (2010) find evidence in support of this conjecture in a recent empirical study of social networks between managers in two German multinational companies. According to this study, the presence of a hierarchical relation between two managers creates the setting for the development of informal social relations (Robins & Pattison, 2002). More specifically, Rank et al. (2010) find that the existence of a formal mandated cooperative tie between managers enhanced the probability that these managers actually exchanged information and advice. This result is generally supportive of Ibarra's (1992) conjecture about the (positive) association between hierarchical and social ties in organizations. Such association may be expected also because relations of hierarchical dependence tend to induce the need for activities of information search, knowledge identification and integration, opinion formation and diffusion, sense making, and consensus building. As we have discussed, these are precisely the organizational activities that - according to Cross et al. (2001) - are typically performed by social networks of advice relations. Extending this reasoning, we predict that advice relations will play a particularly important role in supporting interpersonal relations of hierarchical subordination across the boundaries of organizational units.

> *Hypothesis 3* (H3)*: Advice relations between individuals located in different organizational subunits are more likely to be observed between organizational members connected by formal relations of hierarchical subordination.*

Clearly, it may well be the case that, in certain circumstances, hierarchical relations subsume the functions of advice relations, thus making them unnecessary. Or it could be the case that cultural norms make advice relations between "bosses" and "subordinates" inappropriate or impossible outside the context of hierarchical subordination. These an other possibilities ultimately lead to new empirical questions that can be entertained only if "mandated" and "emergent" relations in organizations are represented jointly, and if hypotheses can be tested about the effect of their interaction. This is precisely what we do in the empirical part of the paper.

RESEARCH DESIGN

Empirical Setting

The empirical part of the study is based on original fieldwork and data that we have collected on relations among members of the top management team and corporate consultants in an international multi-unit industrial group. The effectiveness of multi-unit organizations hinges crucially on their ability to facilitate information sharing, knowledge transfer, relational coordination, and mobilization of dispersed human resources across units separated by formal organizational boundaries (Barlett & Ghoshal, 1989; Hansen, 2002; Tsai, 2001). For this reason, understanding social networks is of considerable importance for understanding how multi-unit organizations can be managed effectively (Nohria & Ghoshal, 1997).

The corporate group selected for study includes five separate, quasi-independent companies involved in the design, manufacturing and sale of high quality products in the global market for leisure motor yachts. The central company in the group plays the double role of independent company and corporate headquarters for the whole group. In external corporate communications membership of the companies in the corporate group is not hidden, but the companies are presented as independent, each with its distinct organizational and product identity, target market segment, customer base, dealer network, and management.

Sample and Data

We started our study by asking the President and the CEO of the group to examine the corporate organizational chart and identify the individuals they considered members of the "top management" team. We arrived at a list of 47 people distributed across the five different companies. Five individuals in the list were corporate consultants working in internationally prominent yacht design and architecture firms. Following the CEO's suggestion, they are included in the sample because of their direct personal involvement in important product design and development decisions. We collected relational and demographic information by means of a questionnaire personally and individually administered to all the 47 top managers in the group (including the five consultants). Examples of demographic information collected include individual educational experience, age, professional experience, formal status, and membership in functional groups and in organizational functions. The research team visited each company. During the data collection the research team spent considerable amount of time in close contact with the management of each of the five companies in the group. The response rate was 100%.

We focus on task advice relations because extant research has demonstrated that advice ties provide a meaningful basis for understanding important aspects of knowledge sharing and knowledge transfer in organizations (Podolny & Baron, 1997). While almost completely independent, the subsidiary companies in the group share frequently at least three kinds of information: technical, commercial and accounting. Sharing technical information involves discussions among the engineers in different subsidiaries about the possibility of standardizing phases of the production process, or aspects of boat design. Sharing commercial information involves, for example, cross-line-of-business discussions within marketing and sales about the trustworthiness of specific dealers, or about the value of potential customers. Sharing accounting information was obviously necessary because of the common requirements imposed by the need to establish and control transfer pricing policies, and consolidate the organization-specific accounting systems at the corporate level. More generally, sharing information through advice relations between managers in different subsidiaries is facilitated by the small degree of overlap in the market segments covered by the individual subsidiaries.

As it is common in research on interpersonal relations within organizations, we collected information on social networks among managers using the so-called roster method (Kilduff & Krackhardt, 2008). Each respondent was presented with a list containing the names of the other 46 individuals in the sample arranged in alphabetical order, and asked to indicate the existence of help and advice relations with each of them. The structured questionnaire was administered personally and individually to each manager. Interviewers, however, also prepared a list of concrete “questions and problems” that would help to root “advice relations” more firmly in the specific business and organizational context. Examples of issues included the evaluation of potential customers, pricing, and flexibility with terms of payment, production delays, and the relation between production costs of product customization. The advice network may be represented as a

47 × 47 binary adjacency matrix recording the presence or absence of advice relations for each possible pairs of individuals in the sample. The advice activity observed is relatively intense: on average, every manager entertains approximately 10 advice ties. Approximately 25% of all the advice ties observed are reciprocated.

To test our hypothesis that knowledge transfer across organizational units is facilitated by the presence of relation hierarchical subordination (H3), we also collected information on the formal organizational hierarchy in the form of formal interpersonal hierarchy of boss-subordinate relations at the dyadic level. For example, the managers responsible for Marketing and Sales working in individual subsidiary companies within the group all reported to the Corporate Vice-President for Marketing and Sales. Information on the network of official interpersonal hierarchical relations was provided directly by the CEO of the group during a series of interviews.

Model Specification

To link our arguments to appropriate statistical models, we consider each potential network tie between organizational members as a random variable. By considering each individual network tie as a random variable, we link our data structure directly to a class of Exponential Random Graphs Models (ERGM) (Snijders, Pattison, Robins, and Handcock, 2006; Wasserman and Pattison, 1996; Robins, Pattison and Wang, 2009).

Exponential Random Graph models assume that the topological structure of an observed network *y* can be explained in terms of the relative prevalence of a set of overlapping subgraph configurations *s(y)* called graph or network statistics (see Robins, Snijders, Wang, Handcock & Pattison, (2007) for a recent review). Each configuration is assumed to have a particular probability of being observed in the given network: the higher is the probability of being expressed in the graph, the higher is the chance of that statistic to occur and vice versa. The probability of a configuration being present in the network is expressed in terms of parameters or "effects." Configurations with a positive parameter value have a greater than chance probability of being observed in any graph represented by the model and vice versa. Configurations and parameters are at the core of ERGMs and, from a statistical point of view, the challenge is to estimate the parameters for each statistic such that the model is a good fit for the given data.

From a statistical point of view, networks are relational data that may be represented mathematically as graphs. A graph consists of a set of *n* nodes and a set of *m* ties that define some sort of relationships between pair of nodes called dyads. The connectivity pattern of a graph can be described by an $n \times n$ adjacency matrix *y* encoding the presence or absence of a tie between node *i* and *j*: $Y_{ij} = 1$ if the dyad (i, j) is connected, $Y_{ij} = 0$ otherwise. The likelihood of an ERGM represents the probability distribution of a random network graph and may be expressed as:

$$p(y \mid \theta) = \frac{\exp\left\{\theta^{t} s(y)\right\}}{z(\theta)}. \qquad (1)$$

This equation states that the probability that an observed graph *y* given the set of parameters *θ* is equal to the exponent of *θ* multiplied by the observed graph statistics *s(y)* divided by a normalizing constant *z(θ)* - a term by which the exponential function in the numerator must be multiplied so that the distribution defined in Equation 1 is a proper probability density function. In the ERGM context, the normalizing constant is calculated as the sum over all possible network graph configurations on *n* nodes (which are $2^{\binom{n}{2}}$ for undirected networks). This sum is therefore extremely difficult to evaluate in practice for networks with more than 20 nodes due to computational complexity. Standard inferential techniques cannot be used in this context.

The basic units for exponential random graph analysis are the subgraph configurations that are a subset of nodes and all the ties between them. Dyads and triads are important structures as they provide a local components - or “motifs” - underlying the entire network graph (Milo et al., 2002). In a directed network, for example, an important dyadic network measure is the density of ties and mutual ties between the actors. Dyadic analysis provides important information regarding the study of fundamental effects such as connectivity, popularity, reciprocity, and transitivity that are known to represent general features of social networks (Newman & Park, 2003). ERGMs are unique in that they allow accounting for structural features of social networks while at the same time providing an inferential framework to test hypotheses about how characteristics of the nodes affect network ties (Lusher, Koskinen & Robins, 2013). This specific feature makes ERGMs particularly useful in research in inter-organizational as well as inter-personal networks (Lomi and Pattison, 2006; Srivastava & Banaji, 2011).

Bayesian Models for Social Networks

The Bayesian approach to statistical inference - named after Reverend Thomas Bayes (1763) - is based on the estimation of posterior probability that is the conditional probability of unknown quantities given the observations. The posterior distribution extracts the information in the data and provides a complete summary of the uncertainty about the unknowns θ (Howson & Urbach, 1993). Prior knowledge about the parameters is summarized by the density $p(\theta)$, the likelihood is $p(y|\theta)$, and the updated knowledge is contained in the posterior density $p(\theta|y)$ as defined by the Bayes theorem:

$$p(q \mid y) = \frac{p(y \mid q)p(q)}{p(y)} \qquad (2)$$

The relative influence of the prior and data on updated beliefs *a posteriori* depends on how much weight is given to the prior (how ‘informative’ the prior is) and the strength of the data. The marginal likelihood or *model evidence* $p(y)$ is the probability of observing the data y given a specific model under study, i.e., the probability that the stochastic structure of the observed network data is explained by the specified model. Unfortunately, marginal likelihoods are generally difficult to compute and exact solutions are only known for a small class of distributions. Bayesian analysis has many advantages: provides rich diagnostic information about the unknown quantities, controlling for exploration of prior assumptions about model parameters. Bayesian inference uses probability intervals (quantile-based highest posterior density) called credible intervals to state the probability that the parameter is between two points. Classical - or "frequentist" approaches are not able to predict that the true value of the parameter has a particular probability of being in the estimated confidence interval given the data actually obtained. In summary, the three steps of Bayesian inference may be summarized as follows: (i) specify a probability model for unknown parameter values that includes some prior knowledge about the parameters; (ii) update knowledge about the unknown parameters by conditioning this probability model on observed data, and (iii) evaluate the fit of the model to the data and the sensitivity of the conclusions to the assumptions. The purpose of Bayesian inference for ERGMs (Koskinen, Robins & Pattison, 2010) is to learn about the posterior distribution (Equation 2) of the ERGM parameters θ of an observed network graph y on n nodes:

$$p(\theta \mid y) = \frac{\exp\left\{\theta^t s(y)\right\}}{z(\theta)} \frac{p(\theta)}{p(y)} \tag{3}$$

Equation 3 provides a probabilistic statement about how likely parameter values are after observing the data y. The likelihood $p(y|\theta)$ is translated into a proper probability distribution that can be summarised by computing expected values, standard deviations, quantiles). In order to carry out Bayesian inference for ERGMs, we make use of the approximate exchange algorithm that circumvents the problem of computing the normalizing constants of the ERGM likelihoods (Caimo

& Friel, 2011). This analysis has been carried out (and may be replicated) using the freely available Bergm package for R (Caimo & Friel, 2013). In this paper we use vague prior distributions (i.e., densities with high spread) for all the ERGM parameters namely Gaussian distributions with mean 0 and large variance (100) in order to allow the network data to drive inference. The reason for this choice is to ensure that the results produced by our Bayesian approach will not be excessively influenced by the choice of the prior distribution so that they can be compared to classical ("frequentist") results.

Variables and Measures

We specify and estimate models that express the probability of observing a network tie between two individuals as a function of (i) membership in various organizational units ("companies"); (ii) individual characteristics, and (iii) characteristics of the advice network constructed by the social interactions of the managers. Table 1 reports the description of each network statistics that we compute in order to model the observed network. The parameter of main theoretical interest is associated with joint membership in the various firms within the corporate group.

Insert Table 1 about here

We want to arrive at a characterization of the effects that joint membership has on the propensity to constrain knowledge-sharing relations within the units. In our empirical model specifications we also control for a number of known effects of individual differences on individual propensities to create network ties. More specifically we control for difference between the members of our organization observed in terms of: (i) *Same gender* (statistic s_7); (ii) *Subunit Membership* (statistic s_8); (iii) *Same nationality* (statistic s_9); (iv) *Same location* (statistic s_{10}); (v) *Some prior experience* (statistic s_{11}); and (vi) *Same function* (statistic s_{12}).

Participants are distributed across 5 organizational subunits. In the sample, 85.1% of the managers are males, 87.2% are Italian (approximately 66% of the overall productive capacity of the group is concentrated in Italy), and the average number of years of prior experience in the group was approximately 8 years. Approximately 38% of the participants worked in production and engineering, 15% in finance and accounting, and 10% in marketing. The remaining participants were members of smaller professional families represented within the group. Together, these potential sources of homophily control for the main individual factors that may affect the tendency of knowledge flows in organizations to be contained within intra-organizational boundaries (McPherson, Smith-Lovin & Cook, 2001). Rivera, Sodestrom & Uzzi (2010) provide a comprehensive review of the literature on homophily as a basis for the formation of dyadic social relations.

Following established empirical ERG modelling practice (Srivastava & Banaji, 2011), characteristics of the advice networks that we explicitly represent in our model include the baseline tendency of social networks toward reciprocity (statistics s_2, s_3, s_6); centralization (statistics s_{13}, s_{14}); multiple connectivity (statistic s_{15}); and clustering (statistic s_{16}). Centralization is often the result of preferential attachment processes, and is associated with differential propensities to be the source, or target, of particular types of ties leading to star-like local configurations. Because the number of network "stars" is a function of the degrees, including parameters corresponding to star-like configurations is equivalent to modelling the degree distribution (Snjiders, Pattison, Robins & Handcock, 2006). We capture core features of the (in and out) degree distributions by controlling for heterogeneity in relational activities revealed by differences in the propensity of individuals to be selected as partner by many others (popularity effect described by s_{13}) and in the propensity of individuals to select multiple others as partners (activity effect described by s_{14}).

Clustering (multiple closure effect described by s_{16}) will occur in a social structure where the individuals tend to collaborate in small informal groups with team-like structures. Tendencies toward closure that may be present in the data are captured by: (i) (generalized) cyclic closure where cycles of three arcs tend to be present in the network; and (ii) a generalized effect for transitive closure, where different types of transitive triads tend to be present in the network. The rationale behind various forms of triadic closure is discussed in Robins, Pattison, and Wang (2009). As a counterpart to the various mechanisms of triadic closure, we also include a parameter for non-closure (multiple connectivity effect described by s_{15}) where two actors are connected by multiple open 2-paths, an effect we call multiple connectivity. Multiple connectivity effects may indicate the presence of many opportunities for brokerage in the network (Burt, 2005). As explained in Robins, Pattison & Wang (2009), inclusion of a multiple connectivity parameter sharpens inferences about the presence of closure in the network. Again, it may be worth noting that multiple connectivity implies the presence of extra-triadic dependencies in the data.

Our empirical analysis is based on two models: Model 1 includes the first twelve statistics defined in Table 1. This is called a “dyadic independence” model meaning that the statistics included in the model consider each dyad of the network independent of the others. Model 2 includes all the statistics of Model 1 plus four “endogenous” network statistics (s_{13}, s_{14}, s_{15}, s_{16}) that relax the dyadic independence assumption underlying Model 1 as they concern relations between 3 or more nodes of the network.

Model Estimation and Interpretation

The main objective of Bayesian inference is the estimation of the posterior parameter distribution. This probability distribution provides information about the parameters after observing the data. We can then calculate the credible intervals of the estimated posterior distribution for each parameter. For a given significance level (that is generally set to 0.95), credible intervals represent the range of values that are likely to be taken by the parameters of a model given the data we have observed. In other words, credible intervals are constructed so that the probability of a certain parameter to take value within the interval (marked by the 2.5% quantile and 97.5% quantile of the posterior distribution) is 0.95. Credible intervals and posterior means are quantities describing the impact of the effects included in the ERGM and can take into account the model-specific information provided by the prior distribution. The value of an ERGM parameter offers an indication on whether a certain relational effects (expressed by the network statistics) are more or less frequent than expected by chance. This means that, for example, a credible interval for a certain parameter that includes only positive values indicates that the effect (or statistics) associated to that parameter is common in the observed network. Moreover, given the posterior distribution, it is possible to calculate the posterior correlation between the parameters in order to get additional insights about the statistical dependence between the estimated variables. The possibility of calculating correlations among the parameters is a unique feature of a Bayesian approach according to which "parameters" are "variables."

Unfortunately, the posterior distribution (Equation 3), as discussed above, is "doubly-intractable" since both the likelihood normalizing constant $z(\theta)$ and model evidence $p(y)$ cannot be evaluated analytically. This makes the use of standard inferential algorithms (such as naïve MCMC algorithms used in ERGMs) infeasible. In order to carry out Bayesian inference for ERGMs, we rely on the approximate exchange algorithm that circumvents the problem of computing the normalizing constant of the ERGM likelihood (Caimo & Friel, 2011). From the posterior density estimates it is possible to calculate the posterior correlation matrix between each pair of parameters. This correlation helps to understand the statistical dependence between the parameters of the model. Because in Bayesian analysis, parameters are themselves variables, the posterior correlation matrix provides further information concerning the uncertainty about the dependence between network effects included in the model.

ANALYSIS

Results

The figures reported in Table 2 and Table 3 shows that both models provide evidence of a strongly negative density effect (parameter $\theta_1$associated to *Number of ties*). This result is consistent with the relatively low density of the advice network, and with the fact that advice ties are costly and hence relatively infrequent. It is important to notice that given the definition of the model in Equation 1, the value of an ERGM parameter represents the conditional log-odds of a tie. For example, the log-odds that a tie between two nodes will form in the network equal the parameter θ_1. This is equivalent to saying that the probability of a tie between any pair of nodes *i* and *j* (having fixed all the other parameters values) is $p\left(y_{ij}=1\middle|\theta_1\right)=\frac{\exp(\theta_1)}{1+\exp(\theta_1)}$. If $\theta_1 < 0$, the probability of observing a tie $p\left(y_{ij}=1\middle|\theta_1\right)<0.5$. Vice versa, if $\theta_1 > 0$, then $p\left(y_{ij}=1\middle|\theta_1\right)>0.5$. In Model 1 (Table 2) we obtained a negative credible interval for *Ties* (θ_1 : -3.44, -2.26) meaning that - all other conditions being equal - the probability of observing an advice tie varies between 0.03 and 0.09.

Positive credible intervals are obtained for *Reciprocity* (θ_2: 0.98, 2.07), *Reciprocity - different membership + hierarchy* (θ_3: 0.48, 4.60), *Subunit Membership* (θ_8: 0.78, 1.87), *Same location* (θ_{10}: 0.07, 0.99), and *Same function* (θ_{12}: 0.04, 0.86). The posterior distributions of the effects *Same gender (θ_7), Same nationality (θ_9),* and *Same prior experience (θ_{11})* lace a significant amount of probability to 0 (as 0 falls inside their credible intervals) meaning that with significant probability the network effects associated to these parameters are not less or more frequent than what would be expected by chance. In a non-Bayesian statistical framework these effects would be declared not statistically significant.

In terms of our hypotheses, estimates of *Subunit Membership* (θ_8) provide clear support for Hypothesis 1 (H1): sharing knowledge by establishing advice relations is much more likely to be observed between managers within, rather than across organizational units. More specifically, ties between members of the same subsidiary unit are 3.2 times more likely to be observed than ties between managers in different subsidiary units. The results obtained also suggest that reciprocity (expressed by θ_2) is an important general feature of the network - but not between members of the same groups (expressed by θ_6). This result deserves attention because it reveals a tendency toward hierarchization of the advice network within the units. Considered together, the estimates of θ_2 and θ_6 provide clear support for Hypothesis 2 (H2): reciprocity is an important feature of knowledge sharing relations between members of different organizational units - over and above a generic tendency toward reciprocity. Hypothesis 3 (H3) is also supported: members of different organizational units are more likely to be connected by reciprocated advice relations if they are also connected by formal relations of hierarchical subordination. The corresponding effect of *Reciprocity - Different Membership + hierarchy* is expressed by parameter θ_3. This parameter captures the joint effect on the presence of network ties between managers of having a reciprocated advice relations (*Reciprocity*), being in different subsidiary units (*Different membership*), and being connected by hierarchical dependence (*Hierarchy*).

As a robustness check, we distinguish further between "sending" an advice tie - or asking advice *(θ_4)*, across organizational boundaries, and being asked for advice *(θ_5)*. The credible intervals for either parameter include zero, which means that the corresponding (directional) effects are indistinguishable from zero. In other words, managers connected by a relation of hierarchical subordination extending across organizational subunits are unlikely to established *directed* advice relations. Managers do not ask for advice to colleagues in different units (and neither are they being asked) unless the relation is reciprocated. We take this as further evidence of the fundamental importance of reciprocity in sustaining boundary-crossing ties within organizations - particularly under conditions of hierarchical dependence.

Insert Table 2 about here

In Model 2 (Table 3) the presence of the endogenous network effects has an important impact in explaining the overall network structure. In particular, parameters corresponding to *Multiple connectivity* (θ_{15}) and *Multiple closure* (θ_{16}) have a negative and positive credible interval, respectively. This means that a multiple closure effect is a common feature of the network structure: knowledge transfer relations tend to form through closure of multiple triads simultaneously.

Insert Table 3 about here

The multiple connectivity effect is less common than it would be expected by chance: it is relatively unlikely to find triadic relations that are not closed at the base. More qualitatively, brokerage is a relatively uncommon feature of the knowledge sharing network that we have observed. The posterior density plots of the main effects of interests are displayed in Figure 1.

Insert Figure 1 about here

The inclusion of endogenous network statistics (Model 2) entails different estimates for the dyadic independent statistics. For instance, the credible interval for the parameter θ_1 in Model 2 is now (-7.81, -4.93). This estimate implies that the probability of observing a tie in model 2 is 0.002. The decrease in the probability of observing a tie from Model 1 to Model 2 is determined by the fact that - in the latter model - the structure of the network is well explained by the endogenous network effects. In other words, the presence of random ties not embedded in network subgraph configurations defined by the endogenous network statistics is comparatively less likely in Model 2. We can also notice that the credible interval for parameter θ_{10} *(Same location)* in Model 2 is now (-0.27, 0.82) placing a significant probability on 0. This means that the covariate effect *Same location* can be expressed through network ties involved in endogenous configurations. This result provides an important insight because it suggests that knowledge sharing in organizations is affected by social - rather than physical distance. Once social distance is properly accounted for, the effects of proximity on the presence of advice relations disappears. We note that out hypotheses continue to receive solid support after controlling for endogenous network structure (Model 2).

A unique aspect of our analysis that is specific to the Bayesian approach concerns the correlation between the estimated parameters. This information provides a better understanding of the structure of dependence existing between the various effects included in the model. The correlation matrix is computed on the estimated posterior distributions of the parameters. In Table 4 we can observe the correlations between the parameter estimates for Model 1. The strongest (negative) correlations are between θ_6 and θ_8 (-0.64) (representing, respectively, *Reciprocity* and *Subunit Membership*) and between θ_9 and θ_{10} (-0.60) (representing, respectively, *Same nationality* *and Same location*).

Insert Table 4 about here

In Table 5 we report the correlations between the parameter estimates for Model 2. In this case we note the presence of an additional strong negative correlation is between parameters θ_1 and θ_{16} (-0.87) meaning that the sign of the multiple closure effect depends is negatively on the density of the network. In other words, there is a tendency of establishing a few advice ties across the whole network. In spite of this, there is a considerable tendency of these ties to self-organise into clusters. This result suggest that the observed structure of the knowledge sharing network within the organization is driven more strongly by closure, rather than preferential attachment mechanisms. The credible intervals for the effects associated to *Popularity* (θ_{13}) and *Activity* (θ_{14}) contain zero. A possible interpretation of these estimates is that the advice network shows no significant tendency toward centralization in the in- and out-degree distribution. Asking and being asked for advice do not seem to be activities that are disproportionately accounted for by a limited number of members within the top management team.

Insert Table 5 about here

Goodness of Fit Diagnostic Analysis

An important contribution of this article is to show how a Bayesian approach to the analysis of advice networks in organizations reveals salient (global) aspects of network structure that alternative approaches are unable to discover. In the Bayesian approach that we develop to the evaluation of the model goodness of fit, the observed network *y* is compared to a set of networks simulated from the estimated model (i.e., the estimated posterior distributions obtained from the empirical parameter estimates). This comparison is carried out in terms of general distributions of network statistics in order to check how well the estimated model is able to reproduce networks resembling the general structural features of the observed network. Network statistics commonly used in the statistical analysis of social network to describe network structure include: (i) the in-degree distribution - the distribution of incoming ties for each node of a directed network; (ii) out-degree distribution - the distribution of outgoing ties for each node of a directed network; (iii) the minimum geodesic distance distribution - the distribution of the length of shortest path distance between two nodes, and (iv) the edgewise shared partner distribution - the distribution of the number of unordered pairs of connected nodes having exactly *k* common neighbors (Hunter, Goodreau, & Handcock 2008). The diagnostic goodness-of-fit analysis consists in comparing the goodness-of-fit distributions of the observed network with the set of goodness-of-fit distributions calculated on networks simulated from the estimated model.

Bayesian goodness-of-fit diagnostics plots are displayed in Figure 2 and Figure 3. The red lines represent the goodness-of-fit distributions of the observed data. The boxplots represent the goodness-of-fit distributions calculated on 100 network graphs simulated from the estimated posterior distribution. In other words, a sample of 100 parameter values is drawn from the estimated posterior distribution and then one network graph is simulated from each of the 100 parameters of the posterior sample drawn. The solid light grey lines displayed in Figure 2 and Figure 3 mark the 95% interval. An estimated model is fitting perfectly a certain observed network if the red line falls inside this interval - a result that is very difficult to obtain in practice.

Insert Figure 2 about here

Model 2 does a much better job than Model 1 at fitting the observed network. This is particularly clear when we compare the fit of the two models in terms of the minimum geodesic distance distribution and edgewise shared partners distribution: the red line in Figure 3 (Model 2) is almost always inside the 95% interval whereas in Figure 2 (Model 1) the red line falls outside the 95% interval for many network statistics. As a numerical basis for the evaluation of the goodness of fit of the two models we count the number of observed network statistics (red line) that are falling outside the 95% interval (grey lines). The lower the number of outliers, the better the model fit. Figure 2 (Model 1) illustrates that the number of statistics of the observed network falling outside the 95% interval is: 7 for the in-degree distribution, 6 for the out-degree distribution, 2 for the minimum geodesic distance distribution, and 17 for the edge-wise shared partners distribution.

Insert Figure 3 about here

Figure 3 (Model 2) shows that the number of statistics of the observed network falling outside the 95% interval is considerably lower: 3 for the in-degree distribution, 1 for the out-degree distribution, 0 for the minimum geodesic distance distribution, and 4 for the edge-wise shared partners distribution. The better fit of Model 2 to high-level transitivity measures (described by the edgewise shared partner distribution) is due to the presence of the endogenous network statistics s_{13}, s_{14}, s_{15}, s_{16} that are included in the model. In more general terms, the results of the goodness of fit diagnostic analysis that we have reported demonstrate that the estimates of Model 2 support our hypotheses and allow us to reconstruct with accuracy important structural features of the global network of knowledge sharing and transfer relations that we actually observed.

DISCUSSION AND CONCLUSIONS

We started this paper by calling attention on the role that formal hierarchical structure plays in our understanding of social networks in organizations. We observed that unlike social groups that are small, informal and based on close and personally selected ties (Freeman, 1992: 1152), groups in organizations are shaped by formal elements of a structural context that tend to aggregate - and occasionally segregate participants around exogenously defined social foci (Feld, 1981). Social selection decisions in organizational settings are typically constrained by design.

We argued that studies of social networks in organizations have largely ignored precisely what makes organizational settings valuable for studying social relations. This is surprising given that the understanding of organizations as meaningful settings for the development of social relations is one of the most enduring insights of classic organizational research (Roethlisberger & Dickson, 1939). We have argued, further, that our current understanding of the "company behind the chart" is bound to remain incomplete without explicit recognition of the role played by the "chart" itself. We developed and tested hypotheses that relate structural organizational characteristics (H1), endogenous dyadic dependence between network ties (H2), and formal relations of hierarchical subordination (H3) to the propensity of interpersonal advice ties to cross the boundaries of organizational units. We focused on boundary crossing relations because of their well-documented implications for organizational innovative performance (Burt, 2004; Reagans & McEvily, 2003; Reagans, & Zuckerman, 2001). We identified the network of interpersonal task advice relations as a fundamental element in the social infrastructure that supports collaborative knowledge transfer and sharing in organizations (Cross et al., 2001; 2002).

We found that despite the strong tendency of subsidiary units to constrain ties within their boundaries (H1), knowledge sharing relations are more likely to be established across organizational subunits when they are reciprocated (H2). We also found that informal knowledge sharing relations across organizational subunits tend to co-occur with mutual relations of interpersonal hierarchical subordination (H3). The results reported were robust to alternative model specifications taking into account salient structural features of the global knowledge sharing network, and individual characteristics of the managers. In more general terms, we found that formal organizational structure both constrains (H1), as well as enables (H3) social organization. Formal structure provides boundaries that tend to be impermeable to informal social relations. This is consistent with the view of organizational units as social foci, or “social, psychological, legal or physical entity around which joint activities are organized” (Feld, 1981: 1016). At the same time, interpersonal relations of hierarchical subordination crosscutting organizational units create the setting for the development of informal social relations. We think that this result bears important implications for future research on social networks and knowledge transfer in organizations. The majority of available studies tends to reduce the representation of formal organization to a control factor - typically taking the form of a variable indexing membership in discrete, non-overlapping units (McEvily et al., 2014). We adopted this analytical representation, but we also went beyond it by incorporating much more detailed and precise information on formal structure - itself considered as a network of dyadic relations of hierarchical subordination. With the partial exception of Rank et al. (2010) we are not aware of other studies based on a similarly accurate reconstruction of the microstructure of hierarchical relations. We believe that future studies should start from the recognition that no social network within organization may be analyzed in isolation, independent of the mandated network encoding information on relations of hierarchical subordination. How independent informal social relations are from relations of formal hierarchical dependence in organizations is something that future empirical research building on our work will have to ascertain.

We also found that the advice network is characterized by a strong baseline level of reciprocity. This is not surprising as the importance of reciprocity in social exchange relations has long been acknowledged, theorized and documented (Gouldner 1960). What our study adds is the result that reciprocity supports advice relations across organizational subunits, but not within. By identifying different components of reciprocity, we were able to document how reciprocity operates to support cross cutting knowledge sharing and transfer relations within organizations (H2). We found that self-organizing tendencies toward reciprocation interact with formal structure to offset the natural tendency of organizations to resemble caveman worlds (Watts, 1999).

We believe our study bears equally significant methodological implications that future research should carry forward. We adopted Bayesian Exponential Random Graph Models to estimate the parameters of theoretical interest while at the same time using the empirical estimates to simulate a distribution of potential networks that we used to assess the capacity of the model to reproduce the observed data. The Bayesian approach that we implemented supports a fully probabilistic treatment of model uncertainty by treating the parameters of Exponential Random Graph models as variables. The posterior correlation structure that we have computed provided valuable information about the dependence between model parameters. The novel Bayesian approach that we have implemented seems to be particularly well suited to the analysis of data characterized by complex dependencies - such as social network data. The credible intervals we reported are probabilistic intervals defining a range of values taken by parameters with a certain level of probability (generally 95%). In more conventional (“frequentist”) statistical framework the confidence interval means that after a large number of repeated samples, a certain proportion of intervals (generally 95%) would include the true value of the parameter so that for each sample the probability that the parameter is contained in a given interval is either 0 or 1.

In the context of this concluding discussion, it seems appropriate to call attention on at least three main limitations of our current work that suggest caution in the interpretation of our results, but also indicate clear directions for future research. First, the results that we have reported are based on a cross-sectional research design that precludes strong causal conclusions. While, at present, this represents an obvious limitation of our study, we are aware that current attempts to provide longitudinal extensions of the models we have adopted in this paper may soon make available to the organizational research community more general dynamic models that may be implemented to alleviate this problem (Koskinen and Lomi, 2013). Second, because the organization we selected for study has a number of unique features, it is important to be cautious in generalizing our results. Replication may be difficult in other kind of companies with different hierarchical structures. Results may also be different for studies that - unlike the present - are conducted on full organizations that include not only top managers, but also other organizational members distributed across a broader range of employment categories. In such cases it is probably reasonable to expect that hierarchy will have a more differentiated and nuanced effect on social organization. The ambition of the case study we have presented, however, was not to arrive at conclusions generalizable across diverse organizational settings. Rather, our purpose was to document and clarify the conditions under which formal and social structure jointly affect knowledge sharing and transfer across intraorganizational boundaries. Third, we reconstructed formal relations of hierarchical dependence as a dyadic relation between individuals. While this strategy was probably appropriate in our empirical context, formal relations of hierarchical dependence are frequently defined among organizational subunits – rather than individuals.

Examples of such relations include functional dependencies defined by technology, or workflow (Thompson, 1967). When this is the case, models for multilevel networks would be better suited to capture the interdependence between formal and informal relations in organizations (Wang et al. 2013).

In closing, it may be useful to return to Granovetter's influential statement according to which (1985:482): "The behavior and institutions to be analyzed are so constrained by ongoing social relations that to construe them as independent is a grievous misunderstanding." The importance and generality of this insight is hard to overstate. In this paper we carried it several steps farther by showing how social relations are shaped by the organizational and institutional settings that they contribute to create.

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Table 1

Description of the Network Statistics Used in the Models Proposed

Statistic (Effect)	Description	Interpretation
s_1 (Ties)	number of ties in the network	overall density of ties
s_2 (Reciprocity)	number of mutual ties y_{ij}, y_{ji}	overall density of mutual ties
s_3 (Reciprocity - different membership+hierarchy)	number of mutual ties y_{ij}, y_{ji}, for which membership(i) ≠ membership(j) and i reports to j	density of mutual ties between nodes with hierarchical relations and same membership
s_4 (Sender - different membership + hierarchy)	number of out-ties for which membership(i) ≠ membership(j) and i reports to j	activity of the nodes with hierarchical relations and same membership
s_5 (Receiver - different membership + hierarchy)	number of in-ties for which membership(i) ≠ membership(j) and i reports to j	popularity of the nodes with hierarchical relations and same membership
s_6 (Reciprocity - Sub-unit Membership)	number of mutual ties y_{ij}, y_{ji}, for which membership(i) = membership(j)	density of mutual ties between nodes with same membership
s_7 (Same gender)	number of ties y_{ij}, for which gender(i) = gender(j)	density of ties between nodes with same gender
s_8 (Homophily - Sub-unit Membership)	number of ties y_{ij}, for which membership(i) = membership(j)	density of ties between nodes with same membership
s_9 (Same nationality)	number of mutual ties y_{ij}, y_{ji}, for which nationality(i) = nationality(j)	density of ties between nodes with same nationality
s_{10} (Same location)	number of ties y_{ij}, for which location(i) = location(j)	density of ties between nodes with same location
s_{11} (Same prior experience)	number of ties y_{ij}, for which experience(i) = experience(j)	density of ties between nodes with same experience
s_{12} (Same function)	number of ties y_{ij}, for which function(i) = function(j)	density of ties between nodes with same function
s_{13} (Popularity)	geometrically weighted in-degree distribution with weight parameter set to log(2)	tendency towards centralisation in in-degree distribution
s_{14} (Activity)	geometrically weighted out-degree distribution with weight parameter set to log(2)	tendency towards centralisation in out-degree distribution
s_{15} (Multiple connectivity)	geometrically weighted nonedgewise shared partner distribution with weight parameter set to log(2)	tendency of non-directly-connected nodes to be connected through multiple others
s_{16} (Multiple closure - clustering)	geometrically weighted edgewise shared partner distribution with weight parameter set to log(2)	tendency to be connected through multiple triadic relations simultaneously

Table 2

Summary of the Posterior Distribution of the Parameters for Model 1

Parameter (Effect)	Mean	2.5% Quantile	Median	97.5% Quantile
θ_1 (Ties)	-2.84	-3.44	-2.83	-2.26
θ_2 (Reciprocity)	1.52	0.98	1.52	2.07
θ_3 (Reciprocity - different membership+hierarchy)	2.32	0.48	2.24	4.60
θ_4 (Sender - different membership+hierarchy)	1.27	-0.38	1.25	3.15
θ_5 (Receiver - different membership+hierarchy)	1.45	-0.18	1.41	3.39
θ_6 (Reciprocity - Sub-unit Membership)	-0.49	-1.45	-0.49	0.50
θ_7 (Same gender)	0.33	-0.04	0.33	0.72
θ_8 (Homophily - Sub-unit Membership)	1.30	0.78	1.30	1.87
θ_9 (Same nationality)	0.25	-0.29	0.25	0.78
θ_{10} (Same location)	0.53	0.07	0.53	0.99
θ_{11} (Same prior experience)	-0.14	-0.48	-0.14	0.21
θ_{12} (Same function)	0.45	0.04	0.45	0.86

Table 3

Summary of the Posterior Distribution of the Parameters for Model 2

Parameter (Effect)	Mean	2.5% Quantile	Median	97.5% Quantile
θ_1 (Ties)	-6.31	-7.81	-6.29	-4.93
θ_2 (Reciprocity)	0.87	0.18	0.86	1.61
θ_3 (Reciprocity - different membership+hierarchy)	2.77	0.33	2.71	5.50
θ_4 (Sender - different membership+hierarchy)	1.18	-0.83	1.12	3.51
θ_5 (Receiver - different membership+hierarchy)	1.67	-0.28	1.61	3.99
θ_6 (Reciprocity - Sub-unit Membership)	-0.30	-1.44	-0.31	0.81
θ_7 (Same gender)	0.22	-0.22	0.21	0.66
θ_8 (Homophily - Sub-unit Membership)	0.83	0.21	0.82	1.48
θ_9 (Same nationality)	0.18	-0.46	0.18	0.78
θ_{10} (Same location)	0.27	-0.27	0.27	0.82
θ_{11} (Same prior experience)	-0.03	-0.44	-0.03	0.40
θ_{12} (Same function)	0.51	0.04	0.51	1.02
θ_{13} (Popularity)	3.94	-0.29	3.76	9.16
θ_{14} (Activity)	1.70	-0.71	1.71	4.11
θ_{15} (Multiple connectivity)	-0.13	-0.19	-0.13	-0.06
θ_{16} (Multiple closure)	1.95	1.39	1.95	2.57

Table 4

Parameters Correlation Matrix for Model 1

	θ_1	θ_2	θ_3	θ_4	θ_5	θ_6	θ_7	θ_8	θ_9	θ_{10}	θ_{11}
θ_2	-0.19										
θ_3	-0.03	-0.04									
θ_4	-0.01	0.03	0.49								
θ_5	-0.02	0.01	0.59	0.37							
θ_6	0.20	-0.53	-0.05	0.06	0.05						
θ_7	-0.56	-0.04	0.01	-0.01	0.00	-0.03					
θ_8	-0.19	0.23	-0.06	-0.05	-0.09	-0.64	0.03				
θ_9	-0.52	0.03	-0.02	-0.02	0.00	-0.09	-0.04	0.15			
θ_{10}	0.01	-0.05	0.04	0.03	0.01	0.05	0.10	-0.25	-0.6		
θ_{11}	-0.47	0.02	0.03	-0.02	0.00	-0.07	0.10	0.05	0.2	-0.23	
θ_{12}	-0.21	-0.08	-0.06	-0.03	-0.03	0.01	0.07	0.08	0.04	0.02	-0.02

Table 5

Parameters Correlation Matrix for Model 2

	θ_1	θ_2	θ_3	θ_4	θ_5	θ_6	θ_7	θ_8	θ_9	θ_{10}	θ_{11}	θ_{12}	θ_{13}	θ_{14}	θ_{15}
θ_2	0.13														
θ_3	-0.01	-0.04													
θ_4	-0.01	0.05	0.48												
θ_5	-0.05	0.03	0.60	0.35											
θ_6	0.04	-0.55	-0.06	0.00	0.06										
θ_7	-0.24	-0.01	-0.01	0.00	0.01	-0.01									
θ_8	0.02	0.20	-0.08	-0.05	-0.11	-0.59	0.00								
θ_9	-0.24	0.03	-0.02	0.01	-0.03	-0.05	-0.04	0.10							
θ_{10}	-0.01	-0.02	0.03	0.02	0.06	0.02	0.12	-0.20	-0.63						
θ_{11}	-0.27	0.00	0.03	0.01	0.00	-0.03	0.13	0.02	0.17	-0.13					
θ_{12}	-0.15	-0.16	-0.03	-0.05	-0.05	0.06	0.00	0.03	0.01	0.01	0.00				
θ_{13}	-0.28	0.02	0.04	0.01	0.04	-0.04	-0.01	-0.03	0.09	0.00	-0.03	0.07			
θ_{14}	-0.46	-0.07	-0.09	-0.04	0.01	0.01	0.05	-0.15	0.02	0.02	-0.03	0.03	0.23		
θ_{15}	0.12	-0.06	-0.09	0.01	-0.06	0.05	-0.02	0.15	0.00	0.02	0.10	-0.05	-0.36	-0.44	
θ_{16}	-0.87	-0.24	0.02	-0.01	0.04	0.04	-0.02	-0.10	0.02	-0.02	0.02	0.09	0.25	0.51	-0.25

Figure 1

Posterior parameter distributions for the main effects under study in Model 2

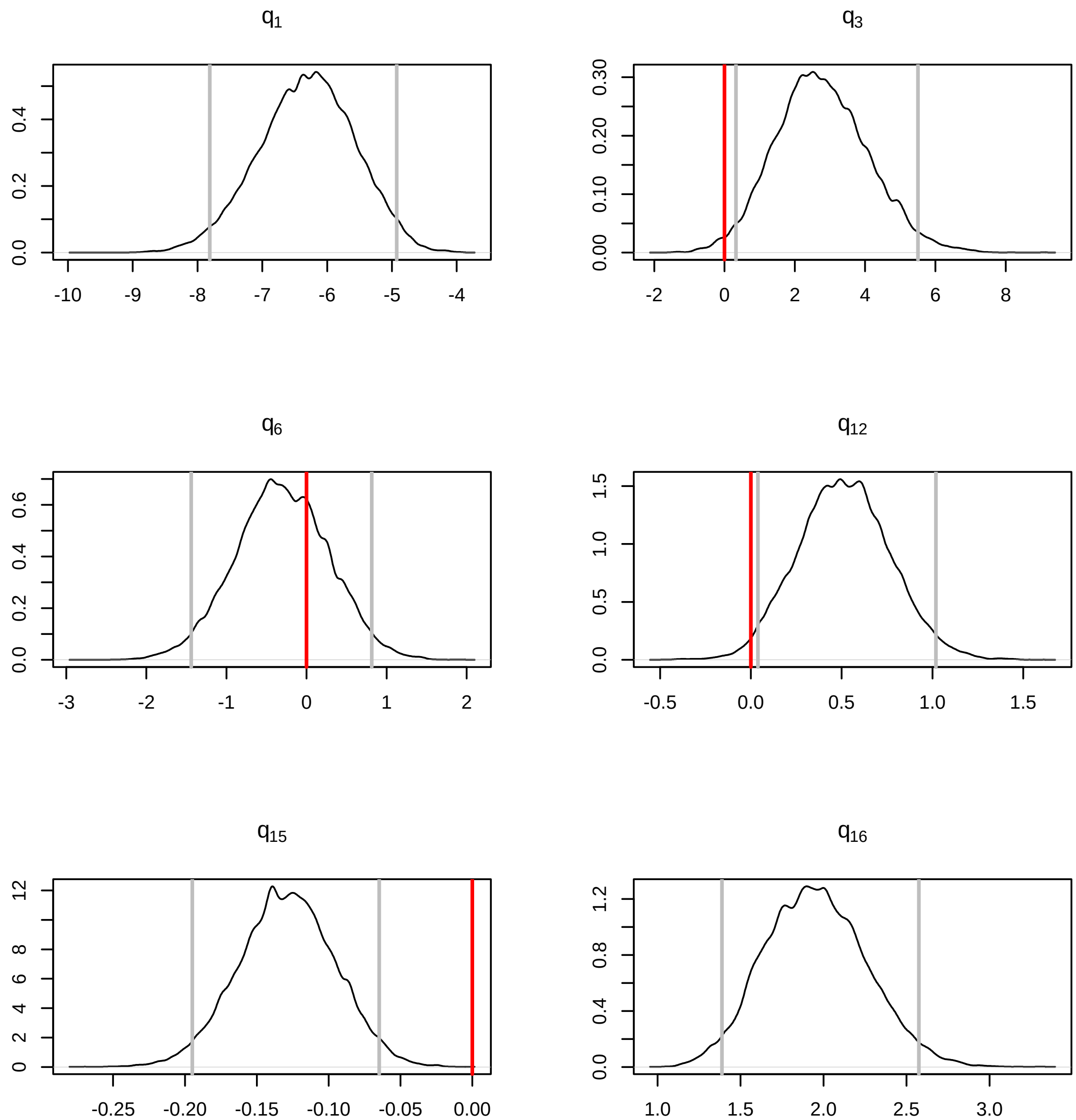


Figure 2

Bayesian Goodness-of-fit Diagnostics for Model 1

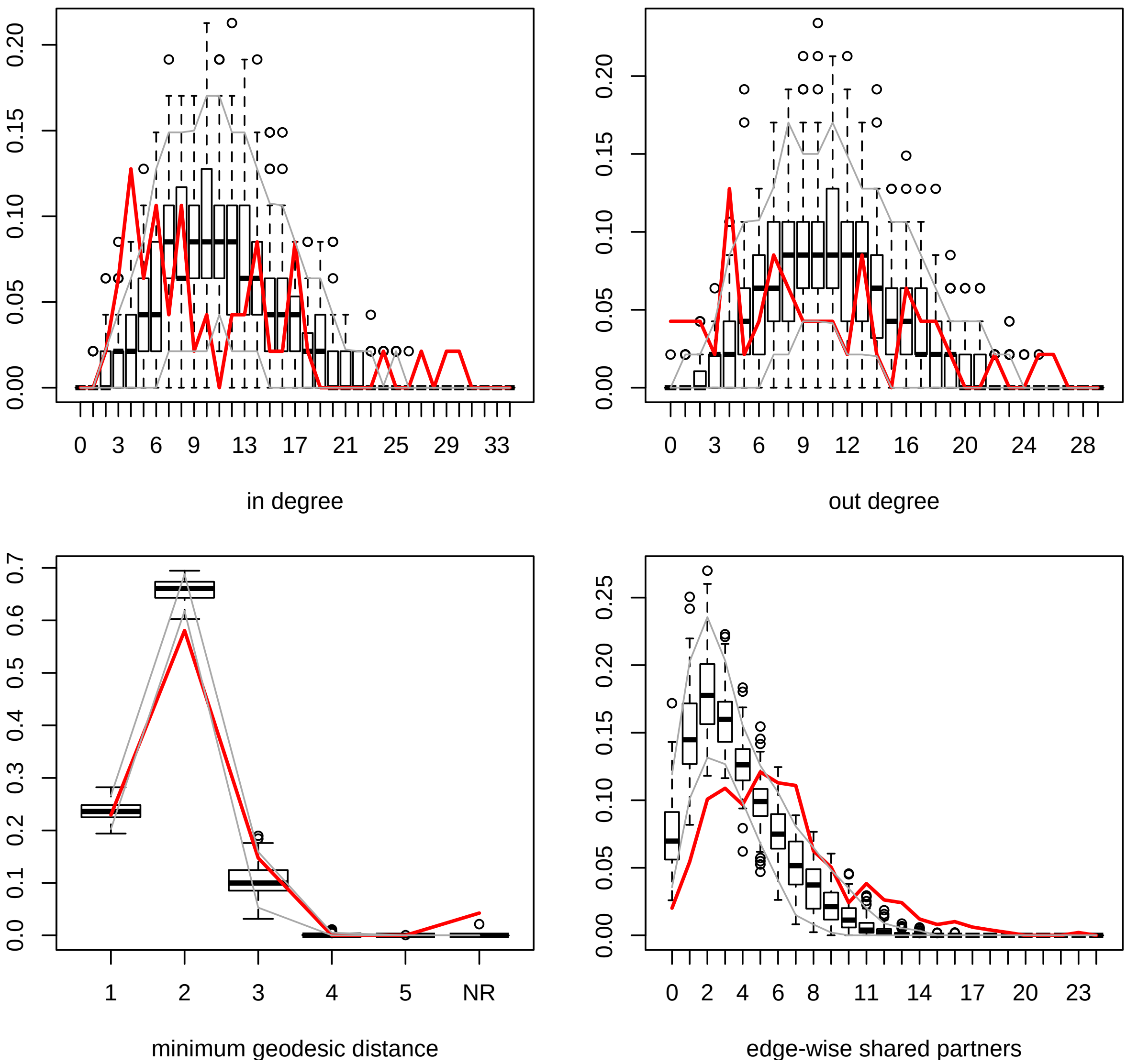
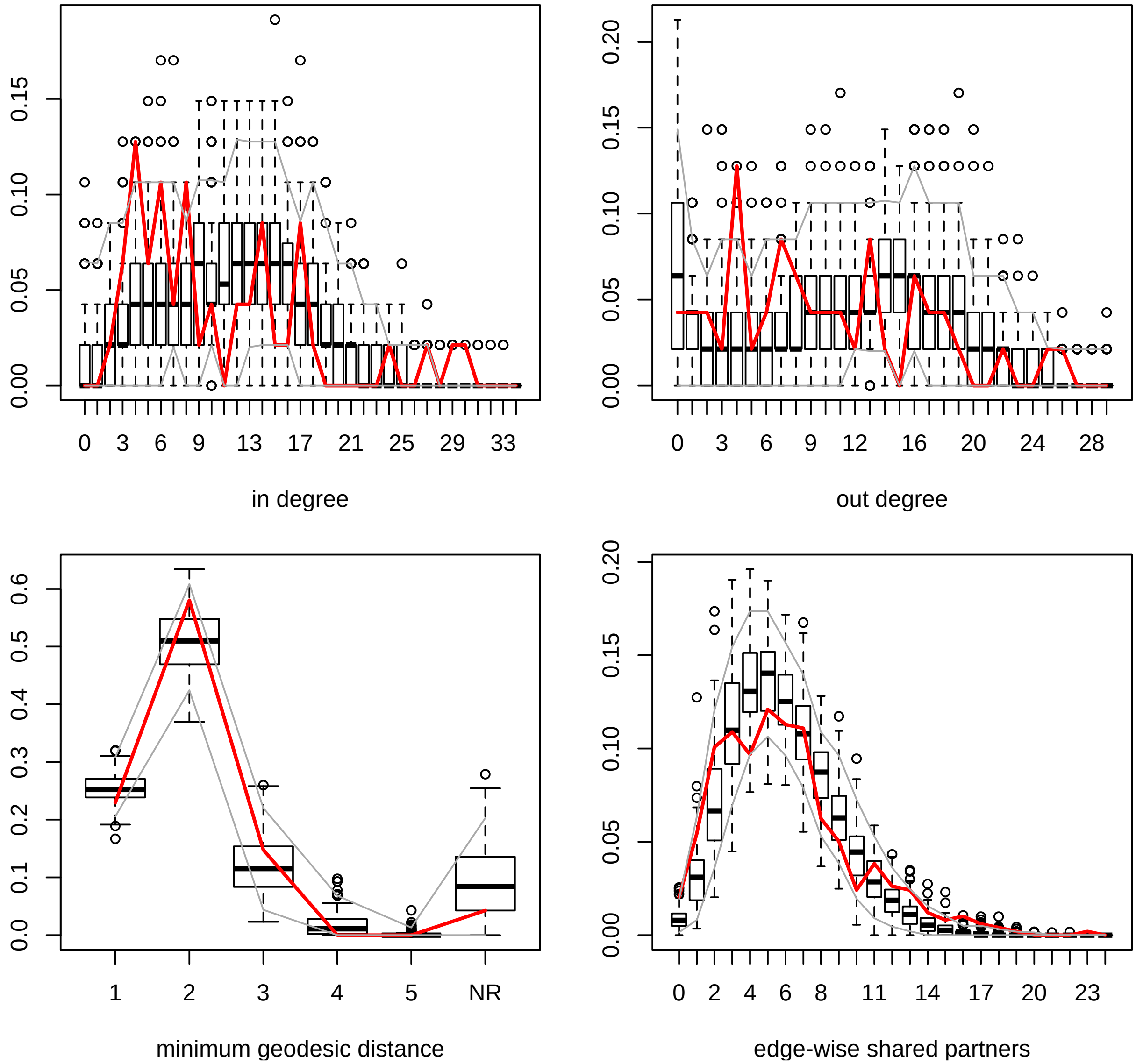


Figure 3

Bayesian Goodness-of-fit Diagnostics for Model 2



APPENDIX

Mathematical Definitions of the Network Statistics

The statistic s_{13} is defined as a function of $ID(y)$: *In-degree distribution*, distribution of the number of incoming ties for each node of a directed network; The statistic s_{14} is defined as a function of $OD(y)$: *Out-degree distribution*, distribution of the number of outcoming ties for each node of a directed network; The statistic s_{15} is defined as a function of $EP_i(y)$: *Edgewise shared partners distribution*, distribution of the number of unordered pairs of connected nodes having exactly *i* common neighbors; The statistic s_{16} is defined as a function of $NEP_i(y)$: *Non-edgewise shared partners distribution*, distribution of the number of unordered pairs of unconnected nodes having exactly *i* common neighbors.

Statistic (Effect)	Formula
s_1 (Ties)	$\sum_{i,j} y_{ij}$
s_2 (Reciprocity)	$\sum_{i,j} y_{ij}y_{ji}$
s_3 (Reciprocity - different membership+hierarchy)	$\sum_{i,j} y_{ij}y_{ji}\mathbf{1}(membership(i) \neq membership(j), i \xrightarrow{reports\ to} j)$
s_4 (Sender - different membership+hierarchy)	$\sum_{i,j} y_{ij}\mathbf{1}(membership(i) \neq membership(j), i \xrightarrow{reports\ to} j)$
s_5 (Receiver - different membership+hierarchy)	$\sum_{i,j} y_{ji}\mathbf{1}(membership(i) \neq membership(j), i \xrightarrow{reports\ to} j)$
s_6 (Reciprocity - Sub-unit Membership)	$\sum_{i,j} y_{ij}y_{ji}\mathbf{1}(membership(i) = membership(j))$
s_7 (Same gender)	$\sum_{i,j} y_{ij}y_{ji}\mathbf{1}(gender(i) = gender(j))$
s_8 (Homophily - Sub-unit Membership)	$\sum_{i,j} y_{ij}y_{ji}\mathbf{1}(membership(i) = membership(j))$
s_9 (Same nationality)	$\sum_{i,j} y_{ij}y_{ji}\mathbf{1}(nation(i) = nation(j))$
s_{10} (Same location)	$\sum_{i,j} y_{ij}y_{ji}\mathbf{1}(location(i) = location(j))$
s_{11} (Same prior experience)	$\sum_{i,j} y_{ij}y_{ji}\mathbf{1}(experience(i) = experience(j))$
s_{12} (Same function)	$\sum_{i,j} y_{ij}y_{ji}\mathbf{1}(function(i) = function(j))$
s_{13} (Popularity)	$e^{\log(2)} \sum_{i=1}^{n-1} \left\{1 - \left(1 - e^{-\log(2)}\right)^i\right\} ID_i(y)$ where $ID_i(y)$ is the the in-degree distribution.
s_{14} (Activity)	$e^{\log(2)} \sum_{i=1}^{n-1} \left\{1 - \left(1 - e^{-\log(2)}\right)^i\right\} OD_i(y)$ where $OD_i(y)$ is the out-degree distribution.
s_{15} (Multiple connectivity)	$e^{\log(2)} \sum_{i=1}^{n-2} \left\{1 - \left(1 - e^{-\log(2)}\right)^i\right\} NEP_i(y)$ where $NEP_i(y)$ is the non-edgewise shared partner distribution.
s_{16} (Multiple closure)	$e^{\log(2)} \sum_{i=1}^{n-2} \left\{1 - \left(1 - e^{-\log(2)}\right)^i\right\} EP_i(y)$ where $EP_i(y)$ is the edgewise shared partner distribution.